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ORIGINAL ARTICLE

Evaluation for Load Bearing Capacity of Each Layer of Pavement in Japan Expressway

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Abstract: An expressway manager in Japan (NEXCO-Nippon Expressway Company: the generic name of three expressway managing companies in Japan) conducts FWD survey to quantitatively evaluate the load bearing capacity of each layer of pavements. The load bearing capacity declines by traffic loads over time, and the declination is deeply related to structural and functional pavement soundness, therefore NEXCO regularly repairs the pavements of all around Japan considering the depth of repair so that the load bearing capacity recovers. Accordingly, it is desirable that it carry out a repair to the pavement layers which recovery in the load bearing capacity is expected, and that they adopt the thickness of the pavement layer which extends the lifetime of the pavements. From the above, this study uses FWD survey data which NEXCO stores, statistically estimates the continuous deterioration hazard model that every declination process of load bearing capacity of pavement follows. This study also statistically estimates the distribution of the remaining lifetimes at the point of service commencement time. In the process, this study considers the difference of the pavement thickness and the repairing history, and thereby provides knowledge that contribute to the decision making in projects of repair and renewal.

Keywords: falling weight deflectometer, pavement structure, pavement repair

1. Introduction

Asphalt pavements of expressways in Japan which East Nippon Expressway Company Limited, Central Nippon Expressway Company Limited, West Nippon Expressway Company Limited (hereinafter, NEXCO) administrate have structures of four layers:

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paving, bedding, upper subbase, and under subbase. The layers from paving to upper subbase are layered together with asphalt concrete. Load bearing capacity of pavement is an indicator that quantitatively expresses the soundness of pavements. The load bearing capacity indicates the capacity to support traffic loads. If the load bearing capacity declines, pavements become unable to support the traffic load and deflect under the load. In the result it could cause damages on the surface and inside the pavements. NEXCO regularly conduct falling weight deflectometer (hereinafter, FWD) survey to measure the load bearing capacity. In FWD survey, deflection sensors measure the deflection of pavements when a weight is fell on the pavement surface. Nine or ten sensors are put according to the distance from the falling center. Using two of the measured figures of the survey, deflection of each layer is calculated.

Accordingly, in this study the authors statistically estimate the declination process of the load bearing capacity of pavements, using large amount of FWD survey data and the continuous deterioration hazard model. In addition, by reflecting the difference in the pavement thickness and the rate of deterioration progression for each repair pattern in the past, the authors provide knowledge that contribute to decision making in repair and renewal projects.

In following part, **Chapter2** describes the basic idea of this study. **Chapter3** describes the general appearance of the continuous deterioration hazard model. **Chapter4** shows a case of empirical analysis targeted at actual expressways with FWD survey data.

2. Basic idea of this study

2.1 Evaluation for load bearing capacity of each layer and repair

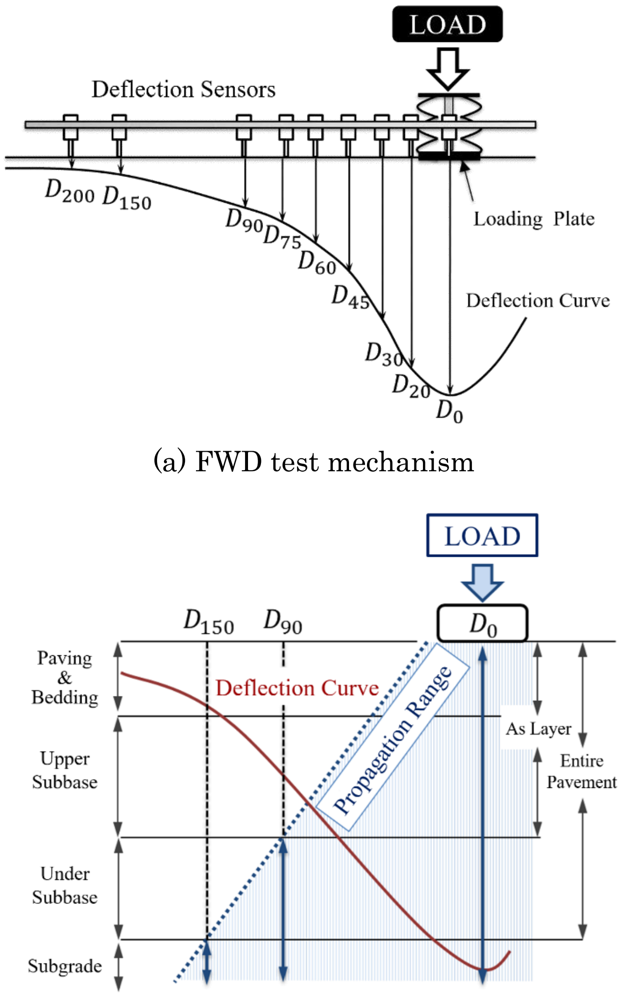
Structural design of expressway pavements in Japan is basically based on T_A method, which is based on road tests by American Association of State Highway Officials (AASHO). When laying asphalt pavement, T_A method decides necessary thickness of each pavement layer using a value obtained with support capacity of subgrade and amount of traffic[1) (hereinafter, T_A value). T_A value means the thickness of the layer assumed when laying from the paving to the subbase with the asphalt concrete for the paving and bedding. T_A value is different for each point on the expressway, so there are various pavement thickness roads in Japan expressway. If pavement thickness differs, the influence of external factors on pavement deterioration is different. Therefore, it is desirable to apply pavement thickness that can hold the load bearing capacity as much as possible, but if we do so, the load bearing capacity declines overtime. In that case, it is desirable to repair all the layers. However, as a matter of fact, repair to the paving and bedding is often carried out in many cases due to time and budget constraints. In that case, the load bearing capacity of subbase does not recover. Because of this, the structural soundness of pavements gradually decreases with the passage of years, so it is necessary to decide the target and the timing of repair that can expect life-extending effect. Therefore, in this study, considering that there are some deterioration factors which is not able to be fully considered by the T_A method in the declining process of the load bearing capacity of each pavement layer, the authors statistically predict the process. In addition, the authors propose a methodology to determine the target layer calculating a management index of each layer necessary for decision making of strategic large scale of repair plan.

2.2 FWD survey data and deterioration control index

Pavement management adopts FWD survey to inspect the load bearing capacity of pavement’s inner structure. FWD is a non-destructive inspection system which applies a shock to the pavement surface and measures deflection caused by doing so. A car equipped with FWD repeats running and measuring, and accumulates data. Measurement by FWD is performed in the order of 1) weight falling to the road surface, 2) measurement of impact pressure, 3) measurement of deflection of each distance from falling center and 4) data recording. Deflection occurs due to the falling weight mentioned in 1). 2) confirms whether the impact given was the proper strength. In 3), nine or ten sensors which is linearly arranged in a range of about 2m in horizontal distance from the falling center measures the deflection of each distance from the falling center. **Figure1(a)** shows the mechanism by which the deflection per distance can be obtained by FWD survey. The value of D_i in **Figure1(a)** represents the deflection measured by the sensor at the position of i cm from the falling center, for example, D_0 is the deflection right under the falling center, D_{90} is the deflection at the position of 90cm from the falling center. In addition, **Figure1(b)** illustrates how the impact given to the pavement surface propagates inside the pavement. When the weight is dropped on the pavement surface, the impact spreads conically in the pavement. From **Figure1(b)**, it can be seen that the deflection observed for each distance from the falling center represents the deflection of different layers. For example, D_0 represents the deflection in the entire pavement, and D_{90} represents the deflection in the layer below the under subbase. Based on this concept, NEXCO defines indices showing the strength of each pavement layer as shown in **Table1**[2].

Table1 Range of load bearing indices

Load bearing index	Range indicating strength
D_0 - D_{90}	As layer
D_0 – D_{150}	Entire pavement
D_{90} - D_{150}	Under subbase



(a) FWD test mechanism

(b) Load spreading and deflection curve

Figure1 FWD test and deflection

2.3 Review of previous studies

As to statistical models that predict deterioration of social infrastructure, many research results have accumulated so far. For example, Tsuda at al.[3] predicted deterioration process of bridges using the Markov deterioration hazard model for estimating the Markov transition probability for data of visual inspection of bridges rated at deterioration state in several stages. The Markov deterioration hazard model is an effective model for expressing discretized deterioration processes. There are also studies on deterioration prediction by applying the Markov deterioration hazard model to expressway pavement targeted in this research. In such case, the Markov deterioration hazard Model is applied after converting the continuous index values by the FWD survey into discrete ratings, but in the stage of converting the continuous values to the discrete values, much information is lost, and the estimation result of the deterioration curve changes depending on the rating setting due to lack of clear criterion.

Tanaka et al.'s[4] accelerated deterioration hazard model is a statistical model that treats the deterioration control index of social infrastructure facilities as a continuous value. Tanaka et al. represented the progression process of neutralization of concrete wall of water purification sedimentation pond using the accelerated deterioration hazard model. The accelerated deterioration hazard model expresses heterogeneity of deterioration rate by social infrastructure, but it is assumed that damage occurrence hazard function defined for each facility does not intersect. As the baseline model of this model, the acceleration equation (baseline deterioration rate equation) $x = t^{1/\alpha}$ is adopted. x represents neutralization depth and is expressed as a function of elapsed time t. The α represents acceleration parameter. By using the baseline deterioration rate equation, the logarithmic value of the elapsed time until the deterioration state of the concrete wall reaches a certain management level can be represented as a linear combination of the covariate and the error term of the deterioration and the damage, and thereby the acceleration deterioration hazard model can be formulated. Traditionally the neutralization rate equation based on the root t law is proposed, but it is nothing other than setting the parameter of the acceleration equation to $\alpha = 2$. In addition, Tanaka et al. estimated the acceleration deterioration hazard model, and showed the neutralization process does not necessarily obey the root t law.

In this study, the authors adopt the continuous deterioration hazard model developed by Mizutani et al.[5] to prevent loss of information by discretizing the deterioration control index. The continuous deterioration hazard model is a generalized model of accelerating deterioration hazard model, and it is able to be adopted for general social infrastructure.

2.4 Continuous deterioration index and deterioration prediction model

In this study, the authors define the deterioration control indices representing the load bearing capacity of each pavement layer, and express the changes over time using the continuous deterioration hazard model.

The statistical deterioration predictions so far adopted a method that rates the deterioration control index observed as continuous value in order to apply the Markov deterioration hazard model, and express the deterioration process through the transition probability between the rates. In doing so, as shown in blue in **Figure2**, the models estimated the declination process of the load bearing capacity converted into the discrete index, as a performance curve.

On the other hand, in this study, as shown in gold in **Figure2**, the authors consider the deterioration indices observed as continuous values as performance, and aim to directly express the temporal transition using the deterioration hazard model. In this study, the authors adopt the methodology to express performance curves using continuous index as the deterioration control index, using the deterioration hazard model. In addition, the authors calculate the management indices to assess the deterioration risks for asset management.

3. Continuous deterioration hazard model

3.1 Deterioration progression process

Let x_i denote the deterioration control index of the target spot i $(i = 1,2,\dots,I)$, and t_i denote the elapsed time of the latest construction (renewal) point. As deterioration progresses, the deterioration index value is considered to be a large value. The

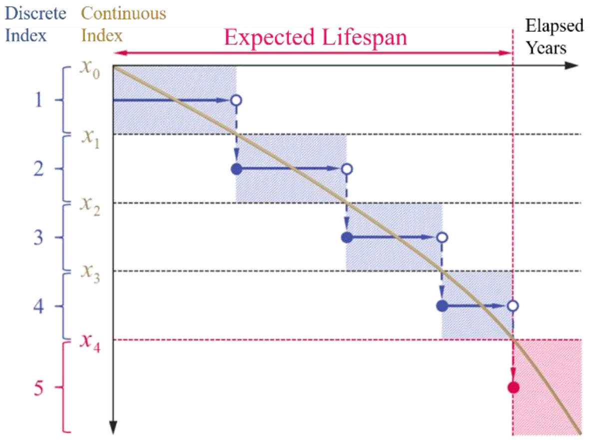


Figure2 Discrete and continuous index

deterioration hazard model representing the progress of deterioration process is defined:

$$x_i = \exp(-B_i)\, f(t_i, \boldsymbol{\beta}) \qquad (1a)$$

$$B_i = \boldsymbol{z_i}\boldsymbol{\theta}' + \sigma w_i \qquad (1b)$$

$$(i = 1,2, \ldots, I)$$

Here, B_i is an index reflecting the heterogeneity of the deterioration characteristics of spot i and can be expressed by the sum of characteristic variable term $\boldsymbol{z_i}\boldsymbol{\theta}'$ and error term σw_i as shown in **Equation (1b)**. In **Equation (1b)**, $\boldsymbol{z}_i = (z_i^1, \ldots, z_i^M)$ is a characteristic variable vector affecting deterioration of the spot i, $\theta = (\theta^1, \ldots, \theta^M)$ is a parameter vector, w_i is a probability error term representing the deterioration factor peculiar to the spot i, and the σ is a division parameter. Also, $f(t_i, \boldsymbol{\beta})$ is a deterioration model representing the deterioration process of the baseline (hereinafter, baseline model), and is a monotonically increasing function with respect to t_i. Also, $\boldsymbol{\beta} = (\beta_1, \ldots, \beta_N)$ is an unknown parameter vector characterizing the baseline model. When $\exp(-B_i) = 1$ holds, the deterioration curve matches the baseline model.

Taking the logarithm of both sides of the **Equation (1a)**, we will obtain the following equation:

$$\begin{aligned} y_i &= \ln f(t_i, \boldsymbol{\beta}) \\ &= \ln x_i + \boldsymbol{z_i}\boldsymbol{\theta}' + \sigma w_i \qquad (2) \end{aligned}$$

However, $y_i = \ln f(t_i, \boldsymbol{\beta})$ is a non-linearized lifetime index. Suppose the probability function term w_i follows the standard Gumbel distribution expressed by the following probability density function:

$$g_w(w_i) = \exp\{-w_i - exp(-w_i)\} \qquad (3)$$

However, $E(w_i) = \gamma$, $\gamma(= 0.57722\ldots)$ is Euler constant. We rewrite Equation (2) as:

$$w_i = \frac{y_i - \ln x_i - \boldsymbol{z_i}\boldsymbol{\theta}'}{\sigma} \qquad (4)$$

And perform variable conversion of probability density function (3). In the result, the probability density function representing the conditional distribution of the lifetime index y_i until the deterioration control index value of the spot i having the deterioration characteristic $\boldsymbol{z_i}$ reaches x_i can be expressed as:

$$\begin{aligned} &h_y(y_i | x_i, \boldsymbol{z_i}) \\ &= \frac{1}{\sigma} g_w\left(\frac{y_i - \ln x_i - \boldsymbol{z_i}\boldsymbol{\theta}'}{\sigma}\right) \\ &= \frac{1}{\sigma}\exp\left\{-\exp\left(-\frac{y_i - \ln x_i - \boldsymbol{z_i}\boldsymbol{\theta}'}{\sigma}\right) \right. \\ &\quad \left. - \frac{y_i - \ln x_i - \boldsymbol{z_i}\boldsymbol{\theta}'}{\sigma}\right\} \qquad (5) \end{aligned}$$

The lifetime index y_i includes the unknown parameter $\boldsymbol{\beta}$. If the first derivative of the lifetime index is expressed as $f_d(t_i, \boldsymbol{\beta}) = df(t_i, \boldsymbol{\beta})/dt_i$, the following equation holds:

$$dy_i = \frac{f_d(t_i, \boldsymbol{\beta})}{f(t_i, \boldsymbol{\beta})} dt_i \qquad (6)$$

Therefore, the probability density function representing the conditional distribution of the actual lifetime t_i until it reaches the control level x_i is expressed as:

$$\begin{aligned} &\tau(t_i | x_i, \boldsymbol{z_i}) \\ &= \frac{f_d(t_i)}{\sigma f(t_i)} \\ &\cdot \exp\left\{-\exp\left(-\frac{\ln f(t_i) - \ln x_i - \boldsymbol{z_i}\boldsymbol{\theta}'}{\sigma}\right) \right. \\ &\quad \left. - \frac{\ln f(t_i) - \ln x_i - \boldsymbol{z_i}\boldsymbol{\theta}'}{\sigma}\right\} \qquad (7) \end{aligned}$$

From the probability density function (3), the survival function is expressed as:

$$S_w = 1 - \int_{-\infty}^{w_i} g_w(w)dw$$
$$= 1 - \exp\{-\exp(-w_i)\} \qquad (8)$$

In the spot i, which has the deterioration characteristic $\boldsymbol{z_i}$, the probability that the deterioration control index value has not reached x_i at the time when the lifetime index y_i has elapsed can be expressed using the following survival function:

$$S_y(y_i|x_i, \boldsymbol{z_i})$$
$$= S_w\left(\frac{y_i - \ln x_i - \boldsymbol{z_i}\boldsymbol{\theta}'}{\sigma}\right)$$
$$= 1 - \exp\left\{-\exp\left(-\frac{y_i - \ln x_i - \boldsymbol{z_i}\boldsymbol{\theta}'}{\sigma}\right)\right\} \quad (9)$$

Furthermore, the survival function for the actual elapsed time t_i is expressed by the following equation:

$$S_t(t_i|x_i, \boldsymbol{z}_i)$$
$$= 1 - \exp\left\{-\exp\left(-\frac{\ln f(t_i) - \ln x_i - \boldsymbol{z_i}\boldsymbol{\theta}'}{\sigma}\right)\right\} \quad (10)$$

Traditional hazard models[6)-9)] assume that the life expectancy of objects is probability distribution, whereas in the continuous deterioration hazard model, the heterogeneity of the deterioration rate of each spot is the cause of the lifetime distribution. As the probability distribution of the probability fluctuation term w_i, it is also possible to adopt a probability distribution other than the Gumbel function. Gumbel distribution has a flexible structure that can express change processes such that the hazard ratio becomes constant, gradually increasing or decreasing with respect to elapsed time. Therefore, in this research, Gumbel distribution is adopted as the probability error variation.

3.2 Formulation of the likelihood function

Let us now consider a case where the deterioration control indexes are actually measured at different points on the time axis for each spot i $(i = 1,2,\dots,I)$. The authors estimate the deterioration hazard model using time series data of the deterioration control indexes observed at each spot, and for the spot i, define sample time axes $t_0^i, t_1^i, t_2^i, \dots$ with $t_0^i = 0$ as the initial time point (in this study, start of service). The point on the sample time axis is called the time point and it is distinguished from the calendar time. The time point t_h^i $(h = 1,2,\dots,H_i)$ is the h th observation point with respect to the deterioration control index of the spot i. **Figure 3** shows the outline of the relationship between the sample time axis, observation time interval and deterioration control index in the data covered by this research. The symbol "-" means the data actually observed, and usable for model estimation. We consider to use the partial information observed at each point in **Figure 3** to estimate the time variation of the deterioration control index shown in gray. In **Figure 3**, assuming that the point of service start is recorded at spot i, the first survey time t_1^i is known as survey data. Information on the survey sample on the deterioration control index of the spot i Ξ_i $(i = 1,2,\dots,I)$ is denoted as $\bar{\Xi}_i = (\bar{x}_i, \bar{t}_i, \bar{\boldsymbol{z}}_i)$. Note that $\bar{\boldsymbol{z}}_i = (\bar{z}_i^1, \dots, \bar{z}_i^M)$ is a vector representing the deterioration characteristics of the spot i. We also assume that $\bar{\boldsymbol{z}}_i$ is constant over time. In addition, the survey point vector $\bar{d}_i$ is expressed as $\bar{t}_i = (\bar{t}_1^i, \dots, \bar{t}_{H_i}^i)$. x_i is expressed as $\bar{x}_i = (\bar{x}_1^i, \dots, \bar{x}_{H_i}^i)$. At this time, the likelihood function is expressed by the conditional probability density function of the actual lifetime: **Equation (7)**, as the following function:

$$\mathcal{L}(\bar{\Xi}_i, \boldsymbol{\beta}, \boldsymbol{\theta}, \sigma)$$
$$= \prod_{i=1}^{I}\prod_{h=1}^{H_i} \tau(\bar{t}_h^i|\bar{x}_h^i, \bar{\boldsymbol{z}}_i)$$
$$= \prod_{i=1}^{I}\prod_{h=1}^{H_i} \left[\frac{f_d(\bar{t}_h^i)}{\sigma f(\bar{t}_h^i)}\right.$$
$$\cdot \exp\left\{-\exp\left(-\frac{\ln f(\bar{t}_h^i) - \ln \bar{x}_h^i - \bar{\boldsymbol{z}}_i\boldsymbol{\theta}'}{\sigma}\right)\right.$$
$$\left.\left. - \frac{\ln f(\bar{t}_h^i) - \ln \bar{x}_h^i - \bar{\boldsymbol{z}}_i\boldsymbol{\theta}'}{\sigma}\right\}\right] \qquad (11)$$

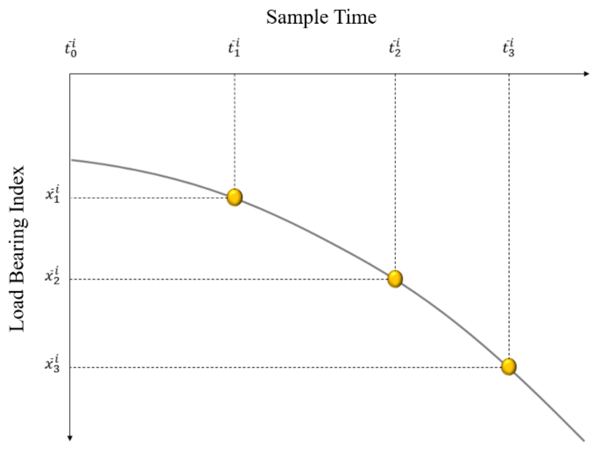


Figure 3 The declining process of the load bearing index

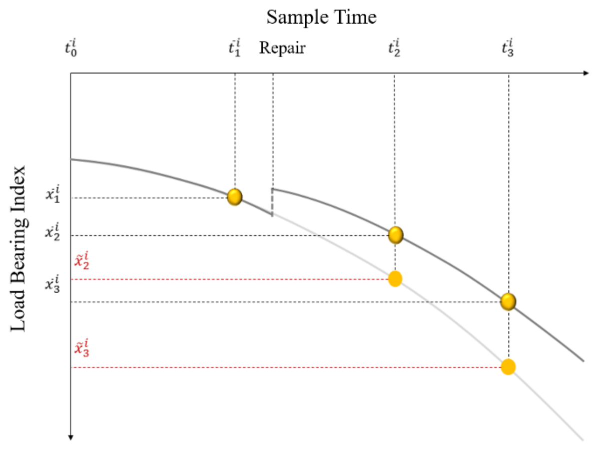


Figure 4 The declining process of the load bearing index after repair

Actually, however, in the domestic expressway, the managers repair the pavements for multiple times, and the load bearing capacity is recovered. The pavements follow the different deterioration processes between before and after repair. If FWD survey data after recovering the load bearing capacity is used in the same way, it is estimated to be smaller than the actual degree of reduction in load bearing capacity. Therefore, in this study, the authors classify the FWD survey data into the categories with similar repair history (hereinafter, repair characteristics), based on the record, and multiply the observed index value by the correction factor, as shown **Figure 4**. Then, estimation is performed using the corrected index value. However, it is assumed that the correction factor is constant for each repair characteristic and the correction factors of different repair characteristics are independent. Let j $(j = 1,2,\dots,J)$ be the number of each repair characteristic , and denote the correction rate as ξ_j. Using the observed index value and the correction factors, the corrected index value is expressed as $\tilde{x}_h^i = \bar{x}_h^i \cdot \xi_j$. The likelihood function using the correction factor can be expressed as:

$$\mathcal{L}(\bar{\Xi}_i, \boldsymbol{\beta}, \boldsymbol{\theta}, \sigma, \boldsymbol{\xi})$$

$$= \prod_{i=1}^{I}\prod_{h=1}^{H_i} \tau(\bar{t}_h^i | \tilde{x}_h^i, \bar{\mathbf{z}}_i)$$

$$= \prod_{i=1}^{I}\prod_{h=1}^{H_i} \left[\frac{f_d(\bar{t}_h^i)}{\sigma f(\bar{t}_h^i)} \cdot \exp\left\{-\exp\left(-\frac{\ln f(\bar{t}_h^i) - \ln\bar{x}_h^i - \bar{\mathbf{z}}_i\boldsymbol{\theta}' - \ln\xi_j}{\sigma}\right) - \frac{\ln f(\bar{t}_h^i) - \ln\bar{x}_h^i - \bar{\mathbf{z}}_i\boldsymbol{\theta}' - \ln\xi_j}{\sigma}\right\}\right] \quad (12)$$

Hereinafter, we call the declining process of the load bearing capacity without repair pattern 1, and that with some kind of repair pattern 2.

In this study, the authors perform iterative calculation of Markov Chain Monte Carlo (hereinafter, MCMC) to generate a random number according to the posterior distribution of unknown parameters of the deterioration hazard model, and calculate statistics to perform model estimation.

3.3 Risk management index

In the continuous deterioration hazard model, the lifetime of the deterioration control index is probabilistically distributed. The probability distribution of the deterioration control index at the time when a certain time T_i has elapsed from the initial time point can also be known for each deterioration category. In this way, the risk management index relating to the declination of the deterioration control index is referred to as "deterioration risk management index". On the other hand, the probability distribution of the elapsed time until the degradation control index reaches a given level can also be formulated using the survival function: **Equation (10)**. Thus, the risk management index relating to elapsed time is referred to as “remaining life index”. In this study, a) the deterioration risk management index, and b) the remaining lifetime index are set as the risk index representing the deterioration characteristics of the deterioration control index.

a) The deterioration risk management index

Consider the present moment when a certain time T_i has elapsed since the initial time point. From **Equation (2)**, the deterioration control index x_i is expressed as:

$$x_i = \exp\left(-\bar{\mathbf{z}}_i\hat{\boldsymbol{\theta}}' - \hat{\sigma}w_i\right)f\left(T_i, \hat{\boldsymbol{\beta}}\right) \quad (13)$$

Note that the symbol “^” represents estimated values. By the variable transformation, the probability density function representing the conditional distribution of the log deterioration control index $\iota_i = \ln x_i$ at the elapsed time T_i can be expressed as:

$$f_\iota(\iota_i|T_i, \bar{\mathbf{z}}_i) = \frac{1}{\hat{\sigma}} f_w\left(\frac{f\left(T_i, \hat{\boldsymbol{\beta}}\right) - \iota_i - \bar{\mathbf{z}}_i\hat{\boldsymbol{\theta}}'}{\hat{\sigma}}\right) \quad (14)$$

In addition, by the variable transformation, the conditional probability density function of the deterioration control index x_i at the elapsed time T_i is expressed as:

$$\begin{aligned} f_{x_i}(x_i|T_i, \bar{\mathbf{z}}_i) &= \frac{1}{\hat{\sigma}x_i} f_w\left(\frac{f\left(T_i, \hat{\boldsymbol{\beta}}\right) - \ln x_i - \bar{\mathbf{z}}_i\hat{\boldsymbol{\theta}}'}{\hat{\sigma}}\right) \\ &= \frac{\kappa x_i^{\kappa-1}}{\rho_i(T_i)} \exp\left(-\frac{x_i^\kappa}{\rho_i(T_i)}\right) \quad (15) \end{aligned}$$

However,

$$\kappa = \frac{1}{\sigma} \quad (16a)$$

$$\rho_i(T_i) = \left\{\exp\left(\frac{\bar{\mathbf{z}}_i\hat{\boldsymbol{\theta}}' - \ln f\left(T_i, \hat{\boldsymbol{\beta}}\right)}{\hat{\sigma}}\right)\right\} \quad (16b)$$

That is, the deterioration control index x_i follows the Weibull distribution $W\left(\mu(T_i), \nu^2(T_i)\right)$. However, $\mu(T_i)$ and $\nu^2(T_i)$ are the expected value and the dispersion of the Weibull distribution, and can be expressed as:

$$\mu(T_i) = \rho_i(T_i)^{1/\kappa}\Gamma\left(\frac{1}{\kappa} + 1\right) \quad (17a)$$

$$\nu^2(T_i) = \rho_i(T_i)^{2/\kappa}\left\{\Gamma\left(\frac{2}{\kappa} + 1\right) - \Gamma^2\left(\frac{1}{\kappa} + 1\right)\right\} \quad (17b)$$

And also, the expected value of the deterioration control index $E[x_i]$ at the elapsed time T_i is calculated from the expression (20a), and expressed as:

$$E[x_i] = \Gamma\left(\frac{1}{\kappa} + 1\right)\exp\left(\frac{\ln f\left(T_i, \hat{\boldsymbol{\beta}}\right) - \bar{\mathbf{z}}_i\hat{\boldsymbol{\theta}}'}{\hat{\sigma}}\right) \quad (18)$$

b) The remaining lifetime index

Let us set the management level $\underline{X}$ for the deterioration control index. The elapsed time from the initial time point of the spot until reaching the management level $\underline{X}$ is called lifetime η_i. At the present time, let us consider the case where the deterioration control index of spot i does not reach the control level and the relationship $\eta_i > T_i$ holds for lifetime η_i. Under the condition that the deterioration control index has not reached the management level $\underline{X}$, the conditional probability (hereinafter, the remaining life distribution) $\tilde{F}_i\left(\tau\middle|\underline{X}, T_i\right)$ that spot i can be used without repairing the facility for a period of τ or more is expressed as:

$$\tilde{F}_i\left(\tau\middle|\underline{X}, T_i\right) = \frac{S_t\left(T_i + \tau\middle|\underline{X}, \bar{\mathbf{z}}_i\right)}{S_t\left(T_i\middle|\underline{X}, \bar{\mathbf{z}}_i\right)} \quad (19)$$

However, $S_t\left(T_i\middle|\underline{X}, \bar{\mathbf{z}}_i\right)$ is the survival function of the deterioration hazard model and is expressed by the **Equation (10)**.

4. Application cases

4.1 Outline of application cases

In this study, the authors focus on the declination process of the load bearing capacity of the expressway pavements. The authors apply data acquired by the FWD survey on the expressways in Japan managed by NEXCO. As of 2017, the oldest route has already used for over 50 years since the start of service, whereas the newest route has only been used for about 5 years. The data used in this study is FWD survey data up to 9 times at each spot in about 9 years, at 13,452 spots. Regarding the repair history, there is the oldest one with the record of 1967, but the older the record, the lower the credibility of the information. Also, not all repairs done in the past are recorded. However, although incomplete, this repair record is very valuable information for analyzing repair effect.

In this study, as shown in **Table 1** above, the indices of the range showing the strength of each pavement layer are determined by the sensor position of the FWD. In the following, for convenience of notation, the value obtained by multiplying each index by 1,000 is expressed as the load bearing index.

4.2 Model estimation policy

In this study, the authors investigate the deterioration process of the load bearing capacity in the standard pavement structure by applying the continuous deterioration hazard model to FWD survey data. At that time, the difference in the pavement thickness is considered, and the performance curve for each thickness is obtained. The pavement thickness is classified by the thickness of the asphalt layer (hereinafter, As layer). In the FWD survey data, the samples of spots where As layer thickness is 18 cm, 20 cm, or 25cm, which have particularly a lot of samples, are used, and these three are defined as the deterioration characteristic categories.

In addition, in this study, the correction rate of the index value is set for each repair characteristic, taking into consideration the effect of recovery in the load bearing capacity by repair. Estimate is performed using the index value corrected from the index value actually observed by the FWD survey. Specifically, samples are classified into 48 categories according to the elapsed years from service start to repair, the elapsed years from repair to FWD survey, repair target layer, number of repair, and the correction rates $\xi_1, \ldots, \xi_{48}$ are set. Using this correction rates, the likelihood function can be derived from **Equation (12)**. However, although there is nothing exactly the same as the pattern of repair, note that when classifying repair characteristics, for the sake of simplicity, somewhat similar patterns are classified as the same repair characteristics.

4.3 Specification of the baseline model

In this application example, in order to flexibly represent the incremental and rapidly increasing process of the index at an arbitrary elapsed time, the authors consider the function monotonically increasing with the lapse of time, and classify the four types of functions shown in **Table 2** as candidates for the baseline. **Table 2** also shows AIC[10] when data without repair history is applied to individual models. For all samples, we derive the AIC of each candidate for the baseline model and determine the statistically most appropriate model. In all indices, when the exponential model was taken as the baseline model, AIC has the smallest value, and therefore, the exponential function model is determined as the most desirable baseline model among the four candidates.

Table 2 Candidates of baseline and their AIC

Model	$f(t,\boldsymbol{\beta})$	**AIC**		
		D_0 - D_{90}	$D_0 - D_{150}$	$D_{90} - D_{150}$
Polynomial	$\beta_1 t^2 + \beta_2 t + \beta_3$	78,293	72,435	74,133
Exponential 1	$\beta_1 t^{\beta_2} + \beta_3$	68,515	69,423	78,661
Exponential 2	$\beta_1 {\beta_2}^t + \beta_3$	59,413	66,215	62,345
Hyperbolic	$\beta_1 \tanh\{\beta_2(t-\beta_3)\} + \beta_3$	98,788	104,702	95,618

4.4 Estimation results

a) Baseline model

Table 3 shows the statistics on the posterior distribution of the unknown parameters of the baseline model sampled in the MCMC method. As shown in the **Table 3**, by using the 90% Bayesian confidence interval and Geweke test statistic[11)], it is possible to evaluate the reliability of the estimated unknown parameter and convergence to the posterior distribution. In this study, if the absolute value of the Geweke test statistic is less than 1.96, the null hypothesis that the sample by the MCMC method converges to the posterior distribution cannot be rejected at the significance level of 5%. In the following, the deterioration prediction by the continuous deterioration hazard model in the case the estimated values of unknown parameters are the expected values of the posterior distributions is explained.

Table 3 Estimated values of baseline parameters

Parameters	Posterior distribution statistics			
	Expected Value	Under 5%	Upper 5%	Geweke Value
D_0 - D_{90}				
β_1	8.996	8.279	9.534	0.996
β_2	1.115	1.102	1.175	1.255
β_3	62.56	56.71	68.35	0.456
σ	1.123	1.120	1.129	-1.403
$D_0 - D_{150}$				
β_1	9.292	8.848	9.758	-1.332
β_2	1.114	1.109	1.156	1.047
β_3	80.13	71.43	89.15	0.998
σ	1.128	1.121	1.132	-0.706
$D_{90} - D_{150}$				
β_1	2.980	2.621	3.215	0.706
β_2	1.120	1.149	1.153	-0.839
β_3	20.94	18.42	23.12	0.669
σ	1.090	1.085	1.097	1.065

b) Heterogeneities between deterioration characteristic categories

By using the deterioration hazard model, it becomes possible to directly quantify the load bearing index based on the amount of deflection, and to quantify the deterioration process of the load bearing capacity with individual deterioration characteristic categories. **Table 4** shows the statistics of the posterior distribution of unknown parameter vector by $\boldsymbol{\theta}$.

Table 4 Estimated values of characteristic variables

As layer Thickness	Posterior distribution statistic			
	Expected Value	Under 5%	Upper 5%	Geweke Value
D_0 - D_{90}				
18 cm	-0.671	-0.765	-0.624	-0.886
20 cm	-0.256	-0.302	-0.212	0.996
25 cm	0.567	0.518	0.622	0.889
$D_0 - D_{150}$				
18 cm	-0.668	-0.732	-0.663	-0.464
20 cm	-0.254	-0.316	-0.203	-1.350
25 cm	0.421	0.381	0.469	-1.116
$D_{90} - D_{150}$				
18 cm	-0.633	-0.682	-0.594	-0.892
20 cm	-0.234	-0.273	-0.187	0.968
25 cm	0.424	0.388	0.473	-1.223

c) Performance curves

Figure 5 shows the deterioration performance curves of the load bearing index in the optimal baseline model in this study, using the estimated values $\widehat{\boldsymbol{\beta}}, \widehat{\boldsymbol{\theta}}, \hat{\sigma}$ of unknown parameters. The performance curves are drawn considering the heterogeneity between deterioration characteristic categories from the baseline model $f(t, \widehat{\boldsymbol{\beta}})$ whose variable are the elapsed years since the start of service. In this study, the expected value of the probability fluctuation term w_i was set to γ (= 0.57722 ⋯).

As shown in **Figure 5**, the deterioration performance curves of the load bearing index show that the performance declines slowly for a certain period from the initial time point, and thereafter the accelerated damage index is increased. From this fact, it is confirmed from the estimation result that once the

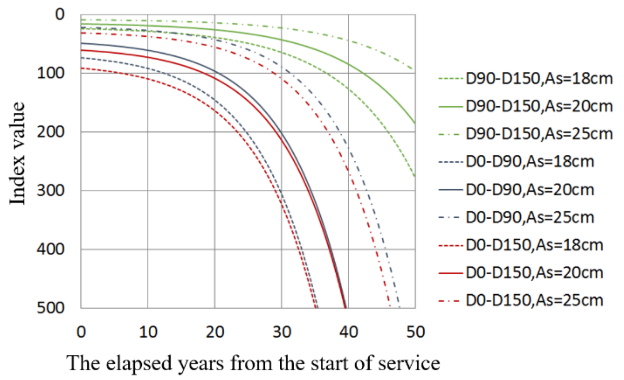


Figure 5 Performance curves

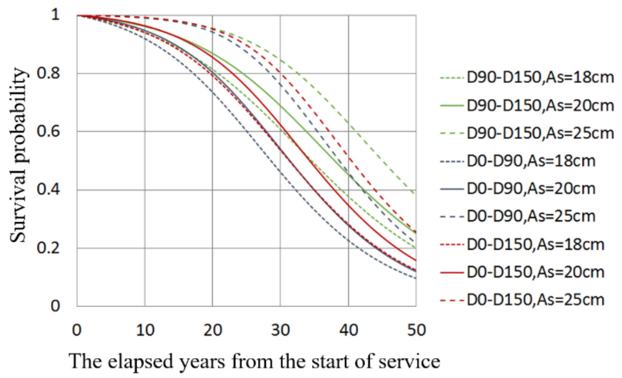


Figure 6 Remaining lifetime distributions

load bearing capacity starts to decline, it gradually decreases drastically.

d) The remaining lifetime index

In implementing asset management of social infrastructure, it is also important to quantify the residual value of each facility. In **Figure 6**, the conditional remaining life distribution that the spot has not reached the management level $\underline{X}$ at the time of service start calculated by the **Equation (19)** is shown for all indices. The management level $\underline{X}$ is 250 for D_0 - D_{90}, 350 for D_0 – D_{150} and 80 for D_{90} – D_{150}. From **Figure 6**, it is found that the probability of exceeding the control level as of the beginning of service becomes 50% when around 25 years for the early ones, and around 45 years for the late ones passes.

5. Conclusion

In this study, the authors adopted the continuous deterioration hazard model and statistically predicted the declination process of the load bearing capacity of each pavement layer from the deflection amount data obtained by the FWD survey. In addition, for the continuous deterioration hazard model, the structure of the model is detailed and the model's parameters are obtained by Bayesian estimation method by MCMC. Advantages of adopting the continuous deterioration hazard model are: 1) it can directly describe the deterioration indices observed as continuous quantities, 2) by using dynamic deterioration process model for baseline model, it adopts a framework to predict the deterioration process as a hybrid type deterioration prediction model of a dynamic method and a statistical method. In addition, multiple risk management indices were derived using the estimated deterioration hazard model. By using these risk management indices, detailed deterioration risk assessment and remaining lifetime assessment of facilities can be evaluated. In this study, classification is done based on repair characteristics, and the repair effect in each characteristic is set as the correction rate. However, by further refining the way of classification, for example, it is also possible to create a group of points where the FWD surveys were conducted and repairs were made almost at the same time, on the same route. In addition to the repair effect, by setting the correction rate based on the date when the FWD survey was carried out, it is possible to correct the influence of the temperature of the road surface on the measured value. In this way, the continuous deterioration hazard model using the correction factor developed in this research can draw a performance curve correcting the effect of various external factors.

On the other hand, there are some challenges left for this research in the future. First, it is an accumulation of the dynamic deterioration process model. In the application case of this study, the baseline model of the continuous deterioration hazard model was statistically determined from among several candidates, and the parameters were estimated. The deterioration hazard model developed in this study can be used as a hybrid type deterioration prediction model of a dynamic method and a statistical method, it is desirable that we accumulate further cases of application to social infrastructure in which dynamic degradation process is defined, and accumulate knowledge about facilities that have not yet been clarified the dynamic deterioration process. Secondly, it is necessary to accumulate knowledge on the degree of recovery of the load bearing capacity of pavements after repair. In this study, the authors statistically estimated the repair effect of each repair characteristic as a correction factor, but if the actual repair effect becomes clear from the viewpoint of dynamics, it is possible to perform a more detailed analysis. Thirdly, it is necessary to acquire knowledge on the load bearing capacity of pavements other than expressways. The deterioration process and the risk management indices evaluated in the application cases of this research are applicable only in the road section where the used database was accumulated. National roads etc. cannot apply the findings obtained in this research because their pavement structures are totally different from those of express ways. However, for many national roads etc. in Japan where pavement deterioration advanced, it is an urgent task to acquire universal knowledge on the declination process of the load bearing capacity.

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