Analysis of Pavement Overlay and Replacement Performance Using Random Parameters Hazard-Based Duration Models

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Abstract: The effectiveness of pavement overlays and pavement replacements in terms of their impact on pavement life is not well understood. This is complicated further by data collection limitations and by the effect that physical deterioration, load volumes, weather, geology, and other factors may have on their effectiveness. Understanding the survivability of overlays and replacements has the potential to provide improved resource allocation and more effective use of state funds. In this paper, pavement overlays and replacements are assessed for their effectiveness on pavement life for urban roads. Using data from Indiana, seemingly unrelated regression equations first are estimated to predict the pavement performance over time. Using these forecasts and historical thresholds, the service life of the pavement is determined and random parameter duration models are estimated to identify influential factors affecting pavement service life. The model-estimation results provide some new insights into the interrelationships among pavement rehabilitation, pavement condition, pavement service life, road functional class, traffic loads and trucks, weather and soil condition, and rehabilitation expenditures. **DOI:** 10.1061/(ASCE)IS.1943-555X.0000208.

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Introduction

Creating accurate models for pavement-performance forecasting has always been a challenging task due to the need to predict the pavement's performance and condition so as to determine optimal times to perform preservation activities and predict their impact on pavement conditions and remaining service life. Past research efforts have used a wide variety of methodological approaches to model pavement performance with respect to maintenance and rehabilitation practices. These modeling methods include linear regression (Prozzi and Madanat 2004; Agarwal et al. 2006; Puccinelli and Jackson 2007); Bayesian models and Markov chains (Butt et al. 1987; Abaza et al. 2004; Hong and Prozzi 2006); nonlinear mixed-effect and joint discrete-continuous models (Madanat et al. 1995; Archilla 2006a); random-effect, mixed-effect, and random-parameter models (Madanat et al. 1997; Archilla 2006b; Lee 2007; Madanat et al. 2010; Aguiar-Moya et al. 2011; Anastasopoulos et al. 2011, 2012c; Khraibani et al. 2012; MacKenzie and Barker 2013); time-series analysis (Smith et al. 1997); universal correlative equations (Livneh 1998); finite element analysis (Ali et al. 2009); and case-based reasoning and performance-based approaches (Morcous et al. 2002; Abaza 2005).

However, evaluating the effectiveness of pavement overlays and replacements in terms of their effect on the service life of the pavement is a complicated task because of the effect that physical deterioration, accumulation of axle loads, weather, subsurface geotechnical conditions, and other factors may have on pavement overlay and replacement effectiveness. Most important, due to the high cost of data acquisition, data limitations can play a significant role in the forecasting accuracy of pavement-performance models. As such, understanding the survivability of pavement overlays and replacements, even when there is limited information, has the potential to provide improved resource allocation and more effective use of highway funds.

The present study extends the traditional pavement-management framework by applying methodologies that can provide new insights into the effectiveness of pavement overlay and replacement strategies with respect to their service life. The analysis goes beyond standard performance modeling and demonstrates a new approach to evaluate pavement overlay and replacement strategies for their effectiveness on pavement life for urban roads.

To do this, an approach to forecast pavement performance is first developed by identifying influential factors that affect performance deterioration. An equation-system approach is used to account explicitly for simultaneous relationships that potentially exist among the pavement performance measures. Next, historical thresholds of the pavement performance condition indicators—which initiate pavement overlay or replacement—are utilized, and combined with pavement performance forecasts, the service life of the pavement overlay and replacement strategies are estimated. Finally, given these service lives, a random-parameter hazard-based duration model is applied and pavement survival curves are estimated.

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Study Approach

The remaining service life of a pavement is defined as the time from its current status to the time that the pavement needs to be treated (because it has reached the end of its structural or functional capacity) to make it operational. The combined use of the pavement's performance forecasting and condition threshold allows an estimation of the pavement's service life.

Herein, the pavement service life for a specific pavement section can be defined as the time period between two consecutive rehabilitations (overlay or replacement), which are initiated when any of the historical performance-condition thresholds are exceeded. For example, consider a hypothetical pavement section, for which the pavement is replaced in 2013. Assume that just two pavement-condition indicators are considered; the international roughness index (IRI) measured in in./mi. (note that 1 in. = 0.025 m, and 1 mi. = 1.61 km) and the pavement condition rating (PCR) measured on a 0–100 scale. Suppose that the determined thresholds for an overlay or replacement action is an IRI $170\ \mathrm{in./mi}$ $(2.68\ \mathrm{m/km})$ and a PCR of 55. The pavement service life, then, is the amount of time, beginning in 2013, for either the PCR or the IRI to surpass these thresholds. Assuming that the IRI is predicted to reach $165\ \mathrm{in./mi}\,(2.60\ \mathrm{m/km})$ in 2024 and $172\ \mathrm{in./mi}\,(2.71\ \mathrm{m/km})$ in 2025 and the PCR is predicted to reach a value of 55 in 2,027 and 51 in 2,028, given the historical thresholds (55 for the PCR and $170\ \mathrm{in./mi}\,(2.68\ \mathrm{m/km})$ for the IRI), the IRI threshold governs and the pavement service life will be 11 year (from 2013 to 2024).

Empirical Setting

The two most commonly implemented rehabilitation strategies in Indiana, resurfacing (3-R; resurfacing, restoration, and rehabilitation) and pavement replacement (4-R; 3-R plus reconstruction) are evaluated for two classes of urban roads on the basis of their service lives (INDOT 2008). This paper considers urban interstate and noninterstate roads in the national highway system (NHS). IRI, PCR, rut depth (RUT), and surface deflection (measured from a falling weight deflectometer and designated as FWD) are the pavement condition indicators that determine the performance of the rehabilitation strategies.

IRI measures irregularities that can result from potholes, patching, and other factors. In Indiana, IRI is measured in in./mi., with lower values indicating a smoother pavement (Shafizadeh and Mannering 2003; Noyce and Bahia 2005). A *rut* is defined as a difference in elevation on the pavement surface across the wheel path or other directions, and typically is measured in inches. Excessive rutting can contribute to vehicle tracking and loss of control during maneuvering (Anastasopoulos et al. 2012d). PCR provides an index ranging from 0 (poorest condition) to 100 (best condition), reflecting the composite effects of varying distress types, severity, and extent upon the overall condition of the pavement. Finally, pavement surface deflection is used to evaluate the flexible pavement structure and the rigid pavement load transfer. The units for the surface deflection used in the analysis are thousandths of an inch from a falling weight deflectometer (FWD) center-of-load deflection, corrected to a 9,000-lb (4,082 kg). load applied on an 11.8-in. (0.30 m) diameter plate, adjusted for temperature 18.3°C (65°F).

With regard to data, pavement and roadway data were gathered from the Indiana Department of Transportation (INDOT) pavement condition and pavement management databases, and from INDIPAVE, a database consisting of pavement conditions and structure, weather, traffic, maintenance, and other information about more than 10,000 1-mi (1.61 km) pavement sections in Indiana. Weather information was also collected from the Indiana State Climate Office.

For all sections, available information includes pavement conditions (IRI, PCR, RUT, and surface deflection), road geometrics, and information on pavement drainage, traffic and truck loads, pavement preservation cost, and weather (temperature and precipitation). The roadway data are divided into homogeneous 1-mi. roadway sections. The section defining information includes shoulder, pavement characteristics, median characteristics, number of lanes, and speed limit (note that the pavement condition indicator measurements are point-based, which may or may not be typical across the homogenous sections). Table 1 presents descriptive statistics of selected variables.

The data contain information about 739 urban interstate and noninterstate road sections of the NHS in Indiana from 1999 to 2007 that have an unknown service life because these pavements have not deteriorated enough to require an overlay or pavement replacement. In addition, separate data was gathered on 306 road sections for which pavement service life is known (overlays or pavement replacements have been conducted) to compare our estimation results to make certain that the performance estimation approach and the 739 observations used here are valid (more on this later in this paper).

Estimation of the Pavement Service Life

The service life of a pavement is approximated by first modeling and forecasting pavement performance, and then by using performance thresholds which trigger the pavement failure mechanism as described previously. Modeling pavement performance over time, by considering degradations in roughness, surface deformation, and structural integrity, presents an interesting statistical problem because performance measures are highly correlated (for example, increases in roughness are usually accompanied or preceded by increases in surface deformations). If one were to estimate all performance-measure equations independently, there would be a loss in estimation efficiency because the correlation of performance measures on the same section of pavement is being ignored.

To account for the correlation in pavement-performance measures, seemingly unrelated regression estimation (SURE) is an obvious estimation approach (see Washington et al. 2011). SURE generalizes ordinary least-squares (OLS) estimation to provide improved parameter estimates by taking into account the correlation between the error terms in each equation. This study follows previous SURE applications by Prozzi and Hong (2008) and Anastasopoulos et al. (2012a), and set the system of the seemingly unrelated regression equations as follows:

$$\begin{aligned}
\mathrm{IRI} &= \boldsymbol{\beta}_1\mathbf{X}_1 + \varepsilon_1\\
\mathrm{PCR} &= \boldsymbol{\beta}_2\mathbf{X}_2 + \varepsilon_2\\
\mathrm{RUT} &= \boldsymbol{\beta}_3\mathbf{X}_3 + \varepsilon_3\\
\mathrm{FWD} &= \boldsymbol{\beta}_4\mathbf{X}_4 + \varepsilon_4
\end{aligned} \tag{1}$$

where IRI is the international roughness index, PCR is the pavement condition rating, RUT is the rut depth, and FWD is the surface deflection; $\mathbf{X}$ is a vector of road section and pavement condition characteristics and other factors that affect pavement performance; $\boldsymbol{\beta}$ is a vector of estimable parameters; and ε is a disturbance term.

Estimation of seemingly unrelated equations is accomplished using generalized least squares (GLS). GLS relaxes the OLS

Table 1. Descriptive Statistics of Selected Variables

Variable	Urban interstates		Urban noninterstates (NHS)	
	Overlay	Pavement replacement	Overlay	Pavement replacement
	Percentage or mean (standard deviation)			
Service life of the pavement (year)	16.707 (5.308)	18.306 (6.405)	14.517 (2.315)	15.261 (3.231)
Base (right after rehabilitation) IRI (in./mi.)	84.126 (30.88)	69.647 (34.541)	91.025 (31.926)	97.377 (42.541)
Base (right after rehabilitation) PCR	93.463 (5.905)	96.447 (4.602)	94.013 (5.434)	94.634 (5.197)
Base (right after rehabilitation) RUT (in.)	0.099 (0.057)	0.077 (0.049)	0.124 (0.061)	0.101 (0.061)
Base (right after rehabilitation) surface deflection (thousandths of an inch)	6.213 (2.917)	2.73 (0.585)	6.64 (3.044)	6.47 (3.18)
Average annual daily traffic (AADT) (in thousands of vehicles per day)	43.402 (61.883)	47.177 (55.464)	23.592 (42.211)	25.010 (38.945)
Percentage of commercial trucks	0.341 (0.186)	0.363 (0.203)	0.237 (0.124)	0.259 (0.174)
Cumulative (over rehabilitation study period) daily number of trucks (in millions)	22.701 (43.128)	27.585 (30.91)	8.248 (1.862)	10.842 (7.528)
Average annual range of temperature over rehabilitation period (from base year to analysis year t) (°F)	22.079 (9.124)	24.537 (12.695)	25.264 (11.904)	23.138 (10.003)
Average annual precipitation over the rehabilitation period (in.)	1.496 (0.339)	1.571 (0.291)	1.514 (0.304)	1.461 (0.298)
Drainage class: excessively or somewhat excessively drained	9.5%	1.9%	2.9%	5.7%
Drainage class: excessively, somewhat excessively or well drained	33.5%	32.1%	31.7%	33.4%
Drainage class: excessively, somewhat excessively, well, or moderately well drained	48.3%	39.8%	49.7%	51.0%
Drainage class: somewhat poorly, poorly, or very poorly drained	51.6%	19.2%	50.2%	48.9%
Drainage class: poorly or very poorly drained	34.1%	19.2%	34.7%	23.7%
Rehabilitation contract final cost per lane-mile (millions U.S. dollars)	0.404 (0.987)	0.658 (0.671)	0.162 (0.346)	0.364 (0.708)
Rehabilitation contract final cost per lane-mile (less than 50,000 U.S. dollars)	51.0%	0.6%	48.5%	28.0%

assumption that disturbances are not correlated (Washington et al. 2011). To see this, recall that OLS parameters are estimated as

$$\hat{\boldsymbol{\beta}} = (\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T\mathbf{Y} \tag{2}$$

where $\hat{\boldsymbol{\beta}}$ is a $p \times 1$ column vector (where p is the number of estimated parameters), $\mathbf{X}$ is an $n \times p$ matrix of data (where n is the number of observations), $\mathbf{X}^T$ is the transpose of $\mathbf{X}$, and $\mathbf{Y}$ is an $n \times 1$ column vector. GLS generalizes this expression by using a matrix that considers the correlation among equation error terms ($\boldsymbol{\Omega}$), so Eq. (2) is rewritten as

$$\hat{\boldsymbol{\beta}} = (\mathbf{X}^T\boldsymbol{\Omega}^{-1}\mathbf{X})^{-1}\mathbf{X}^T\boldsymbol{\Omega}^{-1}\mathbf{Y} \tag{3}$$

In a seemingly unrelated regression estimation, $\boldsymbol{\Omega}$ is estimated from initial OLS estimates of individual equations (Washington et al. 2011).

Pavement Survival Analysis with Random Parameters

A number of studies have used a hazard-based duration approach, such as traditional duration modeling, survival curves, pavement service remaining life survival analysis, and Cox proportional hazard modeling (Gharaibeh et al. 1997; Gharaibeh and Darter 2003; Wang et al. 2005; Prozzi and Madanat 2000; Yang 2007; Yu 2005). For pavement survival data, hazard-based models can be used to study the conditional probability of the pavement service life ending at some time t, given that it has not ended until time t. This conditional probability is important because it will probably increase significantly as the pavement service life increases. To formulate an estimable model, the hazard function is written as (Washington et al. 2011):

$$h(t) = f(t)/[1 - F(t)] \tag{4}$$

where $F(t)$ and $f(t)$ are the cumulative distribution function and the density function of pavement service lives, respectively. This hazard function gives the rate at which the pavement service lives are ending at time t, given that they have lasted up to time t. If this hazard function is upward sloping as time passes $[dh(t)/dt > 0]$, it means that the conditional probability that the pavement service life will end soon (given that it has not ended so far) increases as the pavement lasts longer. If the hazard function is downward sloping $[dh(t)/dt < 0]$, it means that the conditional probability that the pavement service life will end soon (given that it has not ended so far) decreases as the pavement lasts longer. And if the hazard function is constant as time passes $[dh(t)/dt = 0]$, it means that the conditional probability of the pavement service life ending soon (given that it has not ended so far) is independent of the length of time that the pavement has lasted.

To account for the effect of explanatory variables in hazard models, a proportional hazard approach can be used where the explanatory variables act multiplicatively on some underlying (or baseline) hazard function, such that (Washington et al. 2011):

$$h(t|\mathbf{X}) = h_0(t)\exp(-\boldsymbol{\beta}\mathbf{X}) \tag{5}$$

where $\mathbf{X}$ is a vector of explanatory variables, $\boldsymbol{\beta}$ is a vector of estimable parameters, and $h_0(t)$ is the baseline hazard that denotes the hazard when all elements of the explanatory variable vector are zero. In estimating Eq. (5), a common approach is to consider various parametric forms of the underlying hazard function (Prozzi and Madanat 2000; Wang et al. 2005; Yu 2005; Yang 2007). The most widely used parametric forms include the Exponential, Weibull, and Log-logistic models. As an example, for the Weibull model, with parameters $\lambda > 0$ and $P > 0$, $h_0(t)$ in Eq. (5) becomes

$$h(t) = \lambda P(\lambda t)^{P-1} \tag{6}$$

An extension of Eq. (5) is to consider a model that relaxes the assumption that the hazard function is homogenous across observations. In such a model, all the variation in the pavement survivability is no longer assumed to be captured by the variable vector $\mathbf{X}$. This is important because there may be unobserved factors that are not included in $\mathbf{X}$, which may influence the survival of the pavement service life. This unobserved heterogeneity can lead to specification errors that in turn can lead to erroneous inferences regarding the hazard function shape, and to inconsistent parameter estimates (Heckman and Singer 1984; Gourieroux et al. 1984).

A common approach to account for unobserved heterogeneity is to assume that it is gamma-distributed over observations (see Washington et al. 2011). To see how this is done, consider a Weibull model with gamma heterogeneity. With w representing heterogeneity, $g(w)$ the heterogeneity's gamma distribution over the population with mean 1 and variance θ, and $S(t|w)$ a conditional survival function, the unconditional survival function is

$$S(t) = \int_0^\infty S(t|w)g(w)dw = [1 + \theta(\lambda t)^P]^{-1/\theta} \tag{7}$$

resulting in the hazard function

$$H(T) = \lambda P(\lambda T)^{P-1}[S(T)]^\theta \tag{8}$$

If $\theta = 0$, the hazard reduces to the Weibull model [Eq. (6)], and heterogeneity is not present.

To account further for the possibility of unobserved heterogeneity over the pavement service life data, some of or all the parameters can be allowed to vary across observations. Relatively recent research conducted by Train (1997), Revelt and Train (1997), Brownstone and Train (1999), McFadden and Train (2000), Bhat (2001), Eluru et al. (2007), Anastasopoulos and Mannering (2009, 2011), Anastasopoulos et al. (2009a, 2009b), has demonstrated the applicability of a random-parameter approach to account explicitly for the variations of the effect of variables across observations. Greene (2007) developed estimation procedures (using simulated maximum likelihood estimation) for incorporating random parameters in hazard-based duration models, by letting, for each observation i (see also Washington et al. 2011)

$$\boldsymbol{\beta}_i = \boldsymbol{\beta} + \boldsymbol{\omega}_i \tag{9}$$

where $\boldsymbol{\beta}_i$ is a vector of pavement section-specific parameters and $\boldsymbol{\omega}_n$ is a randomly distributed term (for example, normally distributed term with mean zero and variance σ^2).

Estimation of the random parameters model shown in Eq. (9) is undertaken using simulation approaches. Research by Train (2003) and Bhat (2003) suggests that a Halton sequence approach (Halton 1960) is an efficient way of drawing values of $\boldsymbol{\beta}$ from $q(\boldsymbol{\beta}|\boldsymbol{\omega})$ so that accurate approximations are obtained with as few draws as possible. Research by Bhat (2003), Milton et al. (2008), Anastasopoulos et al. (2012b), and others has shown that 200 Halton draws are usually sufficient for accurate parameter estimation (this number of Halton draws will be used in forthcoming model estimations).

Estimation of Pavement Performance

As motivated previously with the stated need to apply SURE, for the majority of the pavement sections within the data sample (739 observations), there are not enough years of pavement data to have a documented full life cycle of the pavement service life. This is typically due to physical difficulties and high costs of the pavement data collection process. Such data limitations can be resolved by forecasting the pavement performance over time and, with the use of pavement performance thresholds, computing the pavement service lives.

Using the available pavement-performance data from the sample of 739 road sections, SURE models were estimated by road functional class (interstates and noninterstates) and by pavement treatment (pavement overlay and replacement). To that end, the parameters' transferability across road functional classes and pavement treatments was tested with likelihood ratio tests [Eq. (11)], and the results indicated that separate models should be estimated. Furthermore, various transformations (logarithmic, exponential, power forms, and so on) of the dependent and independent variables were tested while estimating the models, but the linear relationships provided the best overall fit. Table 2 presents the model estimation results from the SURE models. Note that only the significant variables (at 0.90 level of confidence or higher) are included in the model. The results show that IRI, PCR, RUT, and surface deflection measurements taken the year after the rehabilitation often plays a strong role in the determination of the corresponding pavement condition in the models.

The effect of the pavement conditions in the preceding year $(t-1)$ is also strong. These time-lag variables represent IRI, PCR, RUT, and surface deflection measurements taken the year (t–1), before the analysis year (t), and are highly significant in all the models. It should be noted that the fact that these lagged variables $(t-1)$ may contain unobserved heterogeneity and their residuals may have an escalating effect over time is accounted for by estimating the models with an instrumental variable approach for the lagged variables. That is, the values of the $t-1$ variables predicted by regressions that are estimated on all exogenous variables are used as instruments (see Washington et al. 2011; Anastasopoulos 2009; Anastasopoulos et al. 2012a).

Moving to the effect of traffic, this study shows that the cumulative daily number of commercial trucks over the rehabilitation period is an important influence on the determination (and deterioration) of pavement condition. As expected, it is found that as the number of trucks increases, the IRI, RUT, and surface deflection increase, whereas PCR decreases (for specifics on the effect of truck loads on the pavement performance, see textbook sources such as Mannering and Washburn 2013).

An interesting finding is that the condition of pavement drainage (as visually inspected and ranked by the INDOT) plays an important role in pavement deterioration. Inadequate drainage results in faster deterioration of the pavement condition. Therefore, this paper finds that well-drained pavements have higher PCR and lower IRI, RUT, and surface deflection measurements, whereas poorly drained pavements have lower PCR and higher IRI, RUT, and surface deflection measurements. Note that a number of weather (temperature, precipitation) and geotechnical variables (soil type such as glacial soils, residual soils, lacustrine soils, etc.) variables were considered initially in the models, but after the inclusion of the drainage variables, they all became statistically insignificant. This suggests that the effect of weather and geotechnical consideration on the pavement performance is being largely captured by the drainage indicator variables.

Finally, the variables representing the cost per lane-mile of the contract corresponding to the rehabilitation implemented and completed in the base year (the year when the pavement was rehabilitated), are found to play a key role in the pavement performance. A positive relationship is indicated between the cost amount per lane-mile spent for pavement rehabilitation and the pavement condition.

Table 2. SURE Pavement Deterioration Model Results

	Urban interstates				Urban noninterstates (NHS)			
	Overlay		Pavement replacement		Overlay		Pavement replacement	
Variable	Parameter	*t*-stat	Parameter	*t*-stat	Parameter	*t*-stat	Parameter	*t*-stat
Dependent variable: IRI in period t								
Constant	—	—	1.041	3.42	—	—	—	—
Base (right after rehabilitation) IRI (in./mi.)	0.054	2.21	0.053	2.87	0.083	2.61	0.03	2.08
IRI in period $t-1$ (in./mi.)	1.005	46.85	1.02	40.72	1.023	31.89	1.06	25.73
Cumulative (over rehabilitation study period) daily number of trucks (in 100,000s)	0.01	6.71	0.015	2.07	0.025	1.82	—	—
Drainage class: poorly or very poorly drained	—	—	—	—	1.278	3.99	—	—
Rehabilitation contract final cost per lane-mile (millions U.S. dollars)	−0.232	−2.70	−0.841	−2.12	−0.559	−2.95	—	—
Dependent variable: PCR in period t								
Constant	−0.943	−2.30	—	—	−2.854	−4.33	−16.23	−5.36
Base (right after rehabilitation) PCR	—	—	—	—	—	—	0.12	1.83
PCR in period $t-1$	0.999	33.6	0.934	256.76	0.994	33.04	1.01	18.9
Cumulative (over rehabilitation study period) daily number of trucks (in 100,000s)	−0.014	−3.76	—	—	—	—	—	—
Drainage class: poorly or very poorly drained	−1.31	−2.56	−1.405	−3.1	—	—	—	—
Rehabilitation contract final cost per lane-mile (millions U.S. dollars)	—	—	1.326	3.75	1.077	3.18	—	—
Dependent variable: RUT t								
Constant	0.021	3.92	0.025	7.85	0.009	5.11	—	—
Base (right after rehabilitation) RUT (in.)	0.122	2.67	—	—	−0.072	−2.81	0.073	2.76
RUT in period $t-1$ (in.)	1.043	27.22	1.013	43.49	1.059	25.52	1.081	19.71
Cumulative (over rehabilitation study period) daily number of trucks (in 100,000s)	0.0001	3.17	0.0002	4.62	0.0001	2.12	0.0001	1.85
Drainage class: excessively, somewhat excessively, well, or moderately well drained	−0.011	−3.29	—	—	—	—	—	—
Drainage class: poorly or very poorly drained	—	—	—	—	0.009	2.26	—	—
Rehabilitation contract final cost per lane-mile (millions U.S. dollars)	−0.006	−1.84	—	—	−0.009	−3.54	—	—
Rehabilitation contract final cost per lane-mile (less than US$50,000)	—	—	0.008	3.55	—	—	—	—
Dependent variable: surface deflection t								
Constant	—	—	0.127	2.04	—	—	0.106	2.19
Base (right after rehabilitation) surface deflection (thousandths of an inch)	−0.142	−5.69	−0.075	−3.00	−0.034	−1.76	−0.064	−1.92
Surface deflection in period $t-1$ (thousandths of an inch)	1.189	87.89	1.083	81.12	1.056	112.42	1.085	75.03
Cumulative (over rehabilitation study period) daily number of trucks (in 100,000s)	0.0006	4.21	0.0004	2.06	0.002	2.31	—	—
Drainage class: poorly or very poorly drained	0.059	1.71	0.056	2.30	—	—	—	—
Rehabilitation contract final cost per lane-mile (millions U.S. dollars)	−0.061	−1.97	−0.049	−2.44	—	—	—	—
Rehabilitation contract final cost per lane-mile (less than US$50,000)	—	—	—	—	—	—	0.102	2.17
System's adjusted R^2	0.962	—	0.939	—	0.951	—	0.952	—
Number of observations	168	—	196	—	220	—	155	—

Estimation of Pavement Service Lives

With the estimated SURE equation shown in Table 2, pavement conditions can be forecast. With respect to forecasting the pavement condition in year t using the lag $t-1$ variables, note that the predicted values for each consecutive year are used to predict the sequential year.

With the performance for each road section forecast for IRI, PCR, RUT, and surface deflection [Eq. (1)], pavement-performance thresholds are used to determine when the pavement requires corrective action. For the pavement-performance thresholds used to determine service lives, averages of historical threshold values found in the literature are utilized (Flintsch and Zaniewski 1997; FHWA 1999; Hicks et al. 2000; Shafizadeh and Mannering 2003; Anastasopoulos 2009), as shown in Table 3. Table 3 also presents the estimated pavement service lives by road functional class and rehabilitation strategy. It is shown that for the 739 observations with limited data, the predicted average service life of pavement overlay is 15.1 yr, and of pavement replacement is 16.8 yr, when the corresponding observed historical values are 13.7 and 15.6 yr (with higher standard deviations).

To evaluate the forecasting accuracy of the developed SURE models, the mean absolute percent error (MAPE) is estimated as follows:

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}|\text{PE}_i| \tag{10}$$

Table 3. Estimated Rehabilitation Service Lives for All Observations

Variable	Overlay	Pavement replacement
Average threshold values for IRI/PCR/RUT/surface deflection (in urban interstates)[a]	168.5 in./mi/50.2/0.53 in./12.8 thousandths of an inch	
Average threshold values for IRI/PCR/RUT/surface deflection (in urban noninterstates, NHS)[a]	171.2 in./mi/65.6/0.38 in./14.9 thousandths of an inch	
Average historical rehabilitation service life	13.7	15.6
Standard deviation of historical rehabilitation service life	7.9	6.9
Average rehabilitation service life estimated from sample and using forecasted pavement condition	15.1 year	16.8 year
Standard deviation of rehabilitation service life estimated from sample and using forecasted pavement condition	4.8 year	5.4 year
Numerically estimated rehabilitation service lives (urban interstates)	12 year	14 year
Numerically estimated rehabilitation service lives (urban noninterstates, NHS)	10 year	13 year

[a]Average threshold values from Flintsch and Zaniewski (1997), FHWA (1999), Hicks et al. (2000), Shafizadeh and Mannering (2003), and Anastasopoulos (2009).

where $\mathrm{PE}_i = 100 \cdot (x_i - c_i)/x_i$ is the percentage error for observation i of the actual (x) and predicted (c) value of the pavement condition indicator.

Table 4 presents the forecasting accuracy results through application of the MAPE measure (which eliminates the effect of observed data variability), for both the SURE model estimation results and the individually estimated OLS models. The MAPE values closer to zero signify better accuracy. The range of the MAPE for the SURE models is from 0.0008 (as in the PCR equation of the pavement replacement for the interstate model), which indicates that the forecasts underestimate or overestimate the true values by only 0.08% (almost perfect prediction), to 0.0617 (as in the RUT equation of the pavement replacement for the noninterstates model), which indicates that the forecasts are underestimated or overestimated (with respect to the true values) by 6.17% (still a very good approximation). As seen in Table 4, the SURE models provide much better approximations of the true values than the individually estimated OLS models.

Random-Parameter Duration-Model Estimation Results

The dependent variable for duration-model estimation is determined by using the forecast values from the SURE models to estimate the time (in years) needed for one of the performance measures (IRI, PCR, RUT, or surface deflection) to cross their critical thresholds (as shown in Table 3), which is the predicted pavement service life. Various parametric forms were considered, but the random-parameter Weibull model provided the best statistical fit.

Table 4. MAPE Values for Rehabilitation Strategies by Road Functional Class

Road functional class	Condition indicator	SURE models: Overlay	SURE models: Pavement replacement	OLS models: Overlay	OLS models: Pavement replacement
Urban interstates	IRI	0.0495	0.0335	0.0644	0.0536
	PCR	0.0444	0.0008	0.0737	0.0011
	RUT	0.0120	0.0241	0.0199	0.0318
	Surface deflection	0.0098	0.0133	0.0172	0.0186
Urban noninterstates (NHS)	IRI	0.0104	0.0532	0.0184	0.0777
	PCR	0.0070	0.0260	0.0113	0.0395
	RUT	0.0381	0.0617	0.0556	0.1067
	Surface deflection	0.0014	0.0308	0.0023	0.0511

Table 5 presents the hazard-based model results for the duration of this predicted pavement service life for each road class and rehabilitation strategy (the service life of overlays and pavement replacements are charted separately). A positive parameter estimate for an explanatory variable indicates that as the variable value increases, the hazard function decreases; hence, the duration of pavement service life increases. The signs of all the variables were found to be consistent across the models for the two road classes and rehabilitation strategies. However, the effect of some variables was found to vary across the observations. For these random parameters, the normal distribution provided the best statistical fit. For urban interstate pavement replacement and urban noninterstate overlays, the Weibull model with random parameters and gamma heterogeneity was found to provide the best statistical fit. For urban interstate overlays and urban noninterstate pavement replacement, the gamma heterogeneity was not statistically significant, and the simple Weibull model with random parameters was found to provide the best statistical fit.

Turning to the estimation results in Table 5, the IRI, PCR, RUT, and surface deflection measurements taken the year after rehabilitation are found to play a role in the determination of the pavement service life in all the models. Their effect is fixed across the observations (none of their estimated parameters were random). The model results show that, as expected, the higher the IRI, RUT, and surface deflection, and the lower the PCR after rehabilitation, the shorter the service life of the pavement.

The annual number of commercial trucks over the rehabilitation study period is an important influential factor for the determination of the pavement service life. Here, the annual value over the rehabilitation study period is estimated from the daily number of trucks (extended to a 365-day period). As is well documented in the literature, trucks play a very significant role in the deterioration of pavement conditions (see Tanaka et al. 2012; Mannering and Washburn 2013); consequently, increased truck loading can result in decreases in the pavement service life. The effect of trucks is found to be fixed across the observations and is very significant in most of the models, with the expected result that as the number of trucks increases, the pavement service life decreases.

With regard to the effect of the drainage on the pavement service life, this research finds that well-drained pavements have longer service lives, whereas poorly drained pavements have shorter ones. However, the effect of the poor drainage indicator variable for pavement overlays in urban noninterstates is found to vary across the observations. As shown in Fig. 1, although the majority of the pavement sections with good drainage result in longer pavement service lives, there are some sections that result in shorter pavement service lives, and vice versa. One possible reason for this is that these

Table 5. Random-Parameter, Hazard-Based Duration Model Results

	Urban interstates				Urban noninterstates (NHS)			
	Overlay		Pavement replacement		Overlay		Pavement replacement	
	Weibull with random parameters		Weibull with random parameters and gamma heterogeneity model		Weibull with random parameters and gamma heterogeneity model		Weibull with random parameters	
Variable	Parameter	t-stat	Parameter	t-stat	Parameter	t-stat	Parameter	t-stat
Constant	—	—	1.288	14.37	2.327	13.89	N/A	N/A
Base (right after rehabilitation) IRI (in./mi.)	—	—	—	—	−0.001	−4.38	−0.001	−6.62
Base (right after rehabilitation) PCR	0.026	17.13	0.004	6.23	0.008	4.69	0.015	17.64
Base (right after rehabilitation) RUT (in.)	−1.072	−2.93	—	—	−1.873	−18.3	—	—
Base (right after rehabilitation) surface deflection (thousandths of an in.)	−0.032	−6.91	−0.075	−4.88	−0.039	−3.41	—	—
Annual number of trucks (in 1000s)	—	—	−0.008	−27.7	−0.012	−3.94	−0.003	−7.61
Drainage class: poorly or very poorly drained	—	—	−0.102	−7.41	−0.112	−4.57	−0.040	−3.51
Standard deviation of parameter distribution	—	—	—	—	**0.079**	**1.96**	—	—
Average annual range of temperature (°F) over rehabilitation period (from base year to the analysis year t)	−0.009	−8.83	−0.015	−25.5	−0.004	−3.72	−0.021	−7.71
Standard deviation of parameter distribution	**0.008**	**3.96**	**0.056**	**8.51**	**0.003**	**3.10**	**0.036**	**4.91**
Average annual precipitation over the rehabilitation period (in.)	−0.228	−2.97	−0.238	−6.17	−0.092	−2.91	−0.048	−2.42
Standard deviation of parameter distribution	—	—	—	—	—	—	**0.025**	**4.43**
Rehabilitation contract final cost per lane-mile (millions U.S. dollars)	—	—	0.026	2.58	—	—	0.029	4.45
Standard deviation of parameter distribution	—	—	—	—	—	—	**0.061**	**3.26**
Rehabilitation contract final cost per lane-mile (less than US$50,000)	—	—	—	—	−0.025	−2.93	—	—
θ	—	—	1.112	3.28	1.088	3.41	—	—
P	5.7	15.12	19.41	8.50	6.03	18.22	9.1	18.81
LL(0)	−239.9	—	−277.3	—	−279.2	—	−189.7	—
LL($\boldsymbol{\beta}$)	−57.2	—	−44.8	—	−53.9	—	−30.8	—
McFadden pseudo R^2	0.76	—	0.84	—	0.81	—	0.84	—
Number of observations	168	—	196	—	220	—	155	—

sections are well drained due to expectations of high precipitation, adverse weather, or other unobserved factors (geotechnical conditions may favor the pavement condition to deteriorate faster), which in turn may cause the pavement service life to be less.

The average annual range of temperature (measured in °F) over the rehabilitation period (from base year to the analysis year t) and the average annual precipitation (measured in in.) over the same rehabilitation period are both found to influence pavement service life significantly. Note that a number of temperature and precipitation variables (such as the average annual temperature, the average annual range of precipitation, the average annual standard deviation of temperature and precipitation, and so on) were tested, with the annual range of temperature and the average annual precipitation set of variables providing the best statistical fit for the estimated models. In fact, the pavement service life is found to be negatively related to pavement sections that have wide annual ranges of temperature and high precipitation levels. However, the effect of the weather is not constant across all the pavement sections. In all models, the average annual range of temperature results in random parameters. Fig. 1 shows that given their distributional parameters, approximately 78.1% (on average) of the distributions is less than zero and about 21.9% (on average) is greater than zero. In addition, the average annual precipitation results in a random parameter in the pavement replacement for noninterstates model (and in fixed parameters for the other three models). As shown in Fig. 1, given its distributional parameter, 97.2% is below zero and 2.8% is above. This finding is important because it shows that the effect of the weather on pavement service life cannot be assumed to be uniform across all pavement sections. Here, the possibility exists that there is a class of pavement sections that are located in areas that experience adverse weather but still have long pavement service lives or that there is another class of pavement sections that are located in areas that do not experience adverse weather but still have short pavement service lives. One explanation for this is the extra caution that road agencies may give to the first class of pavement sections by performing routine maintenance on them more often than those of the second class. These mixed effects are also in line with Anastasopoulos et al. (2011), where it is shown that the effect of weather on pavement conditions varies across the observations (for some observations, good weather is affiliated with poor pavement conditions, or bad weather is affiliated with good pavement conditions).

The variables representing the cost per lane-mile of the contract corresponding to the rehabilitation implemented and completed in the base year (the year when the pavement was rehabilitated), are found to play a key role in pavement service life. Table 5 indicates the generally positive relationship between the cost amount per lane-mile spent for pavement rehabilitation and pavement service life. Interestingly, in the model of pavement replacement for urban noninterstates, the effect of the cost per lane-mile of the contract corresponding to the rehabilitation implemented and completed in the base year is found to vary across the pavement sections. Given the distributional parameters, Fig. 1 illustrates that for some pavement sections (most likely those that have a very low benefit-cost ratio resulting from pavement rehabilitation), a large cost per lane-mile for pavement rehabilitation will not necessarily result in

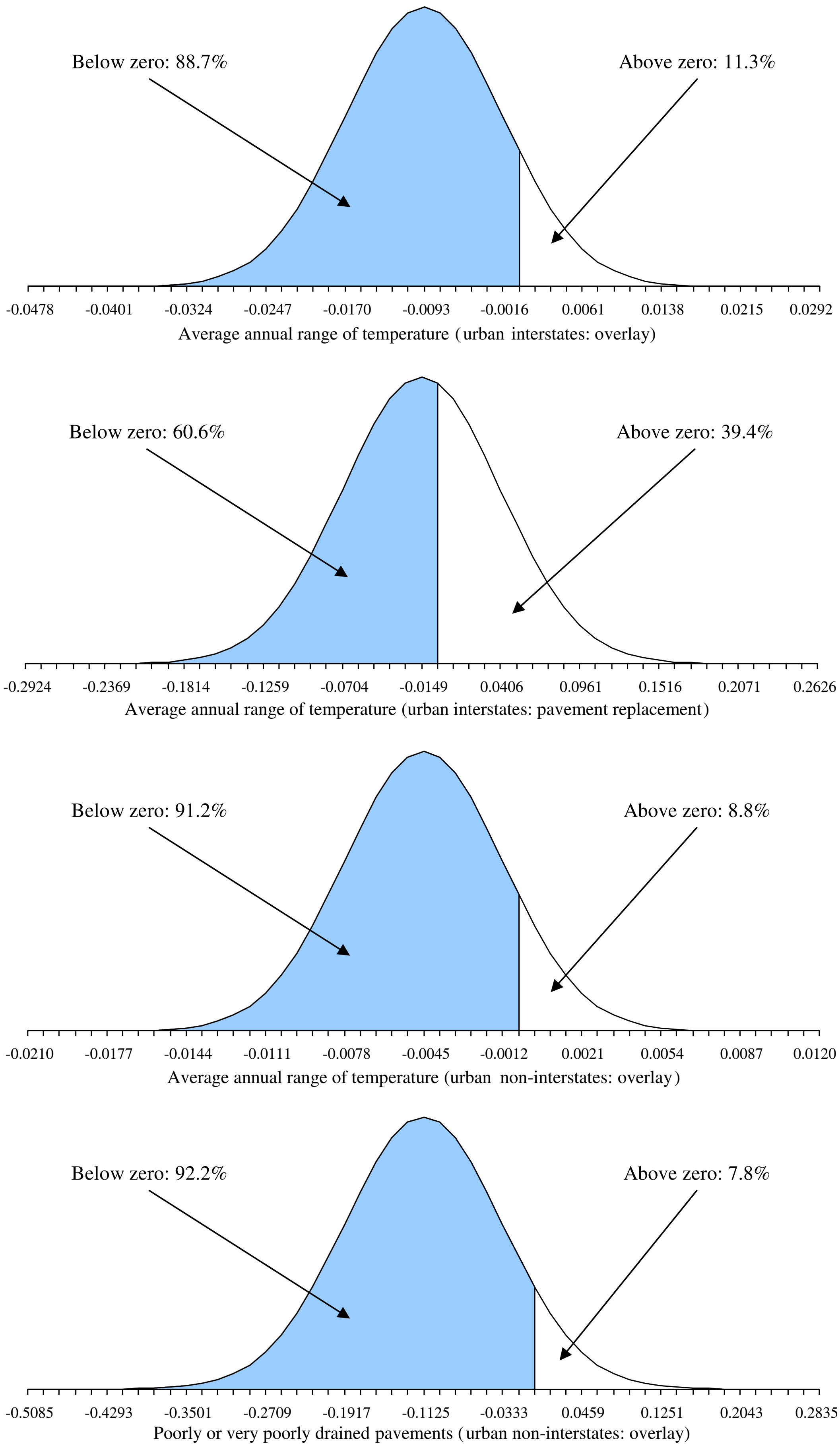

Fig. 1. Distributions of the random parameters

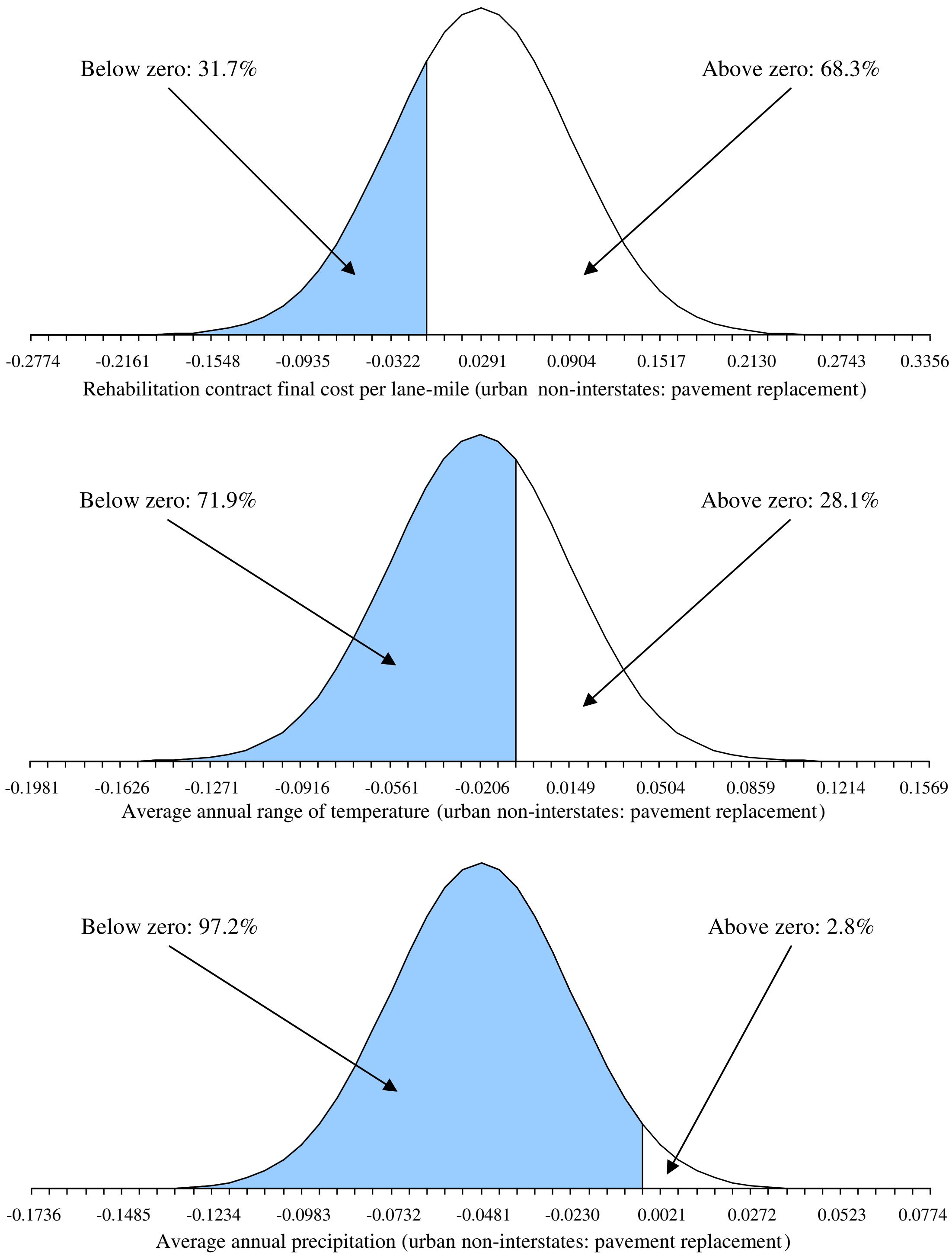

Fig. 1. (*Continued.*)

long pavement service life. On the contrary, for some other sections (most likely those that have a very high benefit-cost ratio resulting from the pavement rehabilitation), a small cost per lane-mile for the pavement rehabilitation may result in long pavement service life. A possible reason for this is that there may be a class of pavement sections that are located on difficult terrain or have unusual geotechnical conditions that require a higher cost per lane-mile to rehabilitate, and at the same time favor more rapid deterioration of the pavement conditions. In contrast, there may be another class of sections located on good terrain that require lower cost per lane-mile to rehabilitate, and at the same time favor less deterioration of pavement conditions.

Turning to the hazard functions of the duration models, Fig. 2 presents plots for each rehabilitation strategy and road class. The hazard function curve for pavement overlays on urban interstates and pavement replacement on urban noninterstates is monotonic, indicating that over time, the pavement service life-ending probabilities increase. On the other hand, for pavement replacement on urban interstates and pavement overlays on urban noninterstates, the hazard function is nonmonotonic, indicating that over time, the pavement service life-ending probabilities increase to a point and then decrease thereafter. The points at which the hazard function changes from increasing to decreasing are computed as 21 yr for the first instance and 15 yr for the second. This finding has

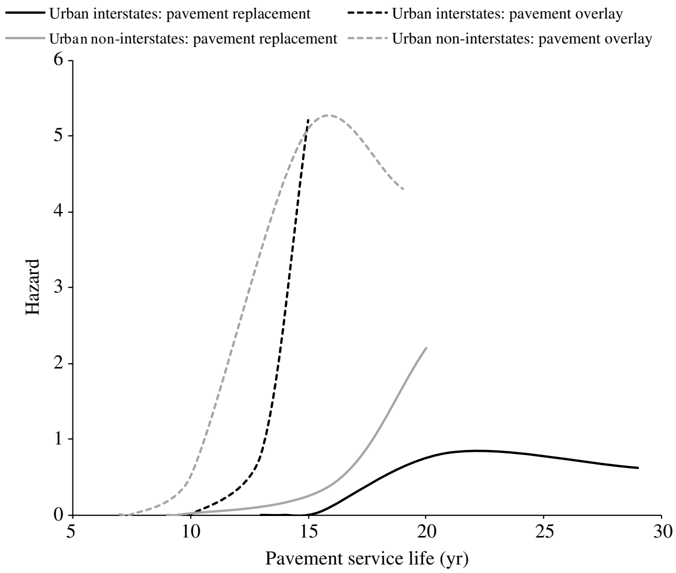

Fig. 2. Hazard functions for the pavement service life models (for pavement overlay and replacement on urban interstates and noninterstates of the NHS)

important implications because it means, for example, that once the pavement service life of an urban interstate section treated with pavement replacement goes over 21 yr, the pavement service life is shorter and is less likely to end soon. Ideally, one would like to see the hazard function increase monotonically over time so that the probability that the pavement service life would end would increase more and more as time passes. However, the analysis herein shows that this is not the general case for Indiana urban interstate and noninterstate roads.

Finally, the survival functions illustrated in Fig. 3 show the pavement service life-ending probabilities given the current pavement service life. For example, for pavement replacement in urban noninterstates, it is shown that the probability that the pavement service life is 7, 13, and 17 yr is approximately 1, 0.4, and 0, respectively.

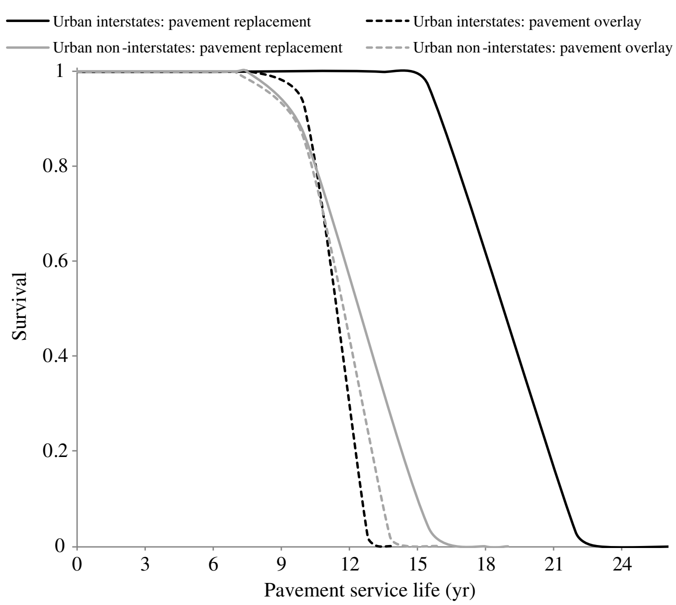

Fig. 3. Survival functions for the pavement service life models (for pavement overlay and replacement, on urban interstates and noninterstates of the NHS)

Table 6. Likelihood Ratio Tests for the Random versus Fixed Parameters and Forecast versus Observed Duration Models

Urban road class	Pavement rehabilitation type	Degrees of freedom	χ^2	χ^2 critical[a]
Likelihood ratio tests: random-parameter versus fixed-parameter models[a]				
Interstate roads	Overlay	1	13.3	10.8
	Pavement replacement	1	12.2	10.8
Noninterstates (NHS)	Overlay	2	14.7	13.8
	Pavement replacement	3	17.7	16.3
Likelihood ratio tests: forecast versus observed models[b]				
Interstate roads	Overlay	5	6.6	9.2
	Pavement replacement	9	10.2	14.7
Noninterstates (NHS)	Overlay	12	7.8	18.5
	Pavement replacement	9	2.2	14.7

[a]0.999 level of confidence.
[b]0.90 level of confidence.

Model Evaluation

To evaluate whether the random-parameter models are statistically superior to their corresponding fixed-parameter models (the hazard-based duration models with the random parameters restricted so that they are fixed across the observations), likelihood ratio tests are conducted as follows:

$$-2[LL(\hat{\boldsymbol{\beta}}_{FP}) - LL(\hat{\boldsymbol{\beta}}_{RP})] \tag{11}$$

where $LL(\hat{\boldsymbol{\beta}}_{FP})$ is the log likelihood at convergence of the "restricted" (fixed-parameter) hazard-based duration model, and $LL(\hat{\boldsymbol{\beta}}_{RP})$ is the log-likelihood at convergence of the "unrestricted" (random-parameter) model. The statistic is chi-square distributed, with degrees of freedom equal to the difference in the number of parameters between the restricted and unrestricted models. The resulting chi-square statistics presented in Table 6 give a greater than 0.999 confidence level, indicating that there is more than 99.9% confidence that the random parameter models are statistically superior to the corresponding fixed parameter models.

Fig. 4 presents a graphical representation of the actual (the observed values and those estimated using the performance models and thresholds) versus the predicted (the forecasts using the hazard-based duration models) pavement service lives for the estimated random parameter and fixed parameter hazard-based duration models, respectively. The mean-predicted over the actual values for the two classes of models indicate that the random-parameter models provide better overall fit relative to the fixed-parameter models. These findings are an outgrowth of the fixed-parameter hazard-based duration model's restriction that the estimated parameters are the same for all observations.

To assess the validity of using forecast pavement-performance values from SURE estimations, separate data were gathered on 306 road sections for which pavement service life is known (overlays or pavement replacements have been conducted). The study then compared duration model estimates based on the forecast data (with the pavement service life forecast using the predicted pavement conditions and applying historical thresholds as shown in Table 3) and (using only observed historical pavement service lives for the 306 road sections) observed models *FM* and *OM* using a likelihood ratio test. This test is as follows:

$$-2[LL(\hat{\boldsymbol{\beta}}_{T}) - LL(\hat{\boldsymbol{\beta}}_{FM}) - LL(\hat{\boldsymbol{\beta}}_{OM})] \tag{12}$$

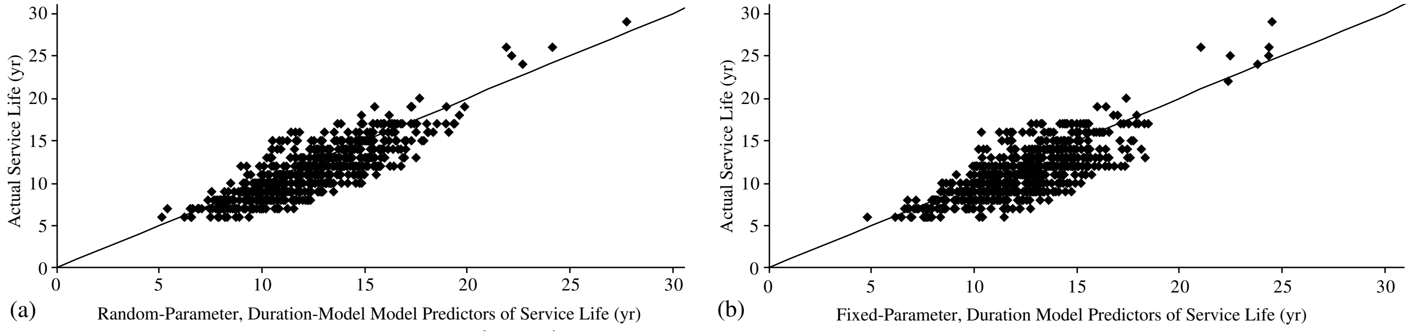

Fig. 4. Mean-predicted over actual service lives of random (a) and fixed (b) parameters hazard-based duration models; the straight lines indicate the equivalence of mean-predicted and actual values

where $LL(\hat{\boldsymbol{\beta}}_T)$ is the log likelihood at convergence of the model estimated with the data from both datasets (*FM* and *OM*), and $LL(\hat{\boldsymbol{\beta}}_{FM})$ and $LL(\hat{\boldsymbol{\beta}}_{OM})$ are the log likelihoods of convergence of the limited and forecasted models, respectively. This chi-square test statistic is chi-square distributed with degrees of freedom equal to the summation of the number of estimated parameters in all models (*FM* and *OM*) minus the number of estimated parameters in the full model *T* (all data included). The resulting chi-square statistic provides the probability that the models have different parameters. The likelihood ratio tests, shown in Table 6, indicate that the null hypothesis that the parameters are equal could not be rejected at the 0.90 level of confidence.

The study also conducted alternate likelihood ratio tests in the following form:

$$-2[LL(\hat{\boldsymbol{\beta}}_{OMFM}) - LL(\hat{\boldsymbol{\beta}}_{FM})] \quad \text{and} \quad -2[LL(\hat{\boldsymbol{\beta}}_{FMOM}) - LL(\hat{\boldsymbol{\beta}}_{OM})] \tag{13}$$

where $LL(\hat{\boldsymbol{\beta}}_{OMFM})$ is the log-likelihood at convergence of the model using the converged parameters from *OM* (using only *OM*'s data) on *FM*'s data (restricting the parameters to be *OM*'s estimated parameters), $LL(\hat{\boldsymbol{\beta}}_{FMOM})$ is the log-likelihood at convergence of the model using the converged parameters from *FM* (using only *FM*'s data) on *OM*'s data (restricting the parameters to be *FM*'s estimated parameters), and $LL(\hat{\boldsymbol{\beta}}_{FM})$ and $LL(\hat{\boldsymbol{\beta}}_{OM})$ is the log-likelihood at convergence of the model using *FM* and *OM* data, respectively. The statistic is chi-square distributed, with degrees of freedom equal to the number of estimated parameters in $\hat{\boldsymbol{\beta}}_{OMFM}$ (or $\hat{\boldsymbol{\beta}}_{FMOM}$), and the resulting chi-square statistic provides the probability that the models have different parameters. As shown in Table 6, the results from the alternative tests were essentially equivalent to the likelihood ratio test presented in Eq. (12) and that the null hypothesis that the parameters are equal could not be rejected at the 0.90 level of confidence. The combination of the tests illustrated in Eqs. (12) and (13) provide strong evidence that this SURE-forecasted modeling approach provides statistically similar explanatory parameter estimates to survival models that use actual observed pavement lives.

Summary and Conclusions

Survival analysis to assess the pavement service life has not been thoroughly implemented in the literature. When implemented, though, a common assumption was that there were no data limitations and that the hazard function (i.e., the conditional probability that the pavement service life will end at some specified time, given that it has not ended up to that time) and the effect of the influential variables on the asset service life are homogenous across observations. The presented methodology builds on past research and overcomes these limitations by forecasting the pavement performance and service life over time and by exploring heterogeneity in the survival process and in the explanatory parameters. The latter is demonstrated by formulating a random-parameter, hazard-based duration modeling approach.

A major finding of this study is that, when analyzing pavement service life, some influential factors may have varying effects. Herein, those are the drainage conditions, rehabilitation costs, and weather (i.e., precipitation and temperature). On the contrary, the effect of the pavement conditions (i.e., IRI, PCR, RUT, and surface deflection), and traffic and truck loads are found to be constant across the observations.

The product of this paper is a quantitative tool that can be used at the project development phase to predict the pavement service life and estimate the effects of different types of pavement rehabilitation. The proposed econometric analyses allow more consistent, efficient, and lower-variance parameter estimates than traditional econometric techniques. Given the complexity of the problem, this study should be viewed as an incremental step toward enabling transportation agencies to make better decisions regarding a number of rehabilitation strategies, allowing the selection of better pavement rehabilitation options. To that end, policy implementation steps could be the subject of future research.

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