

Forecasting Pavement Remaining Service Life with Limited Causal Data

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Abstract: Assessment of pavement remaining service life assists decision making on pavement maintenance and rehabilitation (M&R) such that proper M&R actions can be selected and scheduled to optimize the use of resources over the life cycles of pavements. In this paper, a pavement remaining service life model was developed dealing with the limited causal data present in the pavement management system databases. The model achieves this by including the current pavement condition rating in the model specification and considering the boundary conditions of the pavement deterioration process. Empirical results of model estimation and verification are presented in the context of the Florida pavement condition data sets.

Key words: *Duration models; Failure hazard; Maintenance and rehabilitation; Pavement remaining service life; Survivor curve.*

Introduction

Knowledge of pavement remaining service life (RSL) assists highway agencies in identifying maintenance and rehabilitation (M&R) needs and the required budget and resources and as well as performing proactive planning for the administered roadway networks. Pavement RSL can be defined as the extent of useful life remaining in pavements - in terms of years or equivalent single axle loads (ESALs) - with respect to a failure threshold. Pavement failure is usually categorized as either structural or functional. Functional failure is normally defined as the undesirable condition of certain distress types, such as surface cracks or roughness. Structural failure, on the other hand, is normally based on fatigue due to repetitive loading. Given the pavement surface condition data routinely collected and stored in a pavement management system (PMS) database, the functional failure approach appears to be more attractive for pavement management at the network level. The structural failure approach, which requires the effective thickness or modulus obtained from in-situ measurements, is more suitable for rehabilitation/reconstruction design of pavements at the project level.

Many studies have been undertaken to estimate pavement life or pavement remaining life. AASHTO [1] described several approaches for estimating pavement remaining life both structurally and functionally, solely based on traffic or time. Some studies were based on falling weight deflectometer (FWD) measurements. Park and Kim [2] developed prediction methods for the remaining life of flexible pavements using FWD multiload-level deflections. The procedure involves using both pavement response models and pavement performance models. The former were used to predict critical pavement response from surface deflections and deflection basin parameters; the latter were used to model the relationships between critical pavement responses and actual pavement performance. Finally, data from the Long-Term Pavement Performance database were used to verify the proposed procedure.

In a more recent study, Werkmeister and Alabaster [3] proposed a practical method to estimate the remaining pavement life of low-volume roads using the results of FWD measurements. The method was developed using observations from accelerated pavement tests and field results from Transit New Zealand's asset management database. The models, although straightforward, are more applicable to the project-level analysis given the excessive costs associated with data acquisition. At the network level, methods based on historic pavement condition data routinely collected as part of a PMS appear to be more appropriate. In this regard, many researchers [4-6] have developed pavement performance models with respect to certain pavement condition indices and used them to predict pavement life or remaining life in conjunction with a pavement condition threshold value that triggers necessary maintenance or rehabilitation actions.

Instead of relying on pavement performance models that predict the progression of adverse pavement conditions, some research has focused on developing models to directly predict pavement life or remaining life. In this context, Vepa *et al.* [7] proposed a simple procedure based on survivor curves. The concept of using survivor curves is quite straightforward and easy to implement in the current PMS database setting. The disadvantage of the procedure is that groups of curves have to be developed to account for the variation associated with geographical areas, materials, construction procedures, and so forth. Furthermore, the predictive accuracy of survivor curves might be debatable as rough classification is often made to ensure adequate data in each category for developing survivor curves. In another study, Al-Suleiman and Shiyab [8] presented an approach based on inverting roughness performance models. Specifically, the functions describing roughness over time were inverted to predict the time needed to reach a given failure value of the International Roughness Index (IRI). Given the current age of a pavement, pavement remaining life can be calculated as the estimated pavement life less the current age of the pavement. As the procedure is based solely on roughness data, the same restriction applies that different curves have to be developed for groups of pavements with similar characteristics.

Alternatively, a new breed of models, duration models, has been explored to handle the effects of multiple explanatory variables on pavement life or failure time [9-11]. These models represent a probabilistic approach, where the duration (pavement life or time to

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failure) is treated as a random variable. However, these duration models usually require pavement structure-specific data and environmental data, which typically are not available in the current PMS databases. In this paper, RSL prediction models were developed utilizing data routinely collected in a typical PMS database. The model specification and estimation were presented in the context of the Florida Department of Transportation (FDOT) PMS data set.

Data Description

FDOT has maintained a pavement condition survey database since 1973. This database was standardized in 1986 to incorporate pavement condition data from all seven districts in Florida. Before 1986, separate districts would perform their individual survey by hiring either their own personnel or contractors. To assure the consistency of pavement condition evaluation, only standardized data from 1986 to 2007 were used in this study. For modeling purposes, pavement sections with observed failure were extracted from the database and processed and transformed into two data sets: one for model estimation, consisting of 10,144 data records and one for model validation consisting of 3,393 data records. Each record contains information on a pavement section for a specific year. The original and transformed data in these data sets are discussed below.

The traffic data include truck percentage (TP), expressed as the percentage of trucks in the traffic volume, and average daily traffic (ADT). In light of the magnitude of ADT, the logarithm transformation of ADT was used for modeling ease. In practice, FDOT uses a composite pavement condition index termed pavement condition rating (PCR) to represent overall pavement conditions. PCR is defined as the minimum value of three key indices: cracking, ride quality, and rutting. Each index is rated on a 0-10 scale where 10 represents the best condition and 0 the worst. The PCR of 6.4 is used as the threshold value, indicating failure of the pavements. In other words, a rated pavement section is considered failed when the PCR equals to or below 6.4. Therefore, pavement RSL is defined as the remaining number of years that PCR remains above 6.4. As part of the model development effort to be discussed later, a new variable was created as the natural logarithm of the difference between the current PCR and the failure threshold: $\ln(PCR(t_0) - PCR_f)$, where $PCR(t_0)$ represents PCR value at the current year t_0 and PCR_f represents the failure threshold value.

Flexible pavements have different performance characteristics than rigid pavements. A dummy variable was used to account for the effect of the pavement type. The period between two consecutive

rehabilitation actions for a given pavement section is known as pavement cycle. In consideration of its nominal scale, dummy variables were created with the first cycle as the reference base. Finally, since each rehabilitation indicates the beginning of a new cycle, pavement age is defined as the number of years since the last rehabilitation. These variables are summarized in Table 1.

Theoretical Background

Duration models have been extensively used to analyze time-to-event data. Recent developments in duration modeling have focused on the hazard function. The hazard function can be regarded as the probability of occurrence of the event of interest within a short time interval, conditional on having survived up to the starting time of the interval and relevant explanatory variables. In this paper, the event of interest is referred to as the failure of the pavements, specifically, the failure determined by a threshold value of the pavement condition rating.

Pavement RSL, denoted by T , is defined as a nonnegative random variable representing the number of years that a pavement remains in a serviceable condition from the current year. Let t be a realization of T . The cumulative distribution function $F(t)$ represents the probability that pavement will not remain serviceable for t more years and the survival function $S(t)$ represents the probability that it will remain serviceable for at least t years. The mathematical definitions of $F(t)$ and $S(t)$ are given in Eqs. (1) and (2).

$$F(t) = P(T \leq t), \quad t \geq 0 \tag{1}$$

$$S(t) = 1 - F(t) = P(T \geq t) \quad t \geq 0 \tag{2}$$

Having defined pavement failure as a PCR of 6.4 or less in the previous section, $F(t)$ would actually be the probability that the PCR drops below 6.4 within t years and $S(t)$ is the probability that the PCR remains above 6.4 for at least t more years.

The hazard function describes the instantaneous failure rate of pavements at time t given that the pavements have been in serviceable condition until time t . It can be written as:

$$\lambda(t) = \lim_{h \rightarrow 0} \left(\frac{P(t \leq T < t + h | T \geq t)}{h} \right) \tag{3}$$

where, $\lambda(t)$ is the hazard function at time t and h is a infinitesimally small time interval. If $f(t)$ denotes the probability density function of T , the hazard function can be rewritten as:

Table 1. Description of Variables.

Variable	Description	Min	Max
RSL	Pavement Remaining Service Life (Years from Current Year to Failure)	1	20
PCR	Pavement Condition Rating	0	10
Cycle 2	Dummy Variable: 1 if Pavement Cycle = 2, 0 Otherwise	0	1
Cycle 3	Dummy Variable: 1 if Pavement Cycle = 3, 0 Otherwise	0	1
Cycle 4	Dummy Variable: 1 if Pavement Cycle = 4, 0 Otherwise	0	1
Type	Dummy Variable: 1 for Rigid Pavements, 0 for Flexible Pavements	0	1
logADT	Logarithm Transformation of Average Daily Traffic Per Travel Lane	2.28	4.39
TP	Truck Percent, the Proportion of Heavy Vehicles in Daily Traffic	1%	47%

$$\lambda(t) = \lim_{h \rightarrow 0} \left(\frac{F(t+h) - F(t)}{h} \right) \cdot \left(\frac{1}{1 - F(t)} \right) = \frac{f(t)}{S(t)} \quad (4)$$

Noting that the derivative of $S(t)$ is $-f(t)$, the hazard function can also be written as:

$$\lambda(t) = -\frac{d \log S(t)}{dt} \quad (5)$$

A detailed discussion of the above equations can be found in Greene [12]. In specific empirical applications, selection of the hazard function is of primary interest to ensure modeling success. In the past, various distributions have been used for duration T depending on situations. Among those, the exponential, Weibull, log-logistic, lognormal are the commonly used ones. An exponential distribution implies a constant hazard rate, where the hazard is completely independent of time. A Weibull distribution allows a relatively flexible hazard rate, which can be constant, monotonically increasing or monotonically decreasing depending on the value of the parameter. Log-logistic and lognormal distributions are typically used to model a hazard rate that first increases to a certain time point and then decreases afterward.

Model Specification

In the established PMS databases, structural data such as the thickness of pavement structure, modulus or structural number are usually unavailable or incomplete due to the excessive costs of maintaining these data on a timely basis. Therefore, models relying on such information are impractical to implement in a real PMS comprising thousands of roadway sections. Without specific pavement structural information, the current PCR is included as a surrogate as the existing pavement structural condition can be partially captured by the current PCR, a function of three key distresses, cracking, roughness, and rutting.

To allow for the flexibility of hazard, three commonly-used distributions, Weibull, loglogistic, and lognormal, are assessed and compared. The effects of explanatory variables are considered by replacing λ with a link function of the explanatory variables. Let $X(t)$ represent the pavement condition at time t and X_f be the failure condition threshold, the following link function is finally used:

$$\lambda = f\{X(t), \vec{Z}(t) | \alpha, \beta, \vec{\gamma}, X_f\} = \exp\left\{-\{\alpha + \beta \ln[X(t) - X_f] + \vec{\gamma} \vec{Z}(t)\}\right\} \quad (6)$$

where,

$X(t)$ = pavement condition at time t ;

$\vec{Z}(t)$ = vector of explanatory variables;

X_f = failure threshold;

α = constant term;

β = positive parameter; and

$\vec{\gamma}$ = coefficient vector of explanatory variables.

As seen in Eq. (6), the logarithm of the difference between the pavement condition evaluated at time t and the failure threshold is recommended. The benefit of this specification lies in its consideration of the boundary conditions associated with pavement deterioration process. This aspect is further discussed below with

respect to different survival functions.

Boundary Conditions

For the three commonly used distributions, each involves two parameters: λ and p . The corresponding survival functions are shown in Eqs. (7), (8), and (9) with respect to Weibull, Lognormal, and loglogistic, respectively.

$$S(t) = \exp[-(\lambda t)^p] \quad (7)$$

$$S(t) = \Phi[-p \ln(\lambda t)] \quad (8)$$

where, Φ represents the standard cumulative normal distribution function.

$$S(t) = \frac{1}{1 + (\lambda t)^p} \quad (9)$$

Given the link function specification in Eq. (6), two realistic boundary conditions are readily met for all three survival functions above.

1. When the pavement is in the serviceable condition, i.e., λ is finite, the survival function equals to 1 at $t = 0$.
2. As the pavement approaches the failure condition, i.e. $X(t)$ approaches X_f , in Eq. (8), λ approaches infinity and the survival function approaches zero.

As seen, the proposed link function (Eq. (6)) allows the realistic boundary conditions to be met for all three survival functions. For comparison purposes, a benchmark link function specification that directly includes $X(t)$ is also evaluated. It shows through model estimation in the following section that using $\ln[X(t) - X_f]$, instead of $X(t)$, improve data fitting.

Model Estimation and Selection

Maximum likelihood estimation was used to determine the coefficients of the function used to define λ in Eq. (6). Since only segments with observed failure were included, the logarithm likelihood function takes the form of Eq. (10).

$$\ln L(\alpha, \beta, \vec{\gamma}, p) = \sum \ln f(t | \alpha, \beta, \vec{\gamma}, p) \quad (10)$$

For comparison purposes, two link function specifications were evaluated: one with the current pavement condition rating $PCR(t_0)$ (Specification 1) and one with the logarithm of the PCR difference $\ln[PCR(t_0) - PCR_f]$ (Specification 2). The parameters and associated t statistics are summarized in Tables 2 and 3 for Specifications 1 and 2, respectively.

As seen, the signs and magnitudes of the parameter estimates are similar except for the constant term. Specifically, specification 2 results in increased values of the t statistic for the constant term and the transformed PCR term, which implies more efficient estimates. For the model selection, Akaike Information Criterion (AIC) was used, which is calculated from log likelihood function using Eq. (11).

$$AIC = -2 \log(L) + 2(c + p + 1) \quad (11)$$

Table 2. Estimation Results of Specification 1.

Variable	Weibull		Loglogistic		Lognormal	
	Coefficient	T-statistic	Coefficient	T-statistic	Coefficient	T-statistic
Constant	0.5982	5.815	-0.7806	-6.773	-0.9795	-8.319
PCR	0.3851	45.472	0.5578	65.397	0.5704	63.495
Cycle2	-0.2498	-22.913	-0.3045	-23.789	-0.2841	-21.578
Cycle3	-0.4429	-23.166	-0.4287	-19.124	-0.4089	-16.584
Cycle4	-0.5445	-8.521	-0.5083	-7.796	-0.5057	-6.814
logADT	-0.3537	-16.837	-0.4011	-17.049	-0.3849	-16.041
TP	-1.4991	-21.200	-2.0188	-21.861	-1.9434	-20.097
Type	0.2652	13.689	0.3018	14.401	0.2831	13.473
Scale Parameter (p)	1.8517	127.617	2.818	106.338	1.6084	133.811
log L		-9528.00		-9665.73		-9572.80
AIC		19074.01		19349.46		19163.6
No.of obs. = 10144						

Table 3. Estimation Results of Specification 2.

Variable	Weibull		Loglogistic		Lognormal	
	Coefficient	T-statistic	Coefficient	T-statistic	Coefficient	T-statistic
Constant	3.4428	44.52	3.3878	39.468	3.3391	37.345
$\ln[PCR(t_0) - PCR]$	0.3455	69.706	0.5065	77.039	0.4861	68.62
Cycle2	-0.2333	-22.784	-0.2741	-22.055	-0.2585	-20.084
Cycle3	-0.4211	-22.147	-0.3947	-18.260	-0.3761	-15.758
Cycle4	-0.5021	-7.741	-0.4383	-6.773	-0.4247	-5.654
logADT	-0.3263	-15.851	-0.3748	-16.521	-0.3714	-15.746
TP	-1.3798	-19.481	-1.7520	-19.488	-1.7395	-18.239
Type	0.2599	13.706	0.3036	14.638	0.2954	13.819
Scale parameter (p)	1.889	131.18	2.9268	111.454	1.6396	141.832
log L		-9294.43		-9349.58		-9378.09
AIC		18606.85		18717.16		18774.17
No.of obs. = 10144						

where, c = the number of covariates and p = the number of structural parameters.

The idea of the AIC is to “reward” parsimonious models by penalizing the log-likelihood for the parameters estimated. As seen, replacing $PCR(t_0)$ with $\ln[PCR(t_0)-PCR_f]$ improved data fitting, shown as the reduced AIC values. In other words, given the same number of covariates and structural parameters used in both model specifications, Specification 2 explains more variance in the data set than Specification 1. Thus, Specification 2 is preferred to Specification 1. Among different hazard models under Specification 2, Weibull provides the best fitting to the data and thus is selected as the “best” model. This may be explained that the failure hazard of the pavement overall condition (PCR) follows a monotonically increasing trend, which is better modeled by the Weibull distribution.

Furthermore, the signs and magnitude of the explanatory variables are consistent between the two link function specifications and across different hazard functions. All variables are significant at the 0.01 level. The signs of the explanatory variables are intuitively expected. The positive signs of the coefficients for the variables $\ln[PCR(t_0)-PCR_f]$, PCR, and pavement type imply that pavements in worse condition have a higher failure hazard than those in better condition and rigid pavements have a lower failure hazard compared

to flexible pavements. In contrast, negative signs are associated with logADT, TP, and each additional rehabilitation cycle. They indicate that higher traffic loading contributes to a faster deterioration of pavements. Compared with Cycle 1, which reflects the as-built pavement condition, failure hazard increases with each additional cycle as seen by the increase in the magnitude of the coefficients. This could be attributable to the underlying structural damages accumulated with each additional cycle.

Model Evaluation

Parametric Analyses

To illustrate the impacts of the explanatory variables on pavement failure hazard, a parametric analysis was undertaken for the “best” model: the link function of Specification 2 with Weibull distribution. For this evaluation, each variable was analyzed individually by holding the other variables constant, shown in Figs. 1 to 5.

As shown in Fig. 1, four distinct curves were obtained for the four pavement cycles modeled with higher hazard associated with higher cycles and the hazard difference between different cycles increases with time. Figs. 2 and 3 show that higher traffic volume and truck percentage result in higher failure hazard because of the

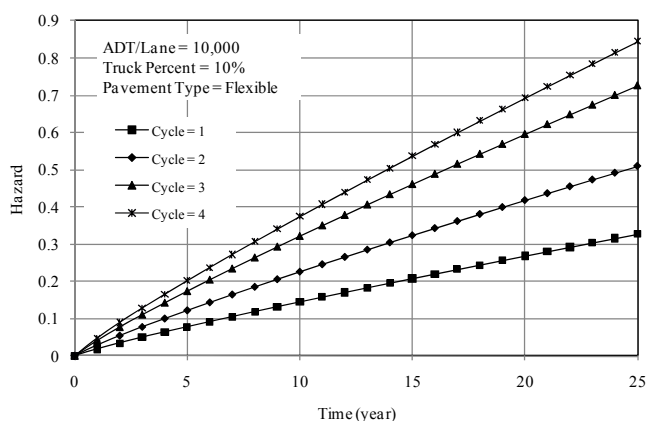


Fig. 1. The Effects of Pavement Cycles on Pavement Failure Hazard.

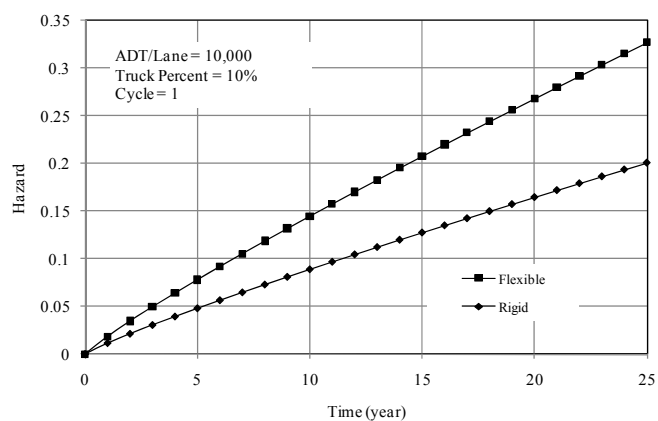


Fig. 4. The Effects of Pavement Types on Pavement Failure Hazard.

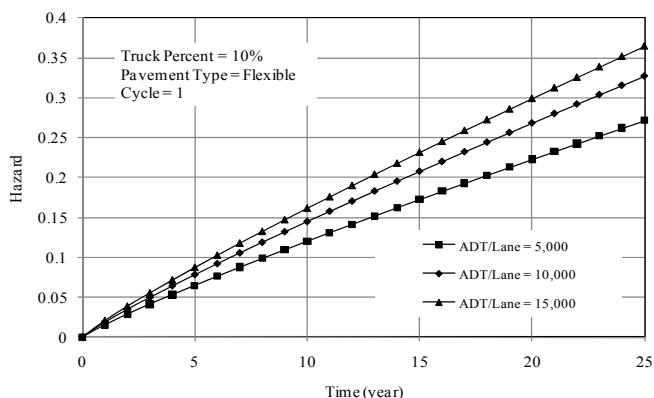


Fig. 2. The Effects of ADT on Pavement Failure Hazard.

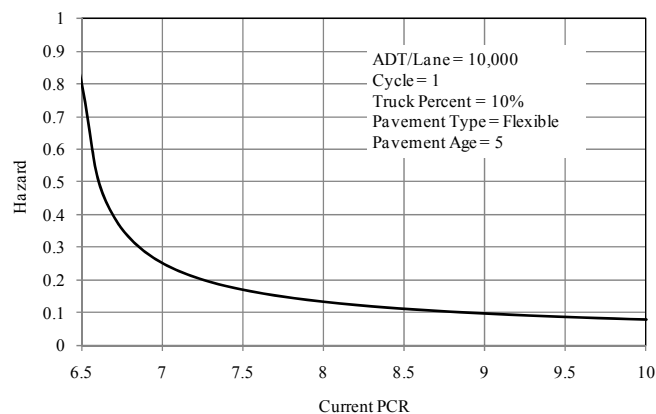


Fig. 5. Pavement Failure Hazard Versus Current PCR.

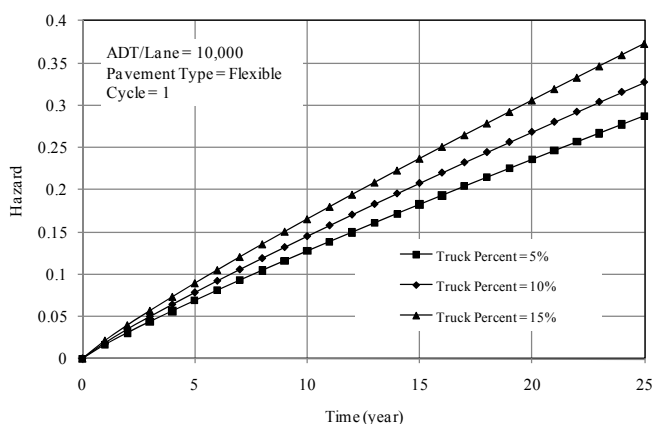


Fig. 3. The Effects of Truck Percentage on Pavement Failure Hazard.

higher traffic loading implied. Fig. 4 indicates that flexible pavements have a higher failure hazard than rigid pavements and the hazard difference increases with time. Finally, the hazard function was also plotted against the current pavement condition rating (PCR) in Fig. 5, indicating a higher failure hazard for worse pavement conditions (lower PCR) and the hazard increases dramatically as the pavement approaches the failure condition.

Model Verification

The “best” model (the link function of Specification 2 with Weibull distribution) was further assessed using a separate data set, which was set aside initially for the purpose of verification. The objective of this assessment is to see if the model developed with the estimation data set performs well with the verification data set. For this purpose, the survival curve predicted by the model was compared with that derived from the verification data set, shown in Figs. 6 and 7 for flexible pavements and rigid pavements, respectively.

As seen, the survival curves fit well graphically. To statistically test if the two curves are same, a special test proposed by Lin and Wang [13] was used. This test overcomes the weakness of commonly-used log-rank and Wilcoxon tests that may have a significant loss of statistical testing power when two survival curves cross, which is our case. The new statistic is constructed based on a standardized summation of the squared differences between the number of observed failures and the number of expected failures. This new statistic follows a standard normal distribution. With the survival curves presented in Figs. 6 and 7, the values of the test statistic were computed to be 0.0759 (P-value = 0.47) for flexible pavements and 0.0245 (P-value = 0.49) for rigid pavements. Therefore, the null hypothesis that there is no difference between the two survival curves cannot be rejected.

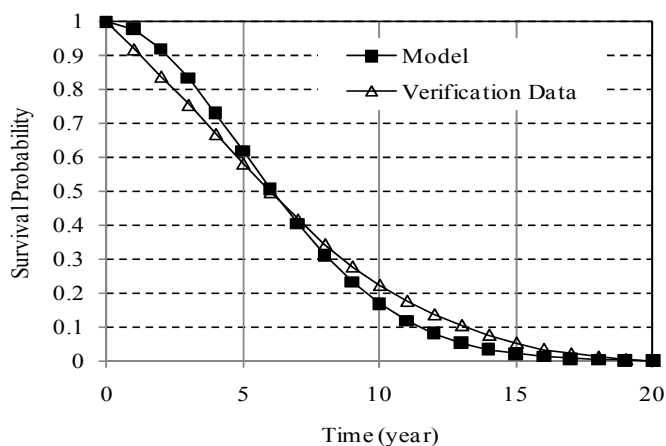


Fig. 6. Comparison of Survival Curves (Flexible Pavements).

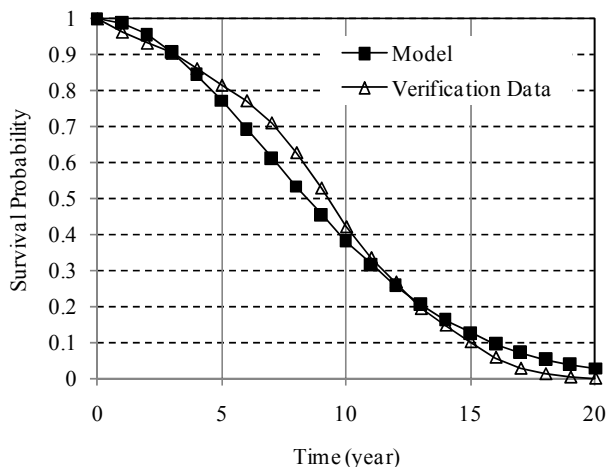


Fig. 7. Comparison of Survival Curves (Rigid Pavements).

Concluding Remarks

In summary, development of accurate and reliable remaining-life prediction models has been a challenging task due to the complexity and uncertainty associated with the pavement deterioration process and a multitude of factors involved. This paper presents a special model specification to deal with the limited causal data present in the existing PMS databases. The specialty of the proposed model lies in its use of current pavement condition rating as a surrogate for relevant pavement structural condition and the consideration of specific boundary conditions associated with pavement deterioration process. Empirical results of model estimation and verification show that the proposed model specification improves the model fitting and thus increases the model explanatory power.

The paper focuses on modeling pavement remaining service life with limited pavement structural data. However, it is strongly recommended that structure-specific information be included as it becomes available in PMS databases through emerging pavement survey technologies. Furthermore, use of current time data, such as annual daily traffic and truck percentages, as predictors is bound to introduce errors as future pavement deterioration is generally

governed by future traffic demand. These errors are regarded as random because future traffic volumes and truck percentages are unknown. As such, the estimated model parameters are intended to capture the pavement deterioration under established traffic patterns. The model may not be adequate when there are significant errors in traffic demand projection.

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