Survival Analysis of Fatigue Cracking for Flexible Pavements Based on Long-Term Pavement Performance Data

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Abstract: The study presented in this paper analyzed the development patterns of fatigue cracking shown in flexible pavement test sections of the long-term pavement performance (LTPP) program. A large number of LTPP test sections exhibited a sudden burst of fatigue cracking after a few years of service. In order to characterize this type of LTPP cracking data, a survival analysis was conducted to investigate the relationship between fatigue failure time and various influencing factors. After dropping insignificant influencing factors, accelerated failure time models were developed to show the quantitative relationship between fatigue failure time and asphalt concrete layer thickness, Portland cement concrete base layer thickness, average traffic level, intensity of precipitation, and freeze-thaw cycles. The error distribution of the accelerated failure time model was found to be best represented by the generalized gamma distribution. The model can also be used to predict the average behavior of fatigue failures of flexible pavements.

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CE Database subject headings: Flexible pavements; Fatigue life; Cracking; Statistical models.

Introduction

Fatigue cracking is a common type of flexible pavement distress primarily caused by accumulation of damage imparted by the traffic loads. Extensive research has been conducted to model and predict fatigue cracking. The performance models can be classified into two major groups: empirical models and mechanistic-empirical models. In an empirical model, cracking is related to measured variables such as axle loads, pavement layer thickness, environmental factors, etc. In a mechanistic-empirical pavement analysis procedure, the performance of pavement is linked to parameters that are mechanics based. Therefore, mechanistic-empirical models correlate the fatigue life to the tensile strain and the stiffness of the asphalt layer (e.g., Epps and Monismith 1972; Shell 1978). The damage caused by each individual load application is then combined using the Miner's Rule (e.g., Huang 1993; ARA 2004). The fatigue models can be calibrated to match the field performance data by using a shift factor (Monismith and Witczak 1982). Or alternatively, the cumulative damage can be related to percent of cracking area by assuming a mathematical function. In the proposed new AASHTO Design Guide (NCHRP 1-37A, ARA 2004, commonly referred to AASHTO 2002 Guide), the selected "transfer" function is a sigmoidal function (ARA 2004). The calibration process and the determination of the transfer function are empirical.

Starting from 1987, the long-term pavement performance (LTPP) program has been monitoring more than 2,400 asphalt and portland cement concrete pavement test sections across the United States and Canada (FHWA 2004). Fatigue cracking of flexible pavements has been continuously monitored on many LTPP test sections, along with pavement structures, loading, materials, environment, and other pieces of information. Some LTPP test sections have been used to calibrate the mechanistic-empirical models in the NCHRP 1-37A (ARA 2004). It would be interesting to build a statistical model to investigate the average fatigue behavior of the LTPP test sections under various potential influencing factors. In a statistical model, the relative importance of these factors can be compared statistically, and the most significant factors can be identified.

Using the LTPP data, the researchers conducted a survival analysis for flexible pavement test sections to investigate the relationship between fatigue cracking and its potential influencing factors. The survival model developed in this study, called the accelerated failure time model, allows researchers to predict fatigue failure time of a pavement.

Research Data Selection

There are eight general pavement studies (GPS) and nine specific pavement studies (SPS) in the LTPP program. The data used in these studies include 486 pavement sections, primarily from three experiments, which were designated as GPS1: asphalt concrete (AC) on granular base, GPS2: AC on bound base, and SPS1: strategic study of structural factors for flexible pavements.

In the LTPP program, distress data are collected using a uniform set of distress definitions, *The Distress Identification Manual for the Long-Term Pavement Performance Project*

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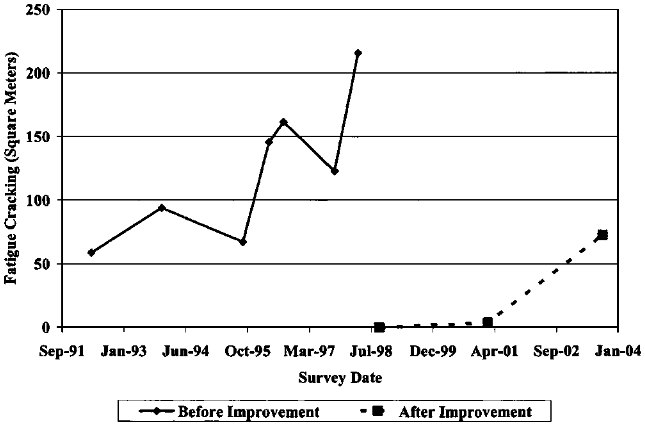

Fig. 1. Decrease of fatigue cracking by pavement improvement (test section no. 241634)

(Miller and Bellinger 2003). The measurement unit for the alligator cracks is the area of asphalt concrete affected by cracking (in square meter) with three severity levels: low, moderate, and high. They were described by Miller and Bellinger (2003), as follows:

- *"Low: An area of cracks with no or only a few connecting cracks; cracks are not spalled or sealed; pumping is not evident.*
- *Moderate: An area of interconnected cracks forming a complete pattern; cracks may be slightly spalled; cracks may be sealed; pumping is not evident.*
- *High: An area of moderately or severely spalled interconnected cracks forming a complete pattern; pieces may move when subjected to traffic; cracks may be sealed; pumping may be evident."*

Along with alligator cracking, the LTPP program also records other types of distress such as longitudinal cracks (in-wheel path and nonwheel path), transverse cracks, block cracks, potholes, etc. The cracking data used in this study were obtained from the LTPP table MON_DIS_AC_REV in the *Monitoring module* (a module contains similar sets of tables) of the LTPP Information Management System (IMS) Release 17.0, dated January, 2004. In addition to the cracking data, potential influencing factors were selected from various LTPP tables. The thickness of pavement layers, subgrade conditions, and percent air voids were obtained from tables in the LTPP *Material Test* module. Traffic data and equivalent single axle loads (ESAL) were queried from the *Traffic* module. Environmental data were acquired from both the LTPP *Climate* and *Automated Weather Stations* modules.

Maintenance and rehabilitation activities effectively reduce the distress level. As shown in Fig. 1, fatigue cracking was significantly reduced after a pavement improvement was applied to a LTPP test section (Test Section 241634). Various maintenance and rehabilitation procedures have different effectiveness in reducing the distress level, which makes it difficult to model. To simplify the modeling task, the study only chose test sections where no significant improvements were recorded after being enrolled in the LTPP experiments, or selected pavement conditions just before the improvement.

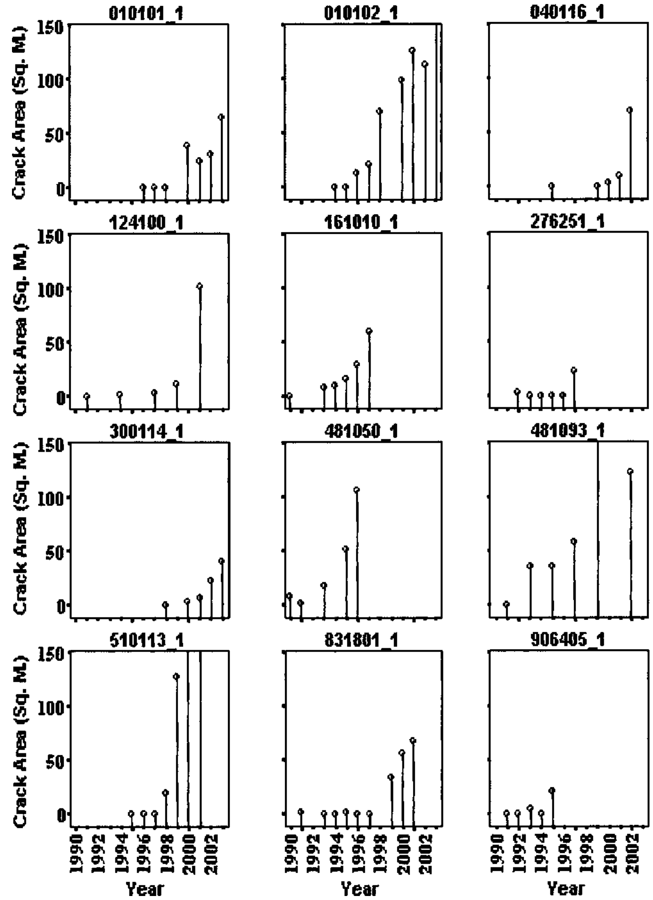

Fig. 2. Rapid increase of pavement fatigue cracking after certain service periods

Rationale for Employing Survival Analysis

Fatigue Cracking Patterns at the Long-Term Pavement Performance Test Sections

One possible regression approach would involve using the fatigue cracking area as a response variable and various performance influencing factors as independent variables. An alternative approach would be selecting a fatigue cracking area as a failure threshold related to a specific time duration or cumulative traffic loads and then using the time or the cumulative traffic loads as a response variable.

Observations of the LTPP fatigue cracking data revealed that most cracking in the wheel path followed this pattern: no significant cracks appear for several years; then cracks appear and soon propagate to a significant level. Fig. 2 shows some typical fatigue cracking development patterns on selected LTPP test sections. To simplify these charts, cracking areas of all severities were added together (Y axis), and the X axis is the year of monitoring. Each plot in Fig. 2 represents a separate test section. The first two digits of the plot subheadings represent the state codes, and the next four digits indicate section identification numbers.

The LTPP fatigue cracking data showed a large amount of variability and lacked any easily discernable trends, especially for sections at a low cracking level (Fig. 3). These variations may be due to recording or classification errors. It is easy to misclassify early stages of fatigue cracking with other types of cracking in asphalt pavements, such as longitudinal cracking. Sources of error

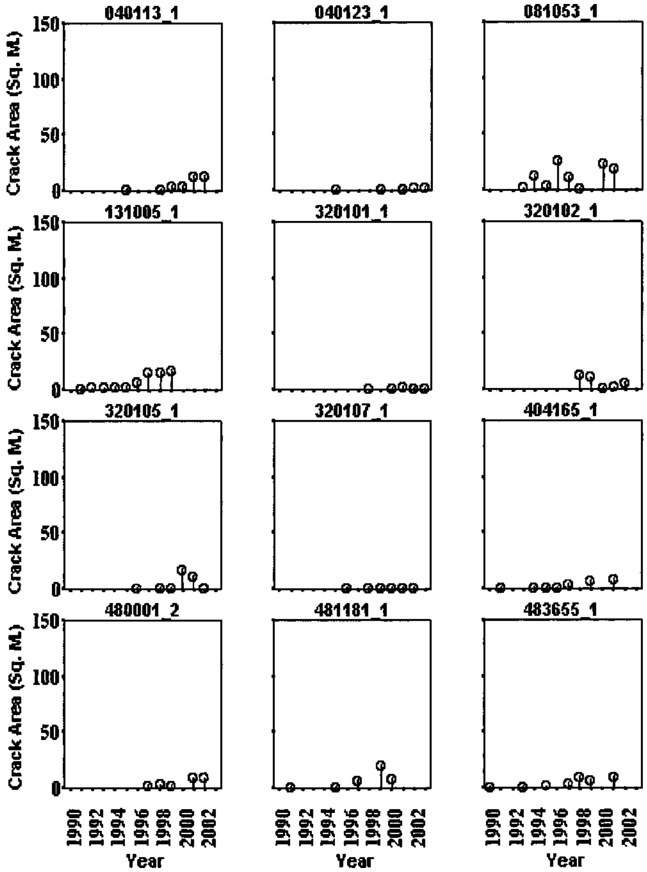

Fig. 3. Variations of annual observed fatigue cracking on pavements with low cracking severity levels

could include interchanging cracks in the wheel path with those not in the wheel path. This is especially true for the longitudinal cracks at the pavement edge. These inconsistencies in the LTPP data have been previously reported by other researchers (Fugro-BRE 2001). To address this issue, studies have suggested adding the area affected by alligator cracking to the area affected by longitudinal cracking (Hall et al. 2002; Seeds et al. 2002). Because the longitudinal cracks were surveyed by length, in order to get the area affected by longitudinal cracks, one has to multiply the crack length by the width of wheel path. The selection of width, however, was not uniformly defined. In addition to the arbitrary definition of wheel path width, the incorporation of the longitudinal cracks in the nonwheel path may overestimate the fatigue cracking. Because of these variations, a consistent pattern of fatigue cracking area cannot be expected on many test sections, which makes it difficult to use the cracking area as a response variable directly. Another challenge of using the cracking area as a response variable is that the auto-correlation between annually collected data violates the "independence" assumption of a standard regression and may cause bias in estimated parameters.

On the other hand, if a significant fatigue cracking level is used to represent the failure event, it would be less affected by misclassification and localized road defects. A high concentration of fatigue cracks would make it easier to be detected by surveyors, and hence it is a good way to define fatigue failure. Even if some cracks were misclassified, at least a large portion of such cracks are truly fatigue cracks. Therefore, defining a uniform fatigue threshold and using time or cumulative traffic loads as a response variable is appropriate. This will also solve the autocorrelation problem. However, due to insufficient traffic information on some LTPP sections, the use of time is a better option as compared to cumulative traffic loads in an empirical analysis.

Censored Cracking Data

The use of failure time at a defined threshold creates a data censoring problem. Data censoring means the expected event does not occur during the observation period of an experiment. Some LTPP test sections did not show any obvious fatigue cracking until the very last survey time. If the expected event is defined as the appearance of significant fatigue cracking, these test sections are called right censored. Some LTPP test sections had exhibited severe fatigue cracking with their earlier surveying records in the LTPP-IMS. These test sections are called left censored because the time when significant fatigue cracking occurred was before the beginning of the experiment. There are also test sections where cracking failure time cannot be determined since they were not continually monitored. These test sections are called interval censored. Censored data are an intrinsic characteristic of many experiments. The exclusion of censored data can cause biased analysis results. For example, the exclusion of right-censored test sections would make the analysis results biased toward shorter life pavements. By using censored data to estimate survival models, the censoring problem can be avoided (SAS Institute Inc. 2004).

Survival Analysis

Previous Work in Survival Analysis

Survival analysis has been previously used in pavement performance modeling. Survival curves were applied to highway pavements starting in the 1930s (Winfrey 1969), although they relied more on empirical methods than statistical procedures. The Highway Design and Maintenance Standards Study (HDM), initiated by the World Bank, employed survival analysis to predict the initiation of fatigue cracking in the HDM-III model (Paterson 1987). The American Association of State Highway Officials (AASHO) road test data were reanalyzed by Prozzi and Madanat using survival analysis and the result indicated that the survival model is more appealing than the original AASHO formulations (Prozzi and Madanat 2000). Most recently, researchers also attempted to employ survival models to predict in situ pavement fatigue performance from laboratory fatigue test results (Tsai et al. 2003).

Determination of Fatigue Failure Threshold

In order to find the failure time, a uniform fatigue failure threshold limit must be defined. When the severity of fatigue cracking exceeds this threshold limit, the pavement is considered to have failed. Thus the time that a pavement can survive without a major fatigue failure can be identified. To find the appropriate limit, a box plot was generated to show the average increase of fatigue cracking area in each following year in relation to the current year data (Fig. 4). In the plot, the *X* axis represents the fatigue cracking area of the current year, including all pavement sections that have the same cracking area. The *Y* axis represents the cracking areas of these pavements in the following year. The plot verifies that the cracking growth can be roughly divided into two stages: slow

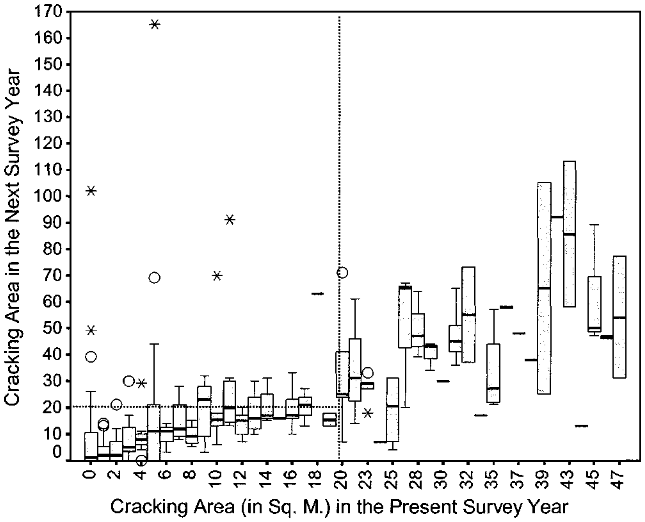

Fig. 4. Average increase of fatigue cracking areas of long-term pavement performace sections with the same present values at the following survey year

growth and rapid growth. The transition point between these two stages is about 20 m^2. In addition, observing the outliers with low cracking (signified here by circles and stars) one can see that most of these outliers are beyond 20 m^2. Therefore, 20 m^2 of fatigue cracking of different severity level was selected as the failure threshold. Each LTPP section has a length of 152.4 m (500 ft), and the typical lane width is 3.66 m (12 ft). Therefore, the total area of the pavement section is 3.66 m $\times$ 152.4 m = 557 m^2. The 20 m^2 threshold corresponds to 3.6% of each LTPP section. If different threshold values are used, the survival time of these pavement sections may change correspondingly.

Survival Models and Fatigue Failure Models

A statistical regression model consists of two components, a systematic component and an error component. The systematic component is used to model measurable and explainable variations in the data, whereas the rest of the variations are left to be handled by error component. The commonly used survival models include semiparametric models and parametric models. If one is only interested in the systematic components, or the independent variables, one could use the semiparametric model. For example, one could use the proportional hazards model (Cox 1972). On the other hand, if one is interested in both the systematic as well as the error components, as in the case of predicting pavement failure time, one needs to use a parametric model, such as the accelerated failure time model (Feigl and Zelen 1965). The accelerated failure time model assumes that the effect of independent variables on a failure time distribution is multiplicative on the event time. One possible form of the accelerated failure time model is as follows (Feigl and Zelen 1965):

$$T = e^{X\beta} T_0 \qquad (1)$$

where T = failure time; T_0 = failure time associated with a baseline distribution function; X = vector of the influencing factors; β = vector of unknown regression parameters.

The model assumes that without the influence of the independent variables, the failure time will follow a baseline distribution (exponential, lognormal, etc.). The effect of the covariates on failure time is to speed up (or slow down) failure time by multiplying a time points (T_0) sampled from the baseline distribution by a multiplier $e^{X\beta}$. This study used the accelerated failure time model. In this paper, influencing factors, covariates, and independent variables signify the same meaning.

Development of the Accelerated Failure Time Model

As can be seen from Eq. (1), an accelerated failure time model needs to specify these two components: the independent variables with their coefficients, and the baseline distribution function for T_0 to model the variations unexplained by the independent variables.

Independent Variables

In the field, various factors influence the performance of flexible pavements. These factors may or may not be fully reproducible in a laboratory setting. Five major classes of these factors were summarized by Haas, which included: traffic, environment, structure, construction, and maintenance (Haas 2001). Most of the factors can be found in the LTPP database and the ones used in this study are summarized in Table 1.

For a test section with multiyear ESAL data, some ESALs were estimated based upon historical data, while others were estimated based upon actual hard data. Additionally, for some test sections where ESALs were missing but load spectra data were available, the study calculated ESALs from the AASHTO equivalent axle load factors (AASHTO 1986). The accuracy of estimated ESALs on some test sections is questionable. In response to possible inaccurate traffic data, ESALs were roughly divided into five levels in this study (as shown in Table 1). It is worthwhile to note that traffic levels are categorized the same way as the Superpave mix design specifications (Asphalt Institute 2001).

The climate related variables, however, are not truly independent. The cross correlations of the climate variables are shown in Table 2. This revealed that some correlations are quite high, e.g., average precipitation and intense precipitation days. During regression analysis, different groups of variables that show less cross correlations were attempted. An alternative method would be to use the principal component scores (Johnson 1998). Three principle component variables for all of the environmental variables were constructed but they were not found significant in various models which were used in this study.

Identification of Baseline Distribution Functions

Baseline distribution functions can be selected in many different ways (NIST/SEMATECH 2004). Ideally, the baseline distribution can be selected to reflect physical cracking development patterns. Different physically meaningful fatigue failure models have been developed for single samples (without considering the external variables). In 1969, Birnbaum and Saunders proposed a distribution model, now known as Birnbaum–Saunders fatigue life distribution, which could be derived from a physical fatigue process where crack growth causes failure (Birnbaum and Saunders 1969). One of the assumptions of the model is that crack growth during any one cycle of applied load is independent of the growth during any other cycle, which is consistent with the Miner's Rule (NIST/SEMATECH 2004). In addition, the crack growth should have approximately the same distribution. Different with the assumptions of the Birnbaum–Saunders fatigue

Table 1. Variables Used in This Study

Classes of factors	Influencing factors	Special comments
Traffic	Average equivalent single axle loads (ESAL)	ESALs are based on historical estimation, monitoring, or calculated from load spectrum data
	Traffic level	To reduce discrepancies between annual ESALs, traffic loads are divided into five levels (level 1, >15 k ESALs/year; level 2, <=15 k but <150 k/year; level 3, <=150 k but <500 k/year; level 4, <=500 k but >1,500 k/year, level 5, <=1,500 k/year)
Structure	Thickness of asphalt concrete	
	Thickness of asphalt treated base	
	Thickness of concrete treated base	
	Thickness of granular base	
	Thickness of subbase	
	Types of subgrades	
	Stiffness of asphalt concrete layers	Average resilient modulus at 25°C for long-term pavement performance Protocol P07 test specimens
Construction	Density from field samples	
Environment	Average precipitation for year	
	Number of intense precipitation days	Number of days for which precipitation >12.7 mm for year
	Number of wet days	
	Average intensity of precipitation	Defined by number of wet days dividing average precipitation for year
	Average total snowfall for year	
	Average snow-covered days	
	Average daily mean temperature	
	Average of daily maximum air temperature for year	
	Average of daily minimum air temperature for year	
	Number of days for which daily maximum air temperature >32.2°C for year	
	Calculated freezing index	
	Number of freeze/thaw cycles for year	

life distribution, the lognormal distribution assumes that the crack growth process is multiplicative. The degradation at the following cycle is proportional to the current total amount of degradation (Kolmogorov 1941). The Weibull distribution is also used to model fatigue failures (e.g., Paterson 1987; Prozzi and Madanat 2000; Tsai et al. 2003). The natural log of Weibull data is extreme value data. Because of this relationship, the Weibull distribution can model failure times for mechanisms for which many random failure processes exist and the first one to reach failure produces the observed failure time (NIST/SEMATECH 2004).

The reasonability of these models, however, depends on the crack development and crack growth processes. On the other hand, fatigue-fracture models assume a lognormal relationship between the rate of stable crack growth and the stress intensity factor. This is based upon linear elastic fracture mechanics, and the lognormal model may be more appropriate than the Birnbaum–Saunders model.

Recently, researchers have suggested the use of some mathematically and computational convenient parametric models, such as exponential, Weibull, lognormal, log logistic, and others (Lawless 2002). An alternative method to select the baseline distribution function is to try different model assumptions and compare their fitness from the observed data. Two methods can be used for this purpose. The first one is to conduct the likelihood-ratio test, and the second one is to check the graph of the Cox-Snell residuals (Cox and Snell 1968). A model is said to be nested within another one if the first model is a special case of the second. A more formal definition of a nested model is given by Vuong (1989). For example, the exponential model is nested within the Weibull model. The Weibull model and lognormal model are nested within a generalized gamma model. The likelihood-ratio test can be used to compare the nested models.

Model Estimation

Estimation of Parameters Using the Maximum Likelihood Method

The accelerated failure time model in Eq. (1) is usually estimated by taking a log transformation and then using the maximum likelihood estimation method (Fisher 1925). Assuming the dependent variable y_i is a function of θ and X_i, where θ is an unknown parameter to be estimated, and y_i and X_i are observed data, the likelihood for the observation i can be expressed as $L_i = p(y_i|\theta, X_i)$. The likelihood function represents the conditional probability of observing y_i given θ and X_i. The maximum likelihood estimation procedure is to find the unknown parameter θ that maximizes the following likelihood function: $L = L_1 \times L_2 \times \cdots \times L_n$. Thus, the probability of observing all the response variables with the independent variables is the highest among all possible values of parameter θ. The θ is often estimated by maximizing the log of the likelihood function for computational convenience. Three functions can be used to construct the likelihood

Table 2. Correlation Matrix of Environmental Variables

	Average precipitation	Intense precipitation days	Average wet days	Average snowfall	Average snow-covered days	Average temperature	Average maximum temperature	Average minimum temperature	Days above 32°C	Days below 0°C	Freeze index	Freeze thaw cycles	Average intense precipitation
Average precipitation	1.000	0.988	0.758	−0.188	−0.233	0.306	0.169	0.425	−0.138	−0.420	−0.270	−0.454	0.812
Intense precipitation days	0.988	1.000	0.683	−0.258	−0.307	0.342	0.214	0.452	−0.094	−0.454	−0.329	−0.463	0.853
Average wet days	0.758	0.683	1.000	0.253	0.228	−0.072	−0.220	0.073	−0.447	−0.040	0.144	−0.189	0.275
Average snowfall	−0.188	−0.258	0.253	1.000	0.911	−0.802	−0.822	−0.748	−0.612	0.760	0.779	0.558	−0.411
Average snow covered days	−0.233	−0.307	0.228	0.911	1.000	−0.841	−0.866	−0.779	−0.620	0.790	0.937	0.510	−0.452
Average temperature	0.306	0.342	−0.072	−0.802	−0.841	1.000	0.977	0.978	0.793	−0.945	−0.829	−0.803	0.439
Average maximum temperature	0.169	0.214	−0.220	−0.822	−0.866	0.977	1.000	0.912	0.848	−0.882	−0.848	−0.691	0.350
Average minimum temperature	0.425	0.452	0.073	−0.748	−0.779	0.978	0.912	1.000	0.705	−0.963	−0.774	−0.876	0.506
Days above 32°C	−0.138	−0.094	−0.447	−0.612	−0.620	0.793	0.848	0.705	1.000	−0.683	−0.595	−0.567	0.106
Days below 0°C	−0.420	−0.454	−0.040	0.760	0.790	−0.945	−0.882	−0.963	−0.683	1.000	0.783	0.917	−0.528
Freeze index	−0.270	−0.329	0.144	0.779	0.937	−0.829	−0.848	−0.774	−0.595	0.783	1.000	0.483	−0.437
Freeze thaw cycles	−0.454	−0.463	−0.189	0.558	0.510	−0.803	−0.691	−0.876	−0.567	0.917	0.483	1.000	−0.485
Average intense precipitation	0.812	0.853	0.275	−0.411	−0.452	0.439	0.350	0.506	0.106	−0.528	−0.437	−0.485	1.000

Table 3. Log Likelihood Values of Models with Different Baseline Distribution Assumptions

Model	Log likelihood
Generalized gamma	−356.5
Weibull	−380.9
Lognormal	−367.5
Exponential	−402.4
Loglogistic	−372.8

function for censored survival data (SAS 2004). If an observation is not censored (the failure time is observed), its likelihood function can be the probability density function of failure time $f(\beta, X_i)$. If an observation is right censored, since its failure time is unknown, one cannot use the probability density function. However, the right censored observation provides information that the pavement can survive at least up to a certain time. This piece of information can be captured by the survival function $S(\beta, X_i)$. The survival function is defined by $S(T)=P(T>t)$, which is the probability that an individual pavement does not fail within time t. If an observation is left censored, the recorded time t provides information that this section must have failed before time t was reached. This can be reflected by its cumulative distribution function $F(T)=P(T\leqslant t)$. For the interval censored observation, the likelihood function can be the difference between two cumulative distribution functions: $F(T2)-F(T1)$, where $T2$ is the upper end of the interval and $T1$ is the lower end of the interval. The log-likelihood function can be estimated by using numerical methods.

Compare the Fitness of Models

Regression analysis was conducted using the LTPP data based upon the different model assumptions. The independent variables which are significant or marginally significant at 5% significance level included: traffic level, thickness of asphalt concrete, thickness of portland cement concrete treated base, intensity of precipitation, and numbers of freeze-thaw cycles. Models using the same set of independent variables but with different baseline distribution assumptions were estimated and their log likelihood values are shown in Table 3. The log-likelihood values indicate the models, in the order of fitness, are generalized gamma, lognormal, loglogistic, Weibull, and exponential. The fatigue life model was not reported since it is not supported by any statistical software packages yet. Comparing the generalized gamma and the lognormal model, the likelihood-ratio chi-square statistic is as follows: $-2\times[-367.5-(-356.5)]=22$ with one degree of freedom, when the critical value is 3.84 at 5% significance level. Therefore, the generalized gamma model fits the data better than the lognormal model. Similarly, the likelihood ratio tests show that the generalized gamma is better than the other models.

The frequently used graphic method to check the assumption of the distribution and the overall fitness of the model is to use the model-based estimate of the cumulative hazard function to form the Cox–Snell residuals $r_i=H(t_i, X_i, \hat{\beta})$, as reported by Cox and Snell (1968) and Hosmer and Lemeshow (1999). The cumulative hazard function is defined by

$$H(t)=\int_0^t h(t)dt$$

where $h(t)$=hazard function, defined by $h(t)=f(t)/[1-F(t)]$.

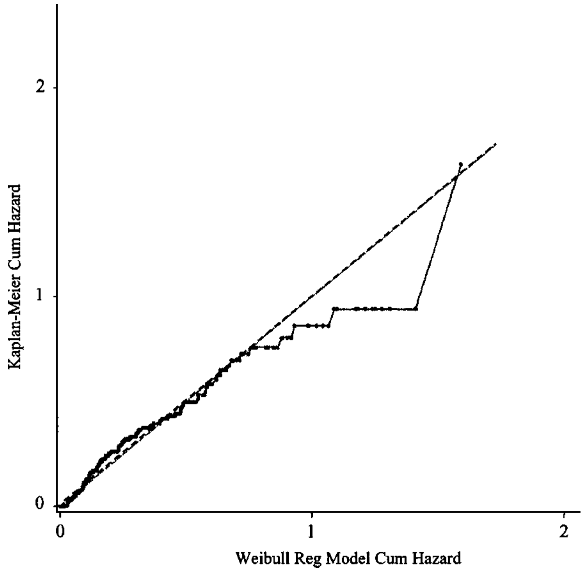

Fig. 5. Graph of the Kaplan–Meier estimate of the cumulative hazard versus the Cox–Snell residuals from the Weibull distribution

If the model fit is good, the residuals should behave like a censored sample from an exponential distribution with parameter equal to one (Cox and Snell 1968). The cumulative hazard function of the exponential distribution with parameter 1 is a straight line with a slope of 1. Therefore, if r_i's are plotted as the X axis, and a nonparametric cumulative hazard estimator of r_i with its censoring indicator is plotted as the Y axis, the plot should be approximately a straight line through the origin and with a slope of 1. The graphical methods cannot handle the right censored and interval censored data. Using the same independent variables, a trial regression was conducted based upon the observed or right censored data only. The cumulative hazard plots of residuals of the lognormal, Weibull, and generalized gamma are shown in Figs. 5–7. The Kaplan–Meier estimator was used as the nonparametric estimate of the cumulative hazard r_i

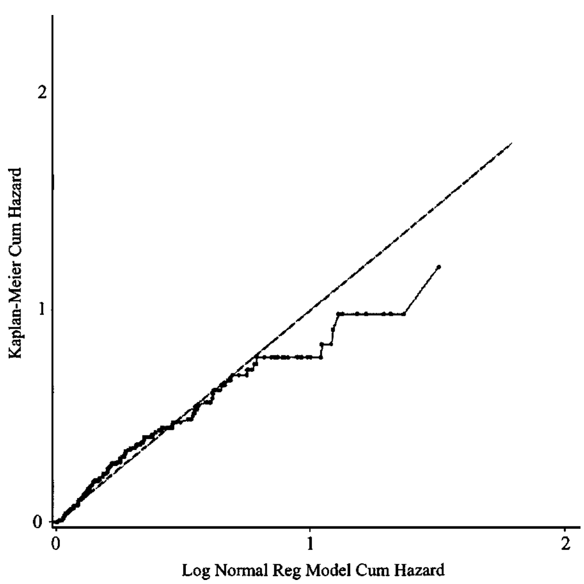

Fig. 6. Graph of the Kaplan–Meier estimate of the cumulative hazard versus the Cox–Snell residuals from the lognormal distribution

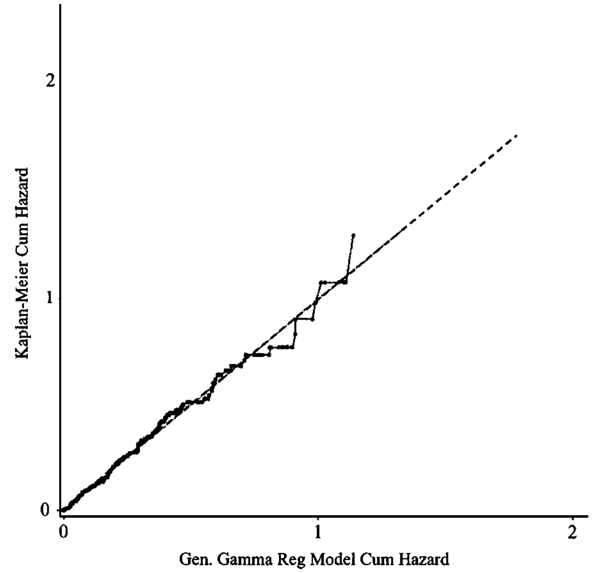

Fig. 7. Graph of the Kaplan–Meier estimate of the cumulative hazard versus the Cox–Snell residuals from the generalized gamma distribution

(Kaplan and Meier 1958). Although the plots are not based upon all of the data, they partially verify that the generalized gamma model fits the data better than the others. Therefore, the generalized gamma model was finally selected by researchers in this study.

Final Estimated Model

Table 4 reports the statistics for the generalized gamma model. During a trial regression analysis, the study found that the traffic level was significant whereas estimated ESALs were not. This may be because estimated ESALs are not very accurate due to the discrepancies between historical and monitored LTPP data. Although asphalt concrete (AC) thickness was only marginally significant at the 5% significance level, it was included in the final model because it improved the fitness of the overall model.

The final model for estimating the failure time is

$$T = e^{(3.959-0.298\text{traffic}+0.014\text{ac}+0.018\text{ctb}-0.1271\text{int\_precip}-0.004\text{ft\_cycles})}(T_0)^{0.767}, \quad (2)$$

where T=expected fatigue failure time in years; traffic=traffic levels; ac=thickness of asphalt concrete surface layer (cm); ctb=thickness of concrete base (cm); int_precip=intensity of

Table 4. Statistics of the Generalized Gamma Model

Parameter	Degree of freedom	Estimate	Standard error	Chi-square	Pr> chi-square
Intercept	1	3.9586	0.2682	217.79	<0.0001
Traffic	1	−0.2977	0.0759	15.36	<0.0001
ac	1	0.0136	0.0072	3.6	0.0576
ctb	1	0.0176	0.007	6.23	0.0126
Int_precip	1	−0.1265	0.0195	42.27	<0.0001
Ft_cycles	1	−0.0037	0.0012	9.03	0.0027
Scale	1	0.2987	0.058		
Shape	1	3.3484	0.3242		

precipitation defined by wet days divided by total precipitation per year; ft_cycles=number of freeze/thaw cycles per year; and T_0 follows a generalized gamma distribution with shape parameter=−1.6831.

The regression results indicate that increasing the thickness of the asphalt concrete layer and the concrete treated base thickness will increase pavement life in terms of fatigue failure; on the other hand, the increase of traffic level, intensity of precipitation, and freeze-thaw cycles will decrease pavement life. As shown in the models, the fatigue failure of flexible pavements is influenced by multiple factors. In addition to pavement structure and traffic, environmental factors influence fatigue cracking as well. The model showed that some environmental factors were more significant than some structural factors, such as the thickness of granular base and asphalt treated base.

The density of asphalt concrete, however, was not found to significantly influence fatigue lives of the LTPP sections. This may be because not all LTPP pavement sections include density data or that there was a significant variation in density data to affect the model. For those sections with density records, many of them only have a few cored samples. A trial regression indicated that asphalt concrete stiffness was not significant. Since the influence of asphalt stiffness on fatigue cracking depends on asphalt thickness, one cannot conclude that the increase of asphalt stiffness by itself will increase or decrease fatigue lives (Queiroz and Visser 1978). However, the LTPP data showed that extreme stiffness values may influence fatigue lives. For example, asphalt stiffness was very low on several test sections with various structural configurations from the test site no. 300100, which survived no more than four years. For this reason, pavement sections with the average asphalt resilient modulus less than 1.5 GPa or more than 9.9 GPa at 25°C were treated as outliers, and were omitted from final regression.

Because the baseline distribution function is skewed, quantiles of the failure time should be used instead of the mean value. For example, the following equation can be used to predict the median failure time:

$$T = 89e^{(-0.298\text{traffic}+0.014\text{ac}+0.018\text{ctb}-0.1271\text{int\_precip}-0.004\text{ft\_cycles})} \tag{3}$$

In this equation, the median value from the baseline distribution function T_0 is combined with the intercept term $e^{3.959}$. The median value means, under a certain combination of covariates, half of the failure time will be above this value, while the other half will be below the median. Similarly, other quantiles can be constructed by replacing T_0 with corresponding quantiles from the baseline distribution function. Fig. 8 shows the predicted survival curve for the test section no. 100105, an SPS site. The predicted 25th percentile, median value, and 75th percentile are 6.7, 12.5, and 31.7 years, respectively, whereas the actual observed failure time was 7 years. One can see although the actual failure time falls within the predicted 25th and 75th percentiles, the range between them is quite large. This means the independent variables in Eq. (2), although they already capture some systematic variations, may not be enough to generate a narrow prediction range. Many of the variations will have to be represented by the baseline distribution function. The predicted median can still provide the general information on the most likely failure time. The survival model seems more suitable for comparing and quantifying the effects of influencing factors than predicting the exact failure time of a pavement.

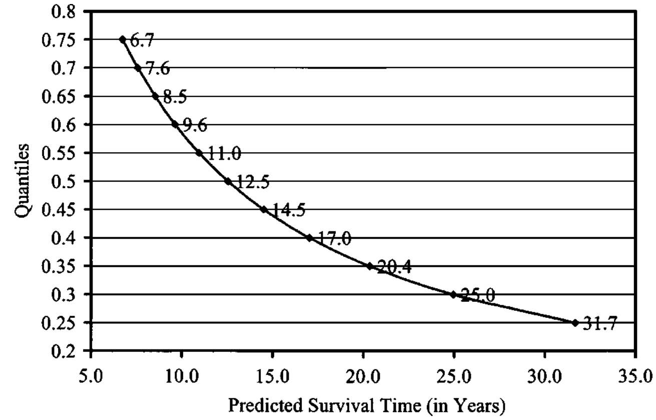

Fig. 8. Estimated quantiles for test section no. 100105

Conclusions

A sudden increase of AC fatigue cracking area is found on many LTPP test sections. In addition, some sections showed problems of inconsistent cracking development trends possibly due to misclassification of crack types. Because of these issues, this study found defining a fatigue failure threshold is better than using cracking areas for regression analysis, and the appropriate threshold was found to be 20 $m^3$20 square meters of fatigue cracking area. Noncontinuous distress surveys create a censoring problem, which can be solved by survival analysis. From 486 LTPP test sections across the United States and Canada, a total of 21 potential influencing factors were used to model fatigue failure times by accelerated failure time models. Six independent variables were found statistically significant and the error distribution was found to be a generalized gamma distribution. The survival model identifies and quantifies the most statistically significant factors influencing fatigue cracking in a wide geographic area and under different situations. In addition, the chance of using some problematic data may also exist. The authors believe that the survival model can provide the general information on the most likely failure time. The survival model seems more suitable for comparing and quantifying the effects of influencing factors than predicting the exact failure time of a pavement.

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