Estimation of Pavement Crack Initiation Models by Combining Experimental and Field Data

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Abstract: Development of deterioration models for pavements is an essential part of maintenance and rehabilitation planning. Often, when pavement-deterioration models are developed for developing countries or states that do not have regularly scheduled condition surveys, the only available data are experimental. Experimental data sets fail to include environmental variables and cannot capture properly the aging process of pavements, so the estimated models suffer from biases. This paper describes the development of a pavement-crack-initiation model by combining experimental and field data to correct for such biases. The American Association of State Highway Officials (AASHO) Road Test is used as the experimental data set, which is combined with field data from the Washington State Department of Transportation. The two models are first estimated separately, correcting for endogeneity biases that may exist in the field model. Joint estimation is used next to quantify the bias in the experimental data set and estimate the parameters of the combined model. This study shows that joint estimation can lead to more robust crack-initiation models compared to those estimated separately by the two data sets. **DOI: 10.1061/(ASCE)IS.1943-555X.0000148.** © *2013 American Society of Civil Engineers.*

CE Database subject headings: Cracking; Pavements; Joints; Stochastic processes; Experimentation; Data collection.

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Introduction

Deterioration modeling is a key component for the management of pavements, as it is an input to optimize maintenance and rehabilitation (M&R) planning. Deterioration models relate indicators of facility conditions to explanatory variables, such as traffic loads, climate factors, age, and M&R history (Madanat et al. 1995). As a result, they can be used to predict the future conditions of facilities and solve for optimal M&R activities. Accurate prediction of deterioration can also provide guidelines for optimal facility design (Madanat et al. 2002).

Considerable research has been conducted in developing deterioration models that can predict pavement-crack initiation. An early pavement-crack-initiation model was developed with the use of data from the American Association of State Highway Officials (AASHO) Road Test, which was an accelerated loading experiment [Highway Research Board (HRB) 1962]. This model suffered from several problems, including the fact that it was developed only for specific climate conditions and subgrade material, used predetermined values for some parameters, and did not correct for censoring bias. Regression models have been proposed as improvements to the initial AASHO model [Queiroz 1981; Empresa Brasilieira de Planejamento de Transportes (GEIPOT) 1982; Madanat et al. 1995].

Further improvements in the estimation of crack initiation and other pavement-distress models became possible with the use of duration models. In addition to capturing the uncertainty of pavement deterioration through probability-density functions, such models allow for censoring bias correction and consequently the exploitation of both censored and uncensored data. Parametric duration models for pavement-crack initiation—based on failure-time theory—were first developed by Paterson and Chesher (Paterson and Chesher 1986; Paterson 1987) and were followed by multiple other stochastic duration models that were based on either experimental or field data sets (Prozzi and Madanat 2000; Shin and Madanat 2003; Loizos and Karlaftis 2005). Semiparametric duration models have also been developed for crack initiation; these models have the advantage of capturing the variation in deterioration over time when this deterioration does not follow a known distribution (Nakat and Madanat 2008).

The individual use of either field or experimental data results in several types of problems during the estimation of deterioration models. Models that have been developed with the use of only in-service (field) pavement data suffer from multicollinearity between explanatory variables (e.g., pavement age and accumulated traffic), censoring, and endogeneity biases caused when endogenous variables are used as explanatory variables (Greene 1997). In addition, field data tend to have higher measurement errors compared to experimental data. Experimental models offer the ability to measure variables that are relevant to pavement deterioration and cannot be easily measured in the field, for example, disaggregate axle loads, and tend to have fewer measurement errors. However, such models are biased with respect to field conditions, since they are unable to capture the effects of realistic traffic (loading is accelerated with respect to the rate of change of climate

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conditions) and construction standards, and as a result, they cannot accurately predict deterioration as it occurs in a real-world setting.

The joint-estimation method was developed to correct these problems by combining multiple data sources. Apart from correcting for multicollinearity and different types of biases, it also allows for more realistic models through the inclusion of more explanatory variables. It can also be used to quantify biases in the experimental data sets. When a new pavement performance model is developed for a geographical location, often the only available data are experimental. Using such experimental data, an initial pavement-deterioration model can be developed, and the model can be updated later as more field data are collected.

Archilla and Madanat (2001) were the first to use joint estimation in pavement-deterioration modeling by combining data from the AASHO and WesTrack road tests to develop rutting models. Joint estimation was also used by Prozzi and Madanat (2004) who combined the AASHO Road Test data set with a field data set constructed during the Minnesota Road Research Project (MnRoad) for the development of a pavement performance model. A more recent attempt has been made by Christofa and Madanat (2010) to estimate pavement-crack initiation by combining field and experimental data from the PARIS database. However, the study suffered from the small size of the experimental data set.

The objective of this paper is the development of a pavement-crack initiation model by combining experimental and field pavement data. The goal is to develop this model using joint estimation to quantify biases in the experimental data and demonstrate the value of using joint estimation for pavement-deterioration models. The Washington State Pavement Management System (PMS) and the AASHO Road Test databases are used for this purpose.

Data

Field Data Set (Washington State PMS)

The Washington State Department of Transportation (WSDOT) has performed pavement condition surveys on a yearly basis since 1983 that covers most of the state highways. Highways were segmented into 161-m (0.1-mile) sections, and the survey measured variables such as pavement cracking and maintenance activities. Climate variables were created by Nakat and Madanat (2008) based on climate-contour maps for the state of Washington.

The description of the relevant variables from the Washington State PMS database and the climate variables can be seen in Table 1. The dependent variable used in our model is the sum of the equivalent single-axle loads (ESALs) from the year of the last overlay (1999) to the year when crack initiation occurs (*CUM_ESAL*), where crack initiation is defined as the occurrence of 5% alligator or longitudinal cracking, whichever occurs first. If cracking does not occur for some section by the end of the observation period, then *CUM_ESAL* is the sum of the ESALs from the last overlay to the end of the observation period, in which case that observation is censored. ESAL is defined as the equivalent single-axle load of 8164 kg (18 kips) for any axle load, P. The field model is estimated using 500 randomly chosen observations out of a total of 1,000. The remaining observations are used to validate the model.

Table 1. Description of Variables in the Washington PMS Database

Variables	Description
E_Long	Existing longitudinal cracking before rehabilitation (%)
Ntbase	Nontreated base thickness (m)
Prep	Annual precipitation (mm)
Tmin	Average monthly minimum temperature of the coldest month (°C)
SURFTHK	Layer thickness of the last overlay (m)
ULT	Sum of the thicknesses of the underlying asphalt layers (m)
Y_ESAL	Traffic in equivalent single-axle loads in year 1999

Experimental Data Set (AASHO Road Test)

A subset of the AASHO Road Test data was used to develop the pavement-cracking initiation model. The AASHO Road Test flexible pavement sections consisted of cross sections having three pavement layers: asphalt concrete surface, granular base, and granular subbase. Thicknesses excluding loop 1, which was not subjected to test traffic, were as follows:

- Asphalt concrete surface thickness: 2.54, 5.08, 7.62, 10.16, 12.7, and 15.24 cm ($D1$);
- Granular base thickness: 0, 7.62, 15.24, and 22.86 cm ($D2$); and
- Granular subbase thickness: 0, 10.16, 20.32, 30.48, and 40.64 cm ($D3$).

The remaining five loops, 2 through 6, were subjected to traffic. The assignment of axle loads and vehicle types to the various lanes and the corresponding ESAL values for the trucks that traveled on the circular loop are shown in Table 2.

The data set consisted of a total of 252 observations (test sections). By the end of the experiment, 185 of these test sections had cracked. Thus, the remaining 67 observations were right-censored (HRB 1962). The dependent variable used in our model is the cumulative ESALs to crack initiation. The independent variables can be seen in Table 3.

There are two types of longitudinal cracking that can be found in the field data set, fatigue cracking and reflection cracking, whereas the experimental data are only subject to fatigue cracking since the pavement had not undergone an overlay. *E_Long* is used in the field model to capture the difference since this variable can be an indicator of the existence of reflection cracking.

Methodology

Pavement cracking can be modeled as a stochastic process, where several explanatory variables affect the probability of crack

Table 2. AASHO Road Test Sections

Loop	Lane	ESAL
2	1	0.0003
	2	0.0125
3	1	0.3975
	2	0.4074
4	1	2.0123
	2	1.3111
5	1	4.8089
	2	3.1108
6	1	15.4946
	2	6.5185

Table 3. Description of Variables in the AASHO Road Test

Variables	Description
$D1$	Surface thickness (m)
$D2$	Granular base thickness (m)
$D3$	Granular subbase thickness (m)

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initiation. Stochastic duration models can be used to model the number of cumulative ESALs to cracking as a function of the explanatory variables. Using the probability-density function for the cumulative ESALs to cracking, the survival function (i.e., the probability that cracking occurs after a given number of ESALs) and the hazard rate (i.e., the instantaneous probability of crack initiation at any given number of ESALs) can be computed (Kalbfleisch and Prentice 2002). Depending on the type of data and the deterioration process considered, different forms for the hazard-rate function can be used.

In this study, a semiparametric hazard-rate function is used, specifically the Cox function. The Cox model was chosen after plotting the nonparametric hazard functions for the two data sets and observing a shape which could not be described by a known parametric distribution (see Fig. 1). The advantage of using the Cox model is that it consists of a parametric component, which is a function of the explanatory variables, and a nonparametric one that can take on any shape. This nonparametric component is the empirical curve that best fits the variations in data with respect to the cumulative number of ESALs to crack initiation (Cox 1972). The Cox function can be written as follows:

$$h(t, \underline{x}, \underline{\beta}) = h_0(t) \times \psi(\underline{x}, \underline{\beta}) \tag{1}$$

where $h_0(t)$ = an arbitrary unspecified baseline hazard function of t, where t = the cumulative number of ESALs to crack initiation. The parametric component is given by

$$\psi(\underline{x}, \underline{\beta}) = e^{\underline{x}.\underline{\beta}} \tag{2}$$

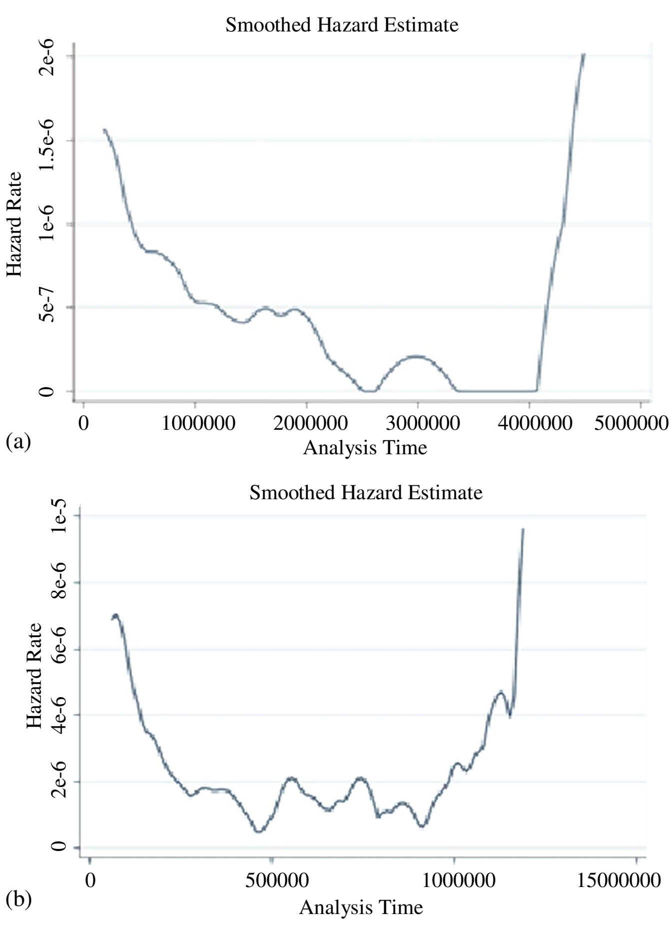

Fig. 1. Nonparametric hazard functions for (a) the experimental data; (b) the field data

where $\underline{x}$ = a vector of independent variables, and $\underline{\beta}$ = a vector of parameters that will be estimated using maximum likelihood methods.

The Cox model is based on the assumption that covariates do not vary with t. In order to check this assumption, Schoenfeld (1982) proposed the use of a set of residuals that do not depend on t such that the residuals can be plotted against t to test the proportional-hazards assumption. A Schoenfeld residual is the observed value for the covariate for the observation that failed minus its expected value. Since Schoenfeld residuals do not vary with t, any trend that is seen when they are plotted against t is a violation of the proportional-hazards assumption.

Before the estimation of the field model, some of the explanatory variables are corrected for endogeneity bias. The endogeneity problem occurs when there is correlation between the error terms and the explanatory variables, resulting in biased and inconsistent estimated parameters. The method of instrumental variables is used to correct for the inconsistency of estimates of parameters of endogenous explanatory variables. For example, such explanatory variables include the thicknesses of the different pavement layers which are design variables selected on the basis of anticipated cumulative ESAL values and climate factors. The method is presented in detail in Washington et al. (2003), and an application can be found in Nakat and Madanat (2008).

Joint estimation is used to develop a model that combines information from both the experimental and the field data sets. The joint-estimation method can be described as follows (Shyr and Ben-Akiva 1996):

Let the field data model be

$$Y^F = g(\underline{\beta}^F, \underline{X}^F, \underline{\alpha}, \underline{W}^F) \tag{3}$$

and the experimental data model be

$$Y^L = g(\underline{\beta}^L, \underline{X}^L, \underline{\gamma}, \underline{Z}^L) \tag{4}$$

where Y^F, Y^L = the dependent variable in the field and experimental model, respectively, e.g., cumulative ESALs to crack initiation; $\underline{X}^F$, $\underline{X}^L$ = vectors of the explanatory variables shared by both the field and experimental model, e.g., thickness of asphalt layers, thickness of nontreated base layers; $\underline{W}^F$ = vector of other explanatory variables in the field model; $\underline{Z}^L$ = vector of other explanatory variables in the experimental model; $\underline{\beta}^L$, $\underline{\beta}^F$ = vectors of parameters for $\underline{X}^L$ and $\underline{X}^F$, respectively; and $\underline{\alpha}$, $\underline{\gamma}$ = vectors of parameters for $\underline{W}^F$ and $\underline{Z}^L$, respectively.

It is expected that a model developed with experimental data only will be biased relative to field conditions, since the loading is accelerated during the experiment. Hence, the factors that are present in real-world settings such as aging of materials and environmental effects cannot be captured with an experimental data set. Based on this observation, the variables $\underline{X}^L$ in the experimental data set, which are expected to have the same effect on pavement cracking as similar variables $\underline{X}^F$ in the field data set, are determined.

In general, parameter estimation results from the optimization of a particular objective function with respect to a set of parameters. In joint estimation, a joint objective function is formulated as the sum of the two objective functions that arise from the two individual data sources and is optimized with respect to all the parameters (Archilla and Madanat 2001). That approach is known as full information maximum likelihood (FIML). While statistically efficient, this simultaneous estimation approach is difficult to implement with standard statistical software.

An easier approach is the limited information maximum likelihood (LIML), which, while statistically inefficient, produces consistent parameter estimates. The approach is sequential and consists of the following steps:

1. The parameters of each model are first estimated separately; i.e., $\underline{\beta}^L$ and $\underline{\gamma}$ are estimated using the experimental data set; and $\overline{\beta}^F$ and $\overline{\alpha}$ are estimated using the field data set.
2. The shared biased parameters in the experimental model, $\underline{\beta}^L$, are constrained to have the same values as the corresponding unbiased parameters, $\overline{\beta}^F$, that were estimated from the field model by using a scalar factor μ such that $\underline{\beta}^L = \mu\overline{\beta}^F$.
3. The experimental model parameters are reestimated allowing for the estimation of the scalar factor μ.
4. Finally, data are pooled from both data sets, and the joint model is estimated. When pooling, the experimental data are first multiplied by the scalar factor μ so that their parameters are corrected for biases. Joint estimation results in new estimates for the shared parameters, $\underline{\beta}^L$ and $\underline{\beta}^L$, and the unshared parameters, $\underline{\alpha}$ and $\underline{\gamma}$.

Results

Field Model

Before the estimation of the field model we need to instrument the endogenous variables that will be included in the model. As stated previously, it is likely that the pavement layers were designed based upon anticipated cumulative ESALs and climate factors so the possible endogenous variables would be the overlay thickness (*SURFTHK*) and the thickness of the underlying asphalt layers (*ULT*). The WSDOT pavement policy documents the variables which are taken into account when designing pavement-layer thicknesses (WSDOT 2011). Of these variables listed, three are similar to those found in the field data set. Additionally, WSDOT emphasizes that every effort should be made to keep overlay thicknesses at 4.572 cm (0.15 ft), and our data set confirms this as it contains almost exclusively thicknesses of 4.572 cm (0.15 ft). This is why the overlay thickness is not considered as an endogenous variable for the final model. Therefore, the only variable that would be endogenous in a crack-initiation model in the field data set is the thickness of the underlying asphalt layers.

Three factors that may affect the design of *ULT* are identified as follows. First, the pavement needs to have enough thickness to provide adequate protection against frost penetration. Low temperatures for extended periods of time cause frost penetration; therefore, sections with the lowest average monthly temperature (*Tmin*) will experience the most frost penetration and as a result need to be thicker. The amount of traffic is also taken into consideration when designing the thickness of asphalt layers as there is usually a desired lifespan of 50 years (WSDOT 2011). In order to accommodate this 50-year lifespan, pavements that are expected to experience heavier traffic will be designed with a thicker asphalt layer. The agency must have some traffic forecasts for individual stretches of highways, and therefore the pavements will be designed thicker in sections that are expected to have higher number of ESALs per year (which could be assumed to follow a similar trend to *Y_ESAL*). The last factor that is used for the correction is the thickness of the nontreated base layer. It is expected that a thicker base adds strength to the pavement. Therefore, sections with thicker base layers do not require as thick of an asphalt layer.

For the endogeneity-bias correction of the underlying asphalt layer thickness, the instrumental variable is defined as a linear function of the previously mentioned variables. The parameters of this function are estimated using the following auxiliary regression.

Table 4. Parameter Estimates of Auxiliary Regression [Eq. (5)]

Variable	Coefficient	t-Value
Constant	0.164	25.97
Ntbase	−0.171	−8.87
Tmin	−0.0109	−13.92
Y_ESAL	7.81×10^{-8}	3.04

$$ULT = \delta_0 + \delta_1 Y_E SAL + \delta_2 Tmin + \delta_3 Ntbase + \varepsilon \quad (5)$$

where $\delta_0 - \delta_3$ = the parameters to be estimated, and ε = the error term. The instrumental variable predicted by the auxiliary regression is named *new_ult*. This instrumental variable is used as a substitute for the measured value of *ULT* in the estimation of the field crack-initiation model.

The estimates of the parameters of the auxiliary regression are shown in Table 4 and confirm the previously mentioned expectations in terms of their signs. The t-statistics reveal that all of the parameter estimates are significant at a 95% level of confidence.

The specification of the proposed field model for the Cox hazard function is as follows:

$$\psi^F(x) = \exp(\beta_1^F SURFTHK + \beta_2^F Ntbase + \beta_3^F new_u lt + \beta_4^F Prep + \beta_5^F Tmin + \beta_6^F E_L ong) \quad (6)$$

where *SURFTHK*, *Ntbase*, *Prep*, *Tmin* and *E_Long* are as described in Table 1, and *new_ult* is calculated as described previously.

Our expectations for the effects of these explanatory variables on the cumulative ESALs to cracking are explained next. It is expected that the factors that lead to a stronger pavement such as *SURFTHK*, *new_ult*, and *Ntbase* have a negative coefficient in the model since they decrease the hazard rate of cracking. The coefficient for *Tmin* is expected to be negative because at lower temperatures, more frost penetration occurs, which weakens the subgrade underneath the pavement when it starts to thaw. Therefore, a higher *Tmin* should reduce the hazard rate. The coefficient for *E_Long* is expected to be positive since existing longitudinal cracking can lead to reflective cracking (which is the bottom-up cracking from the underlying layers propagating through the overlay layer) causing it to crack earlier (Sousa et al. 1996). The coefficient for *Prep* is expected to be positive due to a loss of adhesion that can result from water between the aggregate and the asphalt, stripping away the asphalt film. Additionally, increased precipitation can lead to loss of cohesion where the asphalt softens, weakening the bond between the asphalt cement and the aggregates (Hicks 1991). These issues can cause stripping and raveling, which lead to increased cracking.

The results of the estimation of the parameters are shown in Table 5. The estimation of the model was performed using the survival-analysis package of the R software (Fox 2002; Leucuta 2011). These results confirm the a priori expectations for the signs

Table 5. Parameter Estimates of the Field Model

Variable	Coefficient	t-Value
SURFTHK	−6.31	−1.73
Ntbase	−10.32	−5.55
new_ult	−50.00	−4.79
E_Long	0.0097	4.53
Prep	0.00088	6.85
Tmin	−0.74	−6.75

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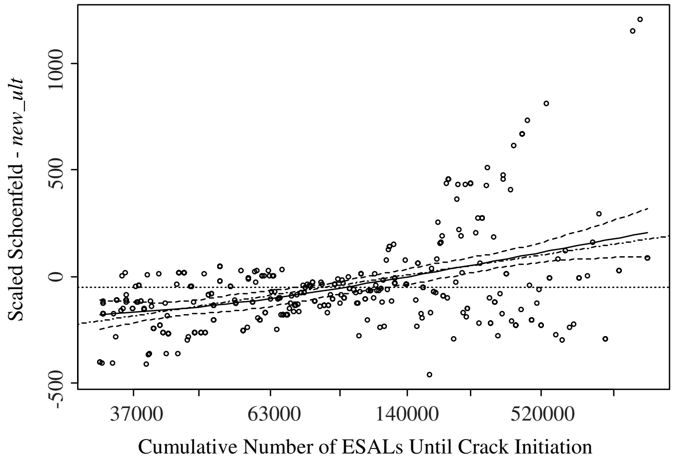

Fig. 2. Scaled Schoenfeld residuals for *new_ult* (field model)

of the coefficients. Furthermore, the *t*-statistics show that all the variables are significant at a 95% level of confidence.

It is also necessary to check the proportional-hazards (PH) assumption for each of the covariates. Figs. 2 and 3 show the plots of the scaled Schoenfeld residuals versus the number of cumulative ESALs to crack initiation for *new_ult* and *Ntbase*. The PH assumptions were checked for all covariates; these two were chosen as they demonstrated the most obvious trend in the data. The solid line is the best fit line, and if the proportional-hazards assumption is validated, this line should be horizontal. It can be seen from the Figs. 2 and 3 that there is an obvious trend in the lines. The coefficient for the covariate is increasing with respect to cumulative ESALs to cracking for both variables, implying that the proportional-hazards assumption is not met, and therefore the Cox model would not have been appropriate for modeling the crack-initiation process.

Experimental Model

As in the case of the field model, the experimental hazard function does not follow any known distribution; therefore, a semiparametric Cox model was estimated. The specification of the proposed model for the Cox hazard function is as follows:

$$\psi^L(x) = \exp(\beta_1^L D1 + \beta_2^L D2 + \beta_3^L D3) \tag{7}$$

where the variables are as described in Table 3.

The parameters for the thicknesses of the surface ($D1$), base ($D2$), and subbase ($D3$) layers are expected to have negative signs, indicating that the thicker those layers are, the lower the hazard rate of cracking. The model does not include any climatic factors as explanatory variables because all of the observations were from a single location, so there was no variation in the environment between sections.

The results of an initial model indicate that, based on a likelihood ratio test, the thicknesses of the base and subbase have the same effect on the resistance of the pavement to crack initiation. Therefore, the sum of the two thicknesses was used instead of the individual thicknesses in the experimental model.

The final experimental model is as follows:

$$\psi^L(x) = \exp[\beta_1^L D1 + \beta_{23}^L (D2 + D3)] \tag{8}$$

The results from the estimation of the final experimental model using the Cox hazard function are shown in Table 6. The parameter estimates confirm the expectations in terms of their signs, and according to the *t*-statistics they are all significant at a 95% level of confidence.

The proportional-hazards assumption was again checked for the experimental data set. Figs. 4 and 5 show the graphs of the scaled Schoenfeld residuals against the number of cumulative ESALs. It can be seen that there is a positive trend for $D1$ but $(D2 + D3)$ is closer to being horizontal, indicating that $D1$ does not pass the proportional-hazards test while $(D2 + D3)$ does.

Joint Model

For the joint estimation of the models the LIML approach is used, as described in the "Methodology" section. Because both the field and experimental models were specified as Cox models, the joint model uses the same form. The parameter for the combined thickness of the granular base and subbase, $(D2 + D3)$, from

Table 6. Parameter Estimates of the Experimental Model

Variable	Coefficient	*t*-Value
$D1$	−56.95	−13.66
$(D2 + D3)$	−15.58	−14.37

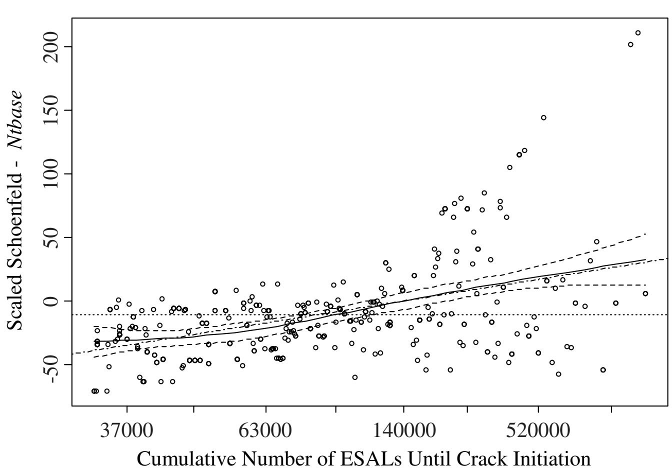

Fig. 3. Scaled Schoenfeld residuals for *Ntbase* (field model)

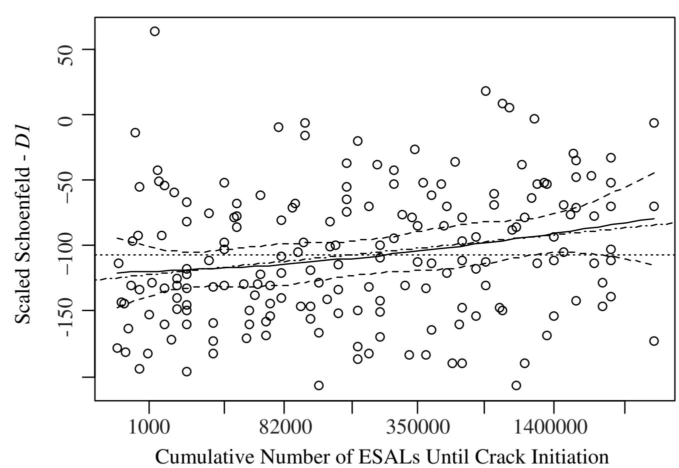

Fig. 4. Scaled Schoenfeld residuals for $D1$ (experimental model)

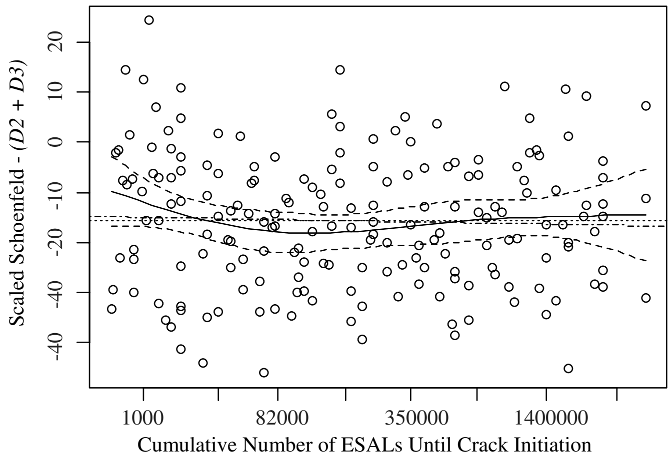

Fig. 5. Scaled Schoenfeld residuals for $(D2 + D3)$ (experimental model)

the experimental model is expected to be biased with respect to the field model and is constrained to have the same value as the equivalent parameter in the field model (Ntbase). Since the experimental tests were performed in the 1960s, it is expected that $D1$ and *new_ult* will behave as two distinct independent variables in the joint estimation, as there have been significant improvements in asphalt technology and mix design during that time span.

To perform joint estimation, $(D2 + D3)$ is multiplied by the parameter estimate β_{23}^F and by a scalar factor μ, and the experimental model is reestimated. The scalar factor μ represents the bias in the experimental data. The new experimental model is as follows:

$$\psi^L(x) = \exp[\beta_1^L D1 + \mu\beta_{23}^F(D2 + D3)] \tag{9}$$

The estimation results indicate a scalar factor μ of 1.51, significant at a 95% level of confidence.

The results suggest that in order to jointly estimate a model all the experimental variables should be multiplied by the estimated scalar factor $\mu = 1.51$ to match the field data. This results in a new $D1$ parameter named *D1_corrected*. Table 7 shows the results of the joint-estimation model. The coefficients have the same signs as when the two models were estimated separately. It is important to note that the t-statistics have improved for all variables, resulting in a more robust model.

Figs. 6, 7, and 8 show the graphical test of the proportional-hazards assumption for *Ntbase*, *new_ult*, and *D1_corrected*. There is no longer an evident positive trend when examining *Ntbase* and *new_ult*. For $D1_{c}orrected$, there is a slight trend at the edges, but it has become more stable. In addition, all other covariates show horizontal trends. Therefore, it can be stated that joint estimation

Table 7. Parameter Estimates of the Joint Model

Variable	Coefficient	t-Value
SURFTHK	−5.96	−1.62
Ntbase	−8.93	−17.86
new_ult	−42.36	−12.29
Prep	0.0010	8.45
Tmin	−0.68	−18.67
E_Long	0.0098	4.50
D1_corrected	−33.13	−14.30

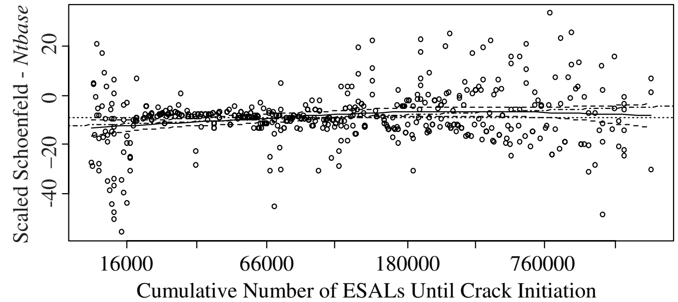

Fig. 6. Scaled Schoenfeld residuals for *Ntbase* (joint model)

provided a more accurate model since the estimated joint model meets the proportional-hazards assumption.

Now that the appropriate assumptions are met, the model can be used to predict the survival of selected data. The remaining 500 field observations that were not used for the estimation can now be used to validate the accuracy of the predictions of the joint model. Some of the data which had very high or very low values for *new_ult* [*new_ult* less than 0.107 m (0.35 ft) or greater than 0.183 m (0.6 ft)] were not used in this prediction, resulting in the use of only 390 out of the 500 data points.

Fig. 9 shows the Kaplan Meier marginal survival function compared against the model prediction for the survival function. It can be seen that the joint model predicts well until the ESALs reach about 300,000. After that point, the joint model starts to underpredict the survival rate. This may be due to routine maintenance activities performed on pavement sections after a certain time, therefore affecting differently pavements that have already cracked and the ones that have not. Records of such maintenance activities were not available in this study, so they could not be incorporated in the model. These potential maintenance activities

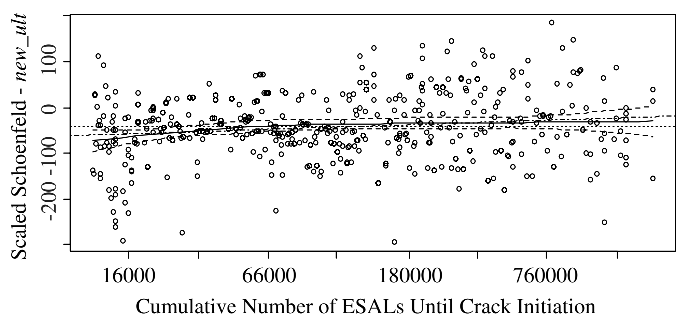

Fig. 7. Scaled Schoenfeld residuals for *new_ult* (joint model)

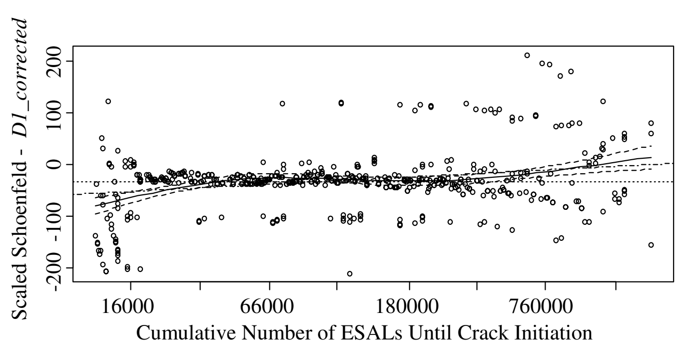

Fig. 8. Scaled Schoenfeld residuals for *D1_corrected* (joint model)

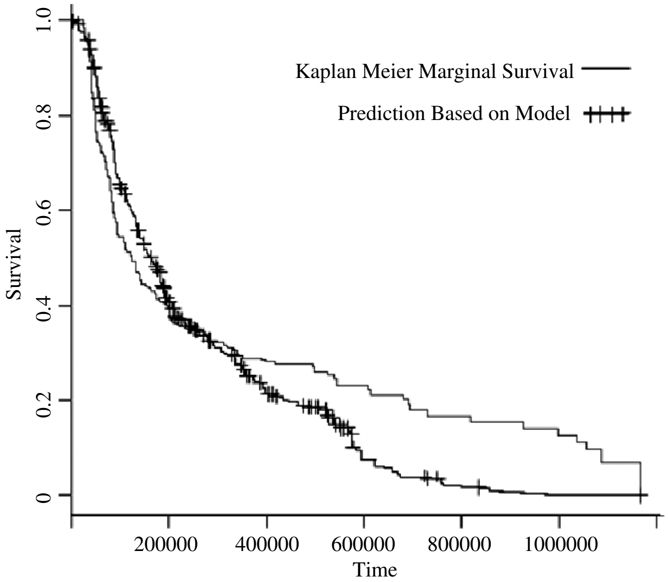

Fig. 9. Kaplan Meier survival function versus survival function predicted from joint model

include crack sealing, patching, fog seals, and chip seals. It is possible that the pavement sections that outperformed the model predictions may have undergone some of these maintenance activities which caused them to last longer than would be expected.

Discussion

This paper presents the estimation of an overlay crack-initiation model using data from the Washington State Pavement Management System (field data) and the AASHO Road Test (experimental data). This model is an improvement over models that were estimated individually using one of the two data sets for the following reasons: first, the jointly estimated model meets the proportional-hazards assumption better than the individual models and therefore is more accurate; second, joint estimation allows for the correction of biases present in the experimental model. This paper has shown the limitations of using merely experimental models to design pavements, since such models fail to include environmental variables and cannot capture properly the aging process of the pavements. Therefore, the parameter estimates are biased and could lead to inaccurate design or M&R decisions.

The estimated value for the coefficient of surface thickness in the experimental model was lower than that of the thickness of the underlying asphalt layer in the field model. This is expected because asphalt technology and mix design have improved significantly since the AASHO Road Test.

Another important result in the joint model is the value of the ratio between the effects of the thickness of the surface overlay and the thickness of the underlying asphalt layer on the rate of pavement cracking. The results show that for this data set, 1 cm of underlying asphalt layer thickness has the same effect on delaying cracking as 7.1 cm of overlay. This shows that designing thicker asphalt layers has a substantial effect on how long it takes the overlay to crack, much more so than the overlay thickness. This could be a consequence of the practice of applying only thin overlays by the WSDOT which are a temporary solution since the main asphalt layer has already cracked.

As expected, the thickness of the underlying asphalt layer was found to have more of an effect than the thickness of the nontreated base. The results indicate that 1 cm of underlying asphalt layer thickness is equivalent to 4.7 cm of nontreated base for this data set. Since existing longitudinal cracking was found to be significant, it supports the point that the existing conditions of the asphalt concrete layer have an effect on crack initiation for overlays. It can also be seen that an increase of 1% in existing longitudinal cracking has about the same effect as an increase of 10 mm of precipitation.

One of the limitations of this study is the fact that the routine maintenance records were not available. It would be valuable to know the effects of the different types of maintenance activities and their frequency on the cumulative number of ESALs to crack initiation. Another limitation related to the maintenance activities is that WSDOT uses only early, thin overlays. Since this varies from state to state, the results of this analysis may not be generalizable.

The final limitation is that in the Washington State PMS data set, only cumulative ESAL data were available rather than the individual axle loads. Guler and Madanat (2011) showed that the power of load for cracking might be different than 4, and actually closer to 8. Since the number of trips and ESALs of individual trucks was not available in the field data set, in this paper ESALs were assumed to have a power of 4 for loading, as is traditionally done.

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