BAU Journal - Science and Technology

Volume 4 | Issue 1
ISSN: 2706-784X

Article 1

December 2022

ASSESSING THE INFLUENCE OF OVERWEIGHT AXLES ON RUTTING LIVES IN FLEXIBLE PAVEMENTS USING PARAMETRIC SURVIVAL ANALYSIS

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Recommended Citation

Hatoum, Ali; Khatib, Jamal; Barraj, Firas; and Elkordi, Adel (2022) "ASSESSING THE INFLUENCE OF OVERWEIGHT AXLES ON RUTTING LIVES IN FLEXIBLE PAVEMENTS USING PARAMETRIC SURVIVAL ANALYSIS," *BAU Journal - Science and Technology*: Vol. 4: Iss. 1, Article 1.
DOI: https://www.doi.org/10.54729/CUBR7851
Available at: https://digitalcommons.bau.edu.lb/stjournal/vol4/iss1/1

1. INTRODUCTION

A typical flexible pavement is a multi-layered structure consisting of an asphalt concrete (AC) layer, a base and subbase course, and then a compacted soil subgrade. These layers are arranged in declining order for which the material with the highest bearing capacity is placed on the top and then followed by materials with the lowest load bearing capacity. Stresses imposed by vehicle movement are transmitted through the pavement granular structure by the interaction of grains.

Rutting, also known as permanent deformation, is considered a primary distress mode in asphalt flexible pavements. The presence of permanent deformation on flexible pavement layers has always been a concern that negatively affects the performance of the pavement by shortening its lifespan and creating a safety hazard for vehicles. Hence understanding the rutting phenomenon is essential to prevent excessive pavement deformation during the pavements life span. According to Miller and Bellinger (2003), rutting is usually affected by the lateral movement or consolidation of material due to vehicle loads, insufficient compaction during construction, unstable mixture, and failure of the lower layers of the pavement structure. The increase in heavy traffic accelerates the beginning of rutting (Reddy and Veeraragavan, 1997). Several studies have been developed to extensively discuss the deterioration of flexible pavement caused by rutting and to assess the influence of several principal combined factors in the development of pavement rutting (Archilla and Madanat, 2000), (Skok et al., 2002), (Zaniewski and Nallamothu, 2003), and (Haddock et al., 2005). Archilla and Madanat (2000) and Sousa and Weissman (1994) stated that permanent deformation relates to several factors including the characteristics of pavement, the type and size of aggregates used, the binder content, and the moisture in the lower layers. Ali (2006) divided the factors that may influence the development of pavement rutting into two categories: internal factors, such as material properties; and external factors, like traffic and environmental conditions.

Vehicle overloading is one of the major factors that accelerates the deterioration of pavement, shortens the lifespan of vehicles, increases fuel consumption, and raises crash accident rates. With the expansion of freight transportation, the effect of traffic loads and overweight axles on pavement performance as well as the relations between pavement maintenance and the presence of overweight vehicles in the transportation system have been studied by several researchers. Hatoum et al. (2022) showed that the increase in the percentage of overloaded axles from 0% to 20% reduces the pavement fatigue life up to 55%. Barraj et al. (2022) pointed out that thick flexible pavement sections are recommended for areas suffering from a scarcity of traffic data. Zhang et al. (2021) used accelerated failure time models to identify the most critical overweighting characteristics that may affect pavement rutting and fatigue life. Dey et al. (2015) showed that fatigue cracking is more sensitive to overweight trucks compared to other pavement distresses such as rutting and roughness. Wu et al. (2017) assessed the damage of oversize and overweight loads considering climatic factors to Texas highways. Another study conducted by Pais et al. (2019) concluded that pavement life-cycle costs increase by 30% in the presence of overweight traffic.

One of the essential components of any pavement management system (PMS) is the development of pavement deterioration models that enable agencies to effectively forecast maintenance, rehabilitation, and reconstruction plans. Most of these developed models are deterministic models that are mainly based on regression analysis (Paterson, 1987), (Prozzi et al., 2004), (Prozzi and Hong, 2008), and (Luo, 2013). The other alternative deterioration models are probabilistic models which are used to estimate the amount of distress as a function of a set of predictors (Hong and Prozzi, 2006), (Amador-Jimenez and Mrawira, 2011), and (Coleri and Harvery, 2011). Survival time analysis is one of the most popular approaches that model the remaining pavement survival time or the number of applied loads until reaches the failure threshold and quantifies the effect of various covariates (independent variables) (Kleinbaum, 2004). Rajbongshi and Thongram (2016) presented the survival analysis of fatigue and rutting failures in flexible pavements and concluded that the survival of pavement structures can well be presented by the three parametric Weibull distributions. Aguiar et al. (2010) proposed a framework to estimate pavement survival models as a function of exogenous variables. Wang (2016) used the survival analysis to assess the effect of using reclaimed asphalt pavements (RAP) on the long-term performance of asphalt concrete overlays.

The data used in previous studies for pavement performance modeling can be categorized into two main groups: pavement condition survey data and accelerated pavement testing data. The Federal Highway Administration (FHWA) Long-Term Pavement Performance (LTPP) data is one of the largest publicly available pavement performance databases that has ever been undertaken. The LTPP includes extensive pavement performance data which helps to better explain pavement performance, support analysis and develop usable engineering products relevant to pavement management, construction, maintenance, and design (Zhang and Wang, 2022), (Wang et al., 2021), (Rezapour et al., 2022), and (El-Ashwah et al., 2021). The study carried out as part of the Strategic Highway Research Program (SHRP) in the early 1980s concentrated on research and development efforts in the highway transportation sector. In 1984, the Transportation Research Board (TRB) published a special report in which six strategic research areas were recommended, one of which being LTPP (FHWA, 2008). The data collection started in 1989 and then after 25 years, these data are available to the public via the Web through the data portal system: LTPPInfoPaveTM (LTPP, 2022). The LTPP data is usually collected and uploaded periodically on a six-month cycle by four regional contractors in a database known as the LTPP National Information System. The information management system consists of 16 general data moduli with 430 tables in a simple row-column format. This database includes information on traffic, environment, monitoring, inventory, materials, maintenance, and rehabilitation for each pavement test section.

This study aims to determine the time to failure of flexible pavement structures associated with rutting, to indicate the most significant factors affecting rutting, and to assess the influence of overweight axles on pavement rutting life using parametric survival analysis. The data used in this study are extracted from the LTPP program. The findings obtained provide researchers and agencies with a good knowledge of the relations between several predictors including overweight axles and pavement performance and hence increase the ability of pavement to continue functioning properly over the design life time.

2. METHODOLOGY

2.1 Survival Analysis:

Survival analysis is used to calculate the expected time “in years” from the beginning of follow-up until the occurrence of defined events, rutting pavement failure in this study, based on reliability theory. 0.5 inch (12.7 mm) is selected to represent the maximum allowable rut depth (Huang, 2004) and (Roberts et al., 1996). The main benefit of using survival analysis is that it can better deal with censored data which represents the incomplete observed responses during the observation phase (SAS institute, 2004). Fig.1 represents the three different types of censored data used to determine the time of failure of flexible pavement. Left-censored occurs when the exact time of failure is unknown and the occurrence of failure happens between time 0 and t before the beginning of study or observation. Right-censored occurs when the failure time doesn’t occur during the observation time.

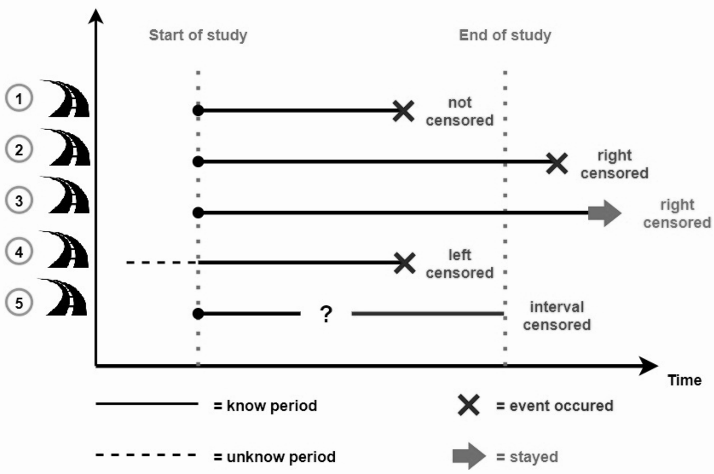

Fig.1: Types of censored data in survival analysis (Adapted from (Pornsawangdee, 2021))

Interval-censored occurs when the pavement under study failed within a certain specified time interval but the exact time of occurrence is unknown. For the study, 188 pavement sections were collected from the LTPP where the total number of censored pavement sections is 39 (21% of the total extracted data).

2.2 Parametric Survival Analysis:

Equation 1 represents the survival function, S(t), which defines the probability (P) that the occurrence of pavement section rutting failure has not happened at time t, where G(t) is the cumulative distribution function of the pavement service life, T is the pavement service life, and g(u) is the density function of the pavement failure (Berthold and Hand, 2003).

$$S(t) = P(T \geq t) = 1\text{-}G(t) = 1-\int_0^t g(u)du \quad (1)$$

Equation 2 represents the hazard function, h(t), which defines the instantaneous potential for the rutting failure event to occur per unit of time, given that the pavement test section has survived up to time t.

$$h(t) = \lim_{\Delta t \to 0} \left(\frac{P(t \leq T \leq t + \Delta t}{\Delta t} \right) = \frac{f(t)}{S(t)} \quad (2)$$

A parametric survival model assumes that the survival time will follow several distributions. The Weibull, the log-normal, and the log-logistic are the most commonly used distributions. These models are used in this study to indicate the influence of various covariates on rutting survival time, particularly the impact of overweight axles on rutting failures. Stata MP/13 software package (2013) was selected to conduct the parametric survival analysis. The survival models are estimated using the maximum likelihood estimation method and the independent variables (predictors) are examined using the likelihood ratio test (Kleinbaum, 2012). The proportional hazards (PH) models and the accelerated failure-time (AFT) models are frequently used to adjust the survival functions for the effects of covariates. Table 1 shows the survival functions for various parametric survival models used in this study.

Table 1: Survival function of various parametric survival models

Regression Models	Metric	Survivor Function S(t)	
Weibull	PH	$\exp(-(\exp(x_j b)t^p{}_j)$	(3)
Weibull	AFT	$\exp(-(\exp(-px_j b)t^p{}_j)$	(4)
Log-normal	AFT	$1\text{-}\Phi\{\frac{\log(tj)-xj\beta}{\sigma}\}$	(5)
Log-logistic	AFT	$\{1+(\exp(-xjb)t_j)^{1/(\gamma}\}^{-1}$	(6)

In the above models, x_j is a vector of covariates or predictors, b is a vector of regression coefficients, and (p,s,γ) are ancillary parameters related to Weibull, log-normal, and log-logistic respectively. The corrected Akaike information criterion (AIC) and the Cox-Snell residuals test are applied to compare the fit of the various models with different distributions and to select the most appropriate parametric model (Ansin, 2015), (Cox and Snell, 1968), and (Lemeshow and Hosmer, 1982).

2.3 Data Collection:

Table *2* lists the extracted independent variables related to climatic, traffic, and pavement materials for the selected pavement sections. These variables are extracted from different tables using LTPP database and then merged according to their identification and state code. The cross correlations are independently tested to verify the multicollinearity of the extracted variables so the variables that have no significant evidence of correlation are only selected for this analysis. Table 2 also lists the calculated means for the selected variables.

Table 2: Extracted independent and dependent variables.

Category	Independent Variables	Abbreviations	Unit	Mean
Traffic	Annual Average Daily Truck Traffic	AADTT	trucks/day	718.336
	Annual Average cumulative Single Axle Load (×1000)	KESAL	#	294.112
	Total Percentage of Overweight Axles (exceeds Federal truck's weight limits :Single Axle:20 Kips, Tandem Axle:34)	%OA	%	14.89
Climatic	Average Annual Precipitation	P	in	34.432
	Average Freezing Indices (FI)	FI	°F-days	625.885
	Average Annual Temperatures	T	°F	54.969
	Average Total Annual Snowfall	S	in	26.183
Pavement Materials	Total Thickness of Asphalt Layer	h_{ac}	in	7.866
	Total Thickness of Base Layer	h_b	in	8.905
	Total Thickness of Subbase Layer	h_{sub}	in	5.499
	Subgrade Material Resilient Modulus	M_r	psi	11502.258
Category	**Dependent Variables**	**Abbreviations**	**Unit**	**Mean**
Pavement Performance Indicator	Pavement Rutting	RUT	in	NA

3. RESULTS AND ANALYSIS

The stepwise selection technique was used to determine the most significant subset of predictors and the best parametric distribution models were identified simultaneously. Table 3 indicates the variables which were significant at 5% significance level for each distribution model. For the three distribution models conducted in this study, the only significant factors, with a p-value less than 5%, were: the annual average daily truck traffic (AADTT), the annual average cumulative single axle load (KESAL), the overweight axles percentages (%OA), the total precipitation (P), the temperature (T), and the thickness of asphalt layer (h_{ac}). The calculated log-likelihood and AIC values are also represented in Table 3. The Weibull model has the smallest AIC value where the calculated AIC for the other two models were found to be similar. The results are similar to those obtained by plotting the Cox-Snell residuals. Fig.2, Fig.3, and Fig.4 showed that the Weibull distribution model is better than the other models since the plot curve is closer to a straight line with unit slope and zero intercepts. The calculated random parameters for Weibull model and the calculated hazard ratios for rutting failure are reported in Table 4.

DOI: https://www.doi.org/10.54729/CUBR7851

Table 3: The most significant subset of predictors with the log-likelihood and AIC values for various parametric distribution model

Model	The Most Significant Subset of Predictors	Log-Likelihood (LL)	AIC
Weibull		-60.828462	137.6569
Log-logistic	AADTT, KESAL, %OA, P, T, h_{ac}	-66.696584	149.3932
Log normal		-66.736879	149.4738

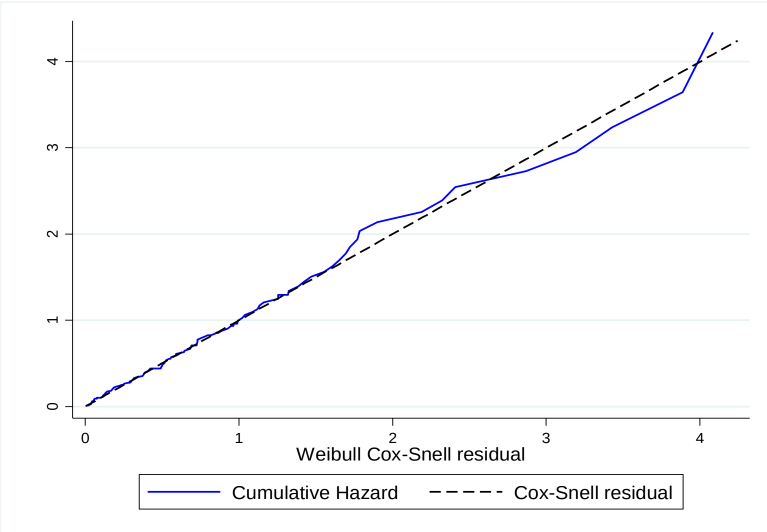

Fig.2: Graph of the Kaplan-Meier (KM) estimate of the cumulative hazard versus the Cox-Snell residuals from the Weibull distribution.

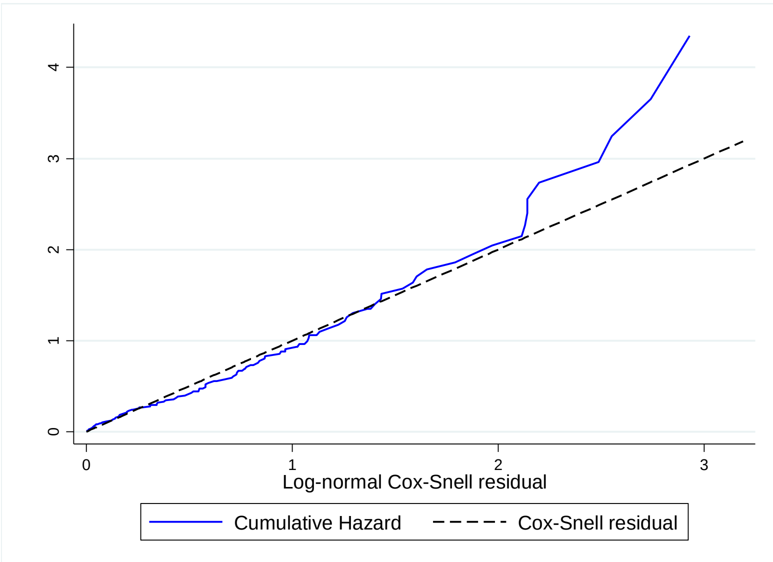

Fig.3: Graph of the Kaplan-Meier (KM) estimate of the cumulative hazard versus the Cox-Snell residuals from the Log-normal distribution.

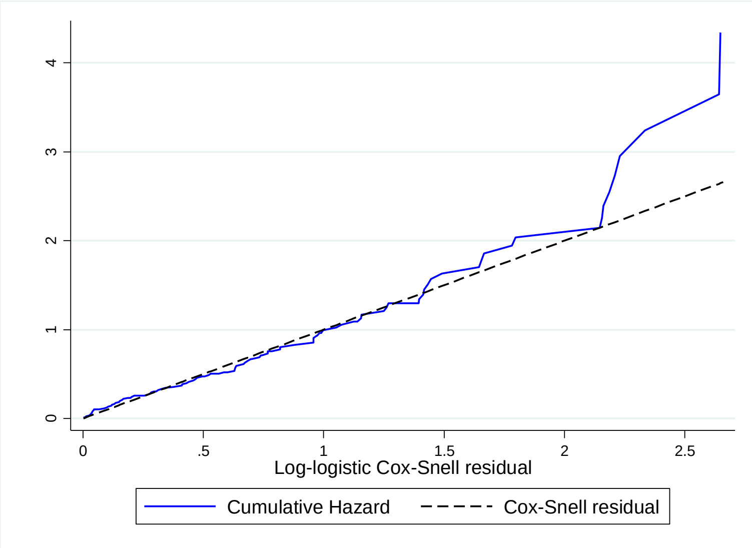

Fig.4: Graph of the Kaplan-Meier (KM) estimate of the cumulative hazard versus the Cox-Snell residuals from the Log-logistic distribution.

All the variables were statistically significant with p-value less than 5%. The Weibull hazard was monotonically increasing since the calculated ancillary shape parameter (p=3.0365) is positive. The test statistic is 13.71 so the null hypotheses for the hazard is constant was rejected. The hazard ratio are also reported in Table 4. A unit increase in the percentage of overweight axles (1%) can be related to 16.24% increase in hazard rate of rutting failure.

Table 4: Weibull parametric regression for pavement failure due to pavement rutting

Variables	Coefficient	Std. Err.	Z score	P-Value	Hazard Ratio
AADTT	0.0012061	0.000208	5.82	p<0.001	1.001207
KESAL	0.0015573	0.000433	3.6	p<0.001	1.001558
%OA	0.1505236	0.024747	7.07	p<0.001	1.162443
P	-0.0186223	0.006288	-2.91	0.004	0.98155
hac	-0.0853098	0.030026	-2.61	0.009	0.9182277
T	0.0213064	0.009918	2.19	0.028	1.021535
_cons	-11.78477	8.85E-06	-10.15	p<0.001	7.62E-06
/ln_p	1.110717	0.081008	13.71	0	1.110717
p	3.036536	0.245984			
1/p	0.3293226	0.026678			

Moreover, a 1 °F increase in temperature corresponds to a 2% increase in hazard rate. Based on the results, the final model to estimate the rutting survival time can be written as follows:

$$S(t\backslash x_j) = \exp\{-\exp(-11.78477 + 0.0012061\times(AADTT) + 0.0015573\times(KESAL) + 0.1505236\times(\%OA) - 0.0186223\times(P) - 0.0853098\times(h_{ac}) + 0.0213064\times(T))\times t^{3.036}\} \quad (7)$$

Using Equation 7, the survival curve of the average pavement section is illustrated in Fig.5. The median survival life, S(t)=0.5, related to the average pavement test section is 13.9 years. Equation 7 was also used to estimate the median survival time at each desired overweight axle value with the other parameters (AADTT, KESAL, P, T, and hac) being the average to assess the influence of overweight axles on rutting survival life. Fig.6 and Fig.7 illustrate the trend of changes in the median survival time with different percentages of overweight axles (%OA). The results showed that the survival time of the rutting life can be reduced by up to 63% in the presence of 20% overweight axles.

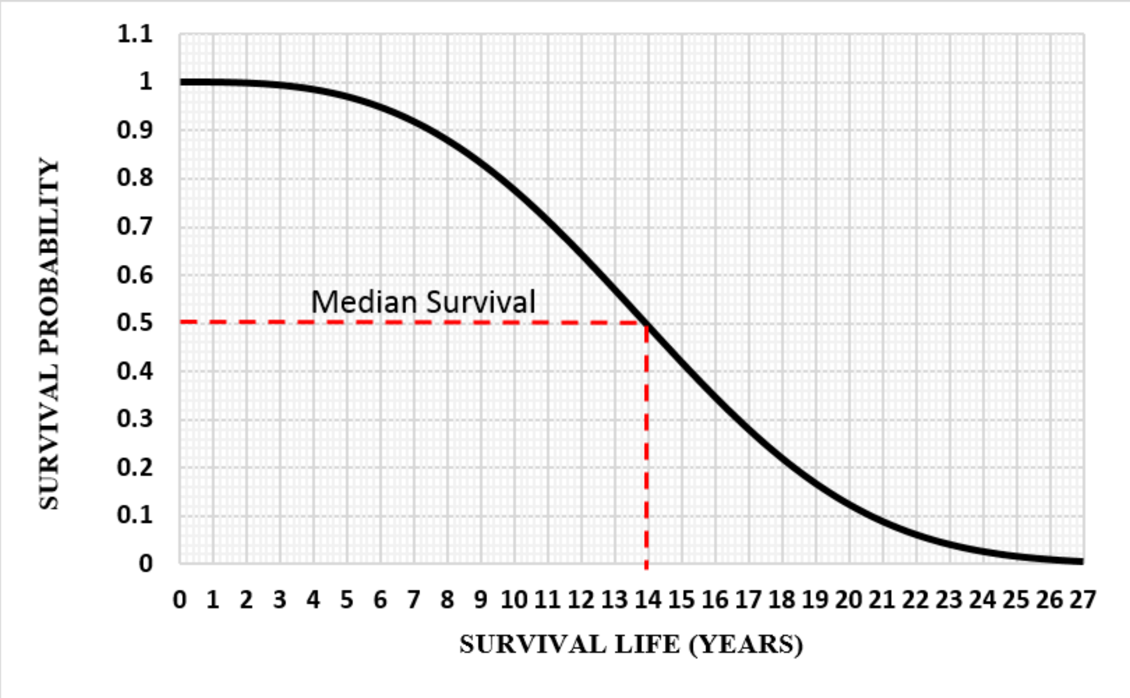

Fig.5: Survival curve of the average pavement section.

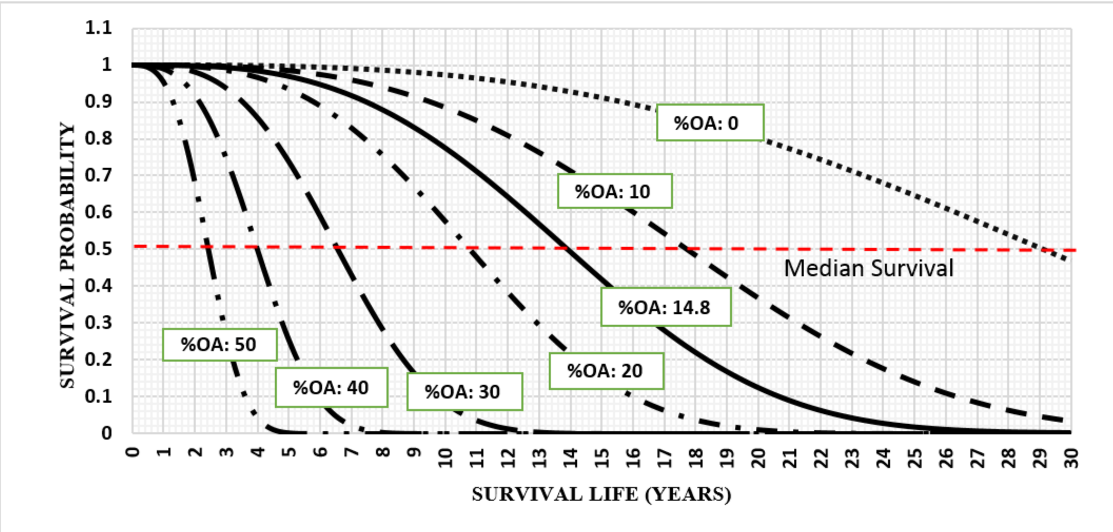

Fig.6: Survival curves for different percentages of overweight axles

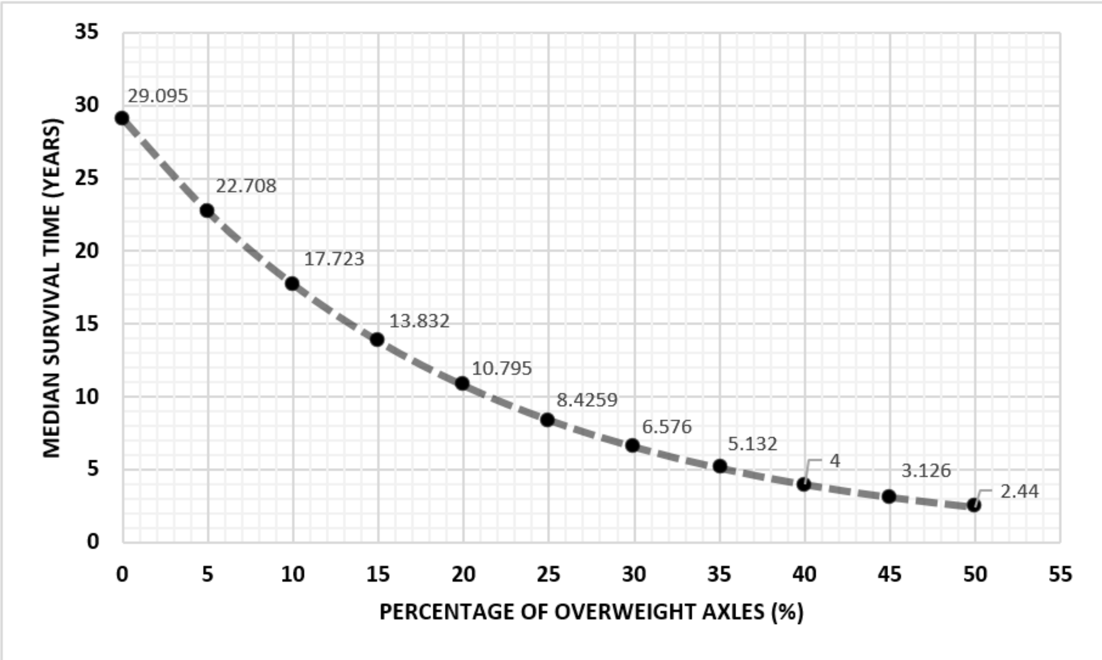

Fig.7: Median survival time for different percentage of overweight axles

4. CONCLUSIONS

The paper focuses on determining the time to failure of asphalt flexible pavement associated with rutting distress, indicating the most significant factors affecting pavement rutting, and evaluating the impact of overweight axles on pavement rutting life using parametric survival analysis. The results indicate that the annual average daily truck traffic, the equivalent single axle load, the percentages of overweight axles, the total precipitation, the temperature and the thickness of the asphalt layer have a significant effect on pavement rutting life. The Weibull model assumption was found to be an effective description for the parametric function. The results also show that a 1% increase in the percentage of overweight axles can be related to a 16.24% increase in the hazard rate of rutting failure. Also, a 1 ^{o}F increase in temperature corresponds to a 2% increase in the rutting hazard rate. The survival time of rutting life can be reduced by up to 63% with the increasing of the percentage of overloaded axles from 0% to 20%.

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