Analysis for Locomotive Wheels' Degradation

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Key Words: reliability; accelerate life testing; Bayesian approach; locomotive wheels; product maintenance strategy

SUMMARY & CONCLUSIONS

This paper undertakes a reliability study using both classical and Bayesian semi-parametric frameworks to explore the impact of a locomotive wheel's position on its service lifetime and to predict its other reliability characteristics. The goal is to illustrate how degradation data can be modeled and analyzed by using classical and Bayesian approaches. The adopted data in the case study have been collected from the Swedish company. The results show that: 1) an exponential degradation path is a better choice for the studied locomotive wheels; 2) both classical and Bayesian semi-parametric approaches are useful tools to analysis degradation data; 3) under given operation conditions, the position of the locomotive wheel could influence its reliability.

1 INTRODUCTION

The service life of a train wheel can be significantly reduced due to failure or damage, leading to excessive cost and accelerated deterioration, a point which has received considerable attention in recent literature [1-9]. One common preventive maintenance strategy (used in the case study) is re-profiling wheels after they run a certain distance. Re-profiling affects the wheel's diameter; once the diameter is reduced to a pre-specified length, the wheel is replaced by a new one. Seeking to optimize this maintenance strategy, researchers have examined wheel degradation data to determine wheel reliability and failure distribution. However, in previous studies, some researchers have noticed that, the wheels' different installed positions could influence the results [9-11]. Recently, to solve the combined problem of small data samples and incomplete datasets while simultaneously considering the influence of several covariates, Lin et al. [11] has explored the influence of locomotive wheels' positioning on reliability with Bayesian parametric models. Their results indicate that the particular bogie in which the wheel is mounted has more influence on its lifetime than does the axel or which side it is on. Therefore, besides the locomotive, we only use the bogie as a main influence factor.

In this paper, a reliability study using both classical and Bayesian semi-parametric frameworks is undertaken, to explore the impact of a locomotive wheel's position (which locomotive and bogie) on its service lifetime and to predict its other reliability characteristics. The remainder of the paper is organized as follows. Section 2 describes the background and dataset for the case study of the wheels. Section 3 presents the models and results from a classical approach's perspective. Section 4 presents the piecewise constant hazard regression model with gamma frailties. Finally, Section 5 offers conclusions and comments for future study.

2 DATA DESCRIPTION

The data were collected by a Swedish railway company from November 2010 to January 2012. We used the degradation data from two heavy haul cargo trains' locomotives (denoted as locomotive 1 and locomotive 2). Correspondingly, there are two studied groups, and $n = 2$. As shown in Figure 2.1, there are two bogies (Bogie I, Bogie II), and for each bogie, there are six wheels.

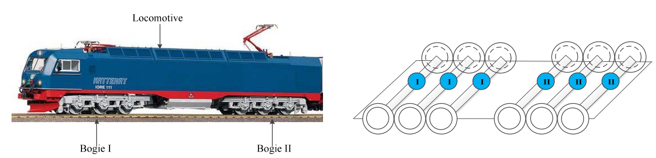

Figure 2.1 Wheel positions specified

The diameter of a new locomotive wheel is 1250 mm. A wheel's diameter is measured after running a certain distance. If it is reduced to 1150 mm, the wheel is replaced by a new one. Therefore, a threshold level for failure, denoted as l_0, is defined as 100 mm (l_0 = 1250 mm -1150 mm). The wheel's failure condition is assumed to be reached if the diameter reaches l_0. We can obtain 3 to 5 measurements of the diameter of each wheel during its lifetime. By connecting these measurements, we plot the degradation data for the locomotive wheels with exponential degradation, power degradation, logaritmic degradation, Gompertz degradation, as well as linear degradation path in Weibull++. The results (see Figure 2.2) show that a better choice is the Gompertz degradation path, exponential degradation path and Power degradation. However, Gompertz was not selected here because normally it needs a total of more than 5 points to converge. In our study, based on the type of physics of failures associated with wear and fatigue, an exponential and power are selected as degradation models.

An exponential model is described by the following function (2.1) and the power one by the function (2.2) from

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reference [12]:

$$\text{Exponential: } y = b \cdot e^{a \cdot x} \tag{2.1}$$

$$\text{Power: } y = b \cdot x^{a \cdot c} \tag{2.2}$$

where y represents the performance (here, it represents the diameter of the wheels), x represents time (here, it represents the running distance of the wheels), and a , b and c are model parameters to be solved for.

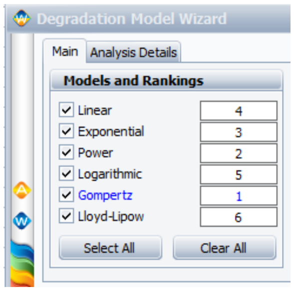

Figure 2.2 Degradation path analyses

Following the above discussion, a wheel's failure condition is assumed to be reached if the diameter reaches l_0 . We adopt the both the Exponential degradation path and power degradation path for all wheels and set $l_0 = y$. The lifetimes for these wheels are now easily determined.

3 CLASSICAL APPROACH

Accelerated Life Tests (ALT) is used widely in manufacturing industries, particularly to obtain timely information on the reliability of product components and materials. In most reliability testing applications, degradation data, if available, can have important practical advantages [13]. Particularly in applications where few or no failures are expected, degradation data can provide considerably more reliability information than would be available from traditional censored failure-time data. Accelerated tests are commonly used to obtain reliability test information more quickly. Direct observation of the degradation process may allow direct modeling of the failure-causing mechanism, providing more credible and precise reliability estimates and basis for often-needed extrapolation. Modeling degradation of performance output of a component or subsystem may be useful, but modeling could be more complicated or difficult because the output may be affected, unknowingly, by more than one physical/chemical failure-causing process.

Once obtained the projected failures values for each degradation model, an accelerated life analysis is done using locomotive and bogie as stress factors. The analysis is performed using a General Log Linear (GLL) life stress relationship (3) with a Weibull probability function [14].

$$L(\underline{X}) = e^{\left(\alpha_0 + \sum_{i=1}^{m} \alpha_i X_i\right)} \tag{3.1}$$

This model can be expressed as an exponential model, expressing life as a function of the stress vector X , where X is a vector of n stressors [14].

For this analysis it was considered for both stress applications of this model and a logarithmic transformation on X, such that $X = \ln(V)$ where V is the specific stress. This transformation generated an inverse power model life stress relationship as shown below for each stress factor [14].

$$L(V) = \frac{1}{KV^n} \tag{3.2}$$

As shown in Figure 3.1, the exponential function for this set of data brings more conservative results and in line with field observation when life data is compared a different stress levels as previously defined.

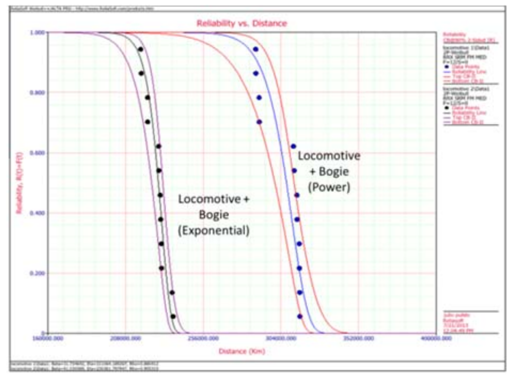

Figure 3.1 Reliability Curve for Degradation Type

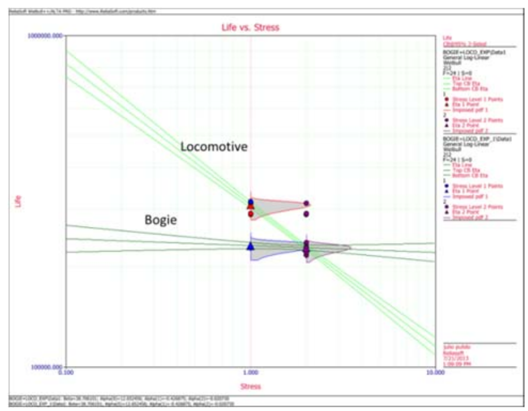

Figure 3.2 Life vs. Stress

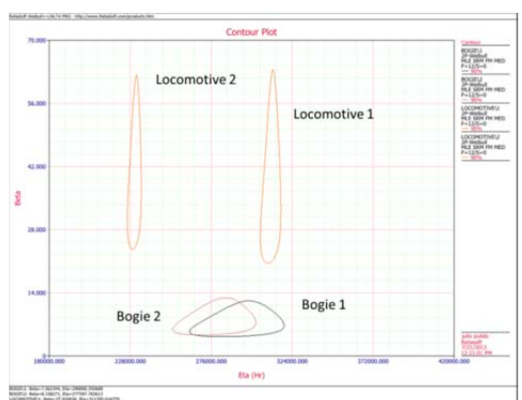

Figure 3.3 Contour Plot

Using the exponential degradation model, a two factors full factorial Design of Experiment analysis was performed and found that the locomotive, bogie and interaction are critical factors. A review of the life stress relationship between the factors indicated the locomotive is a higher contributor to the degradation of the system when compared with the bogie (Figure 3.2 and 3.3).

Figure 3.3 and 3.4 show the reliability values at each operating distance. The figure 3.4 shows Locomotive2 as the one with the highest degradation per distance traveled. Based on the analysis described, the following conclusions can be reached: Independent of the degradation model the locomotive factor is the critical stressors as shown in the data above. Failures modes obtained from the data are similar for locomotive are similar as well for bogies. Of the two stress conditions, level 2 is the highest for locomotive and bogie as shown in Figure 3.3.

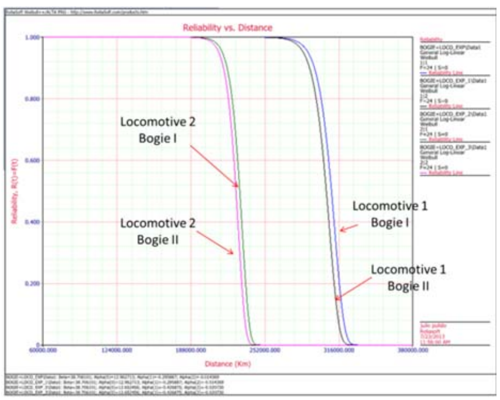

Figure 3.4 Reliability Curves at each Condition

4 BAYESIAN APPROACH

Most reliability studies are implemented under the assumption that individual lifetimes are independent identified distributed (i.i.d). However, sometimes Cox proportional hazard (CPH) models cannot be used because of the dependence of data within a group. A key development in modeling such data is to consider frailty models, in which the data are conditionally independent. When frailties are considered, the dependence within subgroups can be considered an unknown and unobservable risk factor (or explanatory variable) of the hazard function. In addition, since semi-parametric Bayesian methods offer a more general modeling strategy that contains fewer assumptions [15], we adopt the piecewise constant hazard model to establish the distribution of the locomotive wheels' lifetime. It should be pointed out that: considering the results from section 2 and section 3, here, we adopt the results achieved by the exponential degradation path.

The piecewise constant hazard model is one of the most convenient and popular semi-parametric models in survival analysis. Begin by denoting the j^{th} individual in the i^{th} group as having lifetime t_{ij}, where $i = 1, \cdots, n$ and $j = 1, \cdots, m_i$. Divide the time axis into intervals $0 < s_1 < s_2 < \cdots < s_k < \infty$, where $s_k > t_{ij}$, thereby obtaining k intervals $(0, s_1]$, $(s_1, s_2]$, $\cdots$ $(s_{k-1}, s_k]$. Suppose the j^{th} individual in the i^{th} group has a constant baseline hazard $h_0(t_{ij}) = \lambda_k$ as in the k^{th} interval, where $t_{ij} \in I_k = (s_{k-1}, s_k]$. Then, the hazard rate function for the piecewise constant hazard model can be written as

$$h_0(t_{ij}) = \lambda_k, \qquad t_{ij} \in I_k \tag{4.1}$$

Equation (4.1) is sometimes referred to as a piecewise exponential model; it can accommodate various shapes of the baseline hazard over the intervals.

Suppose $\mathbf{x}_i = (x_{1i}, \cdots x_{pi})'$ denotes the covariate vector for the individuals in the i^{th} group, and $\boldsymbol{\beta}$ is the regression parameter. Therefore, the regression model with the piecewise constant hazard rate can be written as

$$h(t_{ij}) = \begin{cases} \lambda_1 \exp(\mathbf{x}_{ij}'\boldsymbol{\beta}) & 0 < t_{ij} \le s_1 \\ \lambda_2 \exp(\mathbf{x}_{ij}'\boldsymbol{\beta}) & s_1 < t_{ij} \le s_2 \\ \vdots & \vdots \\ \lambda_k \exp(\mathbf{x}_{ij}'\boldsymbol{\beta}) & s_{k-1} < t_{ij} \le s_k \end{cases} \tag{4.2}$$

Correspondingly, its probability density function $f(t_{ij})$, cumulative distribution function $F(t_{ij})$, reliability function $R(t_{ij})$ can be achieved [14].

Frailty models are first considered to handle multivariate survival data. In such models, the event times are conditionally independent according to a given frailty factor, which is an individual random effect. Assume the hazard function for the j^{th} individual in the i^{th} group is

$$h_{ij}(t) = h_0(t)\exp(\mu_i + \mathbf{x}_{ij}'\boldsymbol{\beta}) \tag{4.3}$$

In equation (4.3), μ_i represents the frailty parameter for the i^{th} group. By denoting $\omega_i = \exp(\mu_i)$, the equation can be written as

$$h_{ij}(t) = h_0(t)\omega_i \exp(\mathbf{x}_{ij}'\boldsymbol{\beta}) \tag{4.4}$$

Equation (4.3) is an additive frailty model, and equation (4.4) is a multiplicative frailty model. In both equations, μ_i and ω_i are shared by the individuals in the same group, and they are thus referred to as shared-frailty models and actually are extensions of the CPH model. In this paper, we consider the gamma shared frailty model, the most popular model for frailty. From equation (4.4), suppose the frailty parameters ω_i are independent and identically distributed (i.i.d) for each group, and follow a gamma distribution, denoted by $Ga(\kappa^{-1}, \kappa^{-1})$. Therefore, the probability density function can be written as

$$f(\omega_i) = \frac{(\kappa^{-1})^{\kappa^{-1}}}{\Gamma(\kappa^{-1})} \cdot \omega_i^{\kappa^{-1}-1} \exp(-\kappa^{-1}\omega_i) \tag{4.5}$$

In equation (4.5), the mean value of ω_i is one, where κ is the unknown variance of ω_i s.

Suppose $\boldsymbol{\omega} = (\omega_1, \omega_2, \cdots, \omega_n)'$; then

$$\pi(\boldsymbol{\omega}|\kappa) \propto \prod_{i=1}^{n} \omega_i^{\kappa^{-1}-1} \exp(-\kappa^{-1}\omega_i) \tag{4.6}$$

Based on the above discussions, the piecewise constant hazard model with gamma shared frailties can be written as:

$$h(t_{ij})=\begin{cases}\lambda_1\omega_i\exp(\mathbf{x}'_{\mathbf{ij}}\boldsymbol{\beta}) & 0<t_{ij}\le s_1\\ \lambda_2\omega_i\exp(\mathbf{x}'_{\mathbf{ij}}\boldsymbol{\beta}) & s_1<t_{ij}\le s_2\\ \vdots & \vdots\\ \lambda_k\omega_i\exp(\mathbf{x}'_{\mathbf{ij}}\boldsymbol{\beta}) & s_{k-1}<t_{ij}\le s_k\end{cases} \quad (4.7)$$

In equation (4.7), $\omega_i \sim Ga(\kappa^{-1},\kappa^{-1})$.

To analysis the baseline hazard rate λ_k, a common choice is to construct an independent incremental process. However, in many applications [15], prior information is often available on the smoothness of the hazard rather than the actual baseline hazard itself. In addition, given the same covariates, the ratio of marginal hazards at the nearby time-points is approximately equal to the ratio of the baseline hazards at these points. In such situations, correlated prior processes for the baseline hazard can be more suitable. Given ($\lambda_1,\lambda_2,\cdots,\lambda_{k-1}$), we specify that

$$\lambda_k\left|\lambda_1,\lambda_2,\cdots,\lambda_{k-1}\sim Ga(\alpha_k,\frac{\alpha_k}{\lambda_{k-1}})\right. \quad (4.8)$$

Let $\lambda_0=1$. In equation (4.8), the parameter α_k represents the smoothness for the prior information. If $\alpha_k=0$, then λ_k and λ_{k-1} are independent. As $\alpha_k\to\infty$, the baseline hazard is the same in the nearby intervals. In addition, the Martingale λ_k 's expected value at any time point is the same, and

$$E(\lambda_k\left|\lambda_1,\lambda_2,\cdots,\lambda_{k-1})=\lambda_{k-1}\right. \quad (4.9)$$

Equation (4.9) shows that given specified historical information ($\lambda_1,\lambda_2,\cdots,\lambda_{k-1}$), the expected value of λ_k is fixed.

In reliability analysis, the lifetime data are usually incomplete, and only a portion of the individual lifetimes are known. Suppose the j^{th} individual in the i^{th} group has lifetime T_{ij} and censoring time L_{ij}. The observed lifetime $t_{ij}=\min(T_{ij},L_{ij})$.; therefore, the exact lifetime T_{ij} will be observed only if $T_{ij}\le L_{ij}$. In addition, the lifetime data involving right censoring can be represented by n pairs of random variables (t_{ij},υ_{ij}), where $\upsilon_{ij}=1$ if $T_{ij}\le L_{ij}$ and $\upsilon_{ij}=0$ if $T_{ij}>L_{ij}$. This means that υ_{ij} indicates whether lifetime T_{ij} is censored or not. The likelihood function is deduced as

$$L(t)=\prod_{i=1}^{n}\prod_{j=1}^{m_i}[f(t_{ij})]^{\upsilon_{ij}}R(t_{ij})^{1-\upsilon_{ij}} \quad (4.10)$$

In the above piecewise constant hazard model, we denote g_{ij} as $t_{ij}\in(s_{g_{ij}},s_{g_{ij}+1})=I_{g_{ij}+1}$ and the model's dataset as $D=(\boldsymbol{\omega},\mathbf{t},\mathbf{X},\boldsymbol{\upsilon})$. Following equation (4.7) - (4.10), the complete likelihood function $L(\boldsymbol{\beta},\boldsymbol{\lambda}|D)$ for the individuals for the i^{th} group in k intervals can be written as

$$\prod_{i=1}^{n}\prod_{j=1}^{m_i}\left\{[\prod_{k=1}^{g_{ij}}\exp(-\lambda_k\omega_i\exp(\mathbf{x}'_{\mathbf{ij}}\boldsymbol{\beta})(s_k-s_{k-1})]\right.$$
$$\left.\times(\lambda_{g_{ij}+1}\omega_i\exp(\mathbf{x}'_{\mathbf{ij}}\boldsymbol{\beta}))^{\upsilon_{ij}}\times\exp[-\lambda_{g_{ij}+1}\omega_i\exp(\mathbf{x}'_{\mathbf{ij}}\boldsymbol{\beta})(t_{ij}-s_{g_{ij}})]\right\} \quad (4.11)$$

Let $\pi(\cdot)$ denote the prior or posterior distributions for the parameters. Following equation (4.6) and (4.11), the joint posterior distribution $\pi(\omega_i|\boldsymbol{\beta},\boldsymbol{\lambda},D)$ for gamma frailties ω_i can be written as

$$\pi(\omega_i|\boldsymbol{\beta},\boldsymbol{\lambda},D)\propto Ga\left\{\kappa^{-1}+\sum_{j=1}^{m_i}\upsilon_{ij},\right.$$
$$\left.\kappa^{-1}+[\sum_{j=1}^{m_i}\exp(\mathbf{x}'_{\mathbf{ij}}\boldsymbol{\beta})](\sum_{k=1}^{g_{ij}}\lambda_k(s_k-s_{k-1})+\lambda_{g_{ij}+1}(t_{ij}-s_{g_{ij}}))\right\} \quad (4.12)$$

Similarly, the full conditional density of κ^{-1} and $\boldsymbol{\beta}$ can be given by

$$\pi(\kappa^{-1}|\boldsymbol{\beta},\boldsymbol{\omega},\boldsymbol{\lambda},D)$$
$$\propto\prod_{i=1}^{n}\omega_i^{\kappa^{-1}-1}(\kappa^{-1})^{-n\kappa^{-1}}\times\frac{\exp\left(-\kappa^{-1}\sum_{i=1}^{n}\omega_i\right)}{[\Gamma(\kappa^{-1})]^n}\cdot\pi(\kappa^{-1})$$

$$\pi(\boldsymbol{\beta}|\kappa^{-1},\boldsymbol{\omega},\boldsymbol{\lambda},D)\propto\exp\left\{\sum_{i=1}^{n}\sum_{j=1}^{m_i}\upsilon_{ij}\mathbf{x}'_{\mathbf{ij}}\boldsymbol{\beta}-\right.$$
$$\left.\sum_{i=1}^{n}\sum_{m=1}^{n_i}\exp(\mathbf{x}'_{\mathbf{ij}}\boldsymbol{\beta})\omega_i\times\left[\sum_{k=1}^{g_{ij}}\lambda_k(s_k-s_{k-1})+\lambda_{g_{ij}+1}(t_{ij}-s_{g_{ij}})\right]\right\}\times\pi(\boldsymbol{\beta})$$

Let $R_k=\{(i,j);t_{ij}>s_k\}$ denote the risk set at s_k and $D_k=R_{k-1}-R_k$; let d_k denote the failure individuals in the interval I_k. Let $\pi(\lambda_k|\boldsymbol{\lambda}^{(-k)})$ denote the conditional prior distribution for (λ_1, λ_2, $\cdots,\lambda_J$) without λ_k. We therefore derive $\pi(\lambda_k|\boldsymbol{\beta},\boldsymbol{\omega},\kappa^{-1},D)$ as

$$\lambda_k^{d_k}\exp\left\{-\lambda_k\omega_i\exp(\mathbf{x}'_{\mathbf{ij}}\boldsymbol{\beta})\times[\sum_{(i,j)\in R_k}(s_k-s_{k-1})+\sum_{(i,j)\in D_k}(t_{ij}-s_{k-1})]\right\}$$
$$\times\pi(\lambda_k|\boldsymbol{\lambda}^{(-k)})$$

In this model, the installed positions of the wheels on a particular locomotive are specified by the bogie number and are defined as covariates $\mathbf{x}$. The covariates' coefficients are represented by $\boldsymbol{\beta}$. More specifically, $x=1$ represents the wheel mounted in Bogie I, while $x=2$ represents the wheel mounted in Bogie II. β_1 is the coefficient and β_0 is defined as natural variability.

In our study, determining the degradation path requires us to make 3 to 5 measurements for each locomotive wheel. Following the reasoning above, we divide the time axis into 6 sections piecewise. In our case study, no predicted lifetime exceeds 360,000 kilometres. Therefore, k=6, and each interval is equal to 60,000km. For convenience, we let $\lambda_k=\exp(b_k)$, and vague prior distributions are adopted here as the following: Gamma frailty prior: $\omega_i\sim Ga(\kappa^{-1},\kappa^{-1})$; Normal prior distribution: $b_k\sim N(b_{k-1},\kappa)$; Normal prior distribution: $b_1\sim N(0,\kappa)$; Gamma prior distribution: $\kappa\sim$ Ga (0.0001, 0.0001); Normal prior distribution: β_0 ~ N (0.0, 0.001); Normal prior distribution: $\beta_1\sim$ N (0.0, 0.001). At this point, the MCMC calculations are implemented with the software WinBUGS [16].

Following the convergence diagnostics, we consider the following posterior distribution summaries (Table 4.1). Statistics summaries include the parameters' posterior distribution mean, SD, MC error, and the 95% highest posterior distribution density (HPD) interval.

Parameter	mean	SD	MC error	95% HPD
β_0	-12.08	4.184	0.4019	(-22.17,-4.802)
β_1	0.04517	0.4889	0.02025	(-0.948,0.9669)
κ	0.1857	0.1667	0.008398	(0.008616,0.6128)
ω_1	0.5246	0.2878	0.01401	(0.06489,1.064)
ω_2	1.473	0.5807	0.01596	(0.6917,2.948)
b_1	-0.3764	4.113	0.1619	(-8.316,5.933)
b_2	0.3571	4.95	0.2429	(-8.836,8.181)
b_3	2.272	4.61	0.3029	(-6.4,10.81)
b_4	7.301	4.106	0.3938	(0.2106,17.13)
b_5	5.223	4.225	0.3281	(-3.166,13.41)
b_6	10.03	3.993	0.3802	(2.72,19.3)

Table.4.1 Posterior Distribution Summaries

In Table.4.1, $\beta_1 > 0$ means that the wheels mounted in the first bogie (as $x=1$) have a shorter lifetime than those in the second (as $x=2$). However, the influence could possibly be reduced as more data are obtained in the future, because the 95% HPD interval includes 0 point. In addition, the small value of β_1 ($\approx$0.045) also indicates that, in this case, the heterogeneity among the wheels installed in different bogies exists but not significant. Because $\kappa < 0.5$, the heterogeneity among the locomotives does exists but is not significant either. However, the frailty factors exist obviously. For instance, $\omega_1 < 1$ suggests that the predictive lifetimes for those wheels mounted on the first locomotive are longer than if the frailties are not considered; in fact, $\omega_2 > 1$ indicates the opposite conclusion.

Baseline hazard rate statistics based on the above results ($b_1, \cdots, b_6$) are shown in Table 4.2. At the fourth piecewise interval, the wheels' baseline hazard rate increases dramatically (1481.78). It is interesting to point out that, at the fifth piecewise interval, it decreases (185.49); and it increases again since the sixth piecewise (22697.27).

Piecewise (1000km)	1	2	3	4	5	6
	(0, 60]	(60, 120]	(120, 180]	(180, 240]	(240, 300]	(300, 360]
λ_k	0.069	1.43	9.7	1481.78	185.49	22697.27

Table.4.2 Baseline Hazard Rate Statistics

The statistics on reliability $R(t)$ for the wheels mounted in different bogies are listed in Table 4.3 and Figure 4.2.

It should be pointed that, both Figure4.2 show change points in the wheels. For example, the reliability declines sharply at the fourth and the sixth piecewise interval. From Figure 4.1 and Figure 4.2, the change points appearing from the fourth piecewise interval indicate that after running about 180 000 kilometers, the locomotive wheel has a high-risk of failure. Although the difference is not that obvious, the wheels installed in the first bogie should be given more attention during maintenance. The results could also support related predictions for spares inventory. Last but not least, the frailties between locomotives could also be caused by the different operating environments (e.g., climate, topography, and track geometry), configuration of the suspension, status of the bogies or spring systems, operation speeds, the applied loads and human influences (such as drivers' operations, maintenance policies and the lathe operator). Specific operating conditions should be considered when designing maintenance strategies because even if the locomotives and wheel types are the same, the lifetimes and operating performance could differ.

Distance (1000 km)	Reliability $R(t)$			
	Locomotive 1		Locomotive 2	
	Bogie I	Bogie II	Bogie I	Bogie II
60	0.999872	0.999866	0.99964	0.999624
120	0.999466	0.999442	0.998502	0.998433
180	0.99458	0.994331	0.984857	0.984162
240	0.330536	0.314054	0.044672	0.038695
300	0.840949	0.834245	0.614843	0.601179
360	8.98E-12	2.77E-12	9.61E-32	3.54E-33

Table.4.3 Reliability Statistics

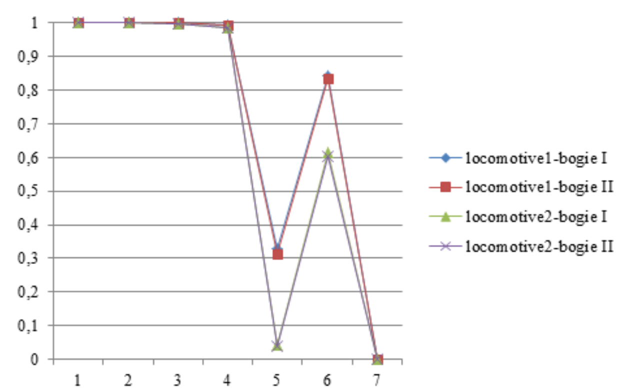

Fig.4.2 Plot of the reliabilities

5 CONCLUSIONS

This paper proposes a reliability study using both classical and Bayesian semi-parametric frameworks to explore the impact of a locomotive wheel's position on its service lifetime and to predict its other reliability characteristics. The results of the case study suggest that an exponential degradation path for the wheels is a better choice. With classical approach, both Accelerated Life Tests (ALT) and Design of Experiment (DOE) technology are carried on to determine the how each critical factor, locomotive or bogie, affects the prediction performance. Within the Bayesian semi-parametric approach, the piecewise constant hazard rate is used to establish the distribution of the wheels' lifetime. The results of the case study suggest the wheels' lifetimes differ according to where they are installed (in which bogie they are mounted) on the locomotive. The gamma frailties help with exploring the unobserved covariates and thus improve the model's precision. We can determine the wheel's reliability characteristics, including the baseline hazard rate $\lambda(t)$, reliability $R(t)$, etc. The results also indicate the existence of change points. As Figure 4.1 and Figure 4.2 show, wheel reliability can be divided into two stages: stable and unstable at 180 000 kilometers. The results allow us to evaluate and optimise wheel replacement and maintenance strategies (including the re-profiling interval, inspection interval, lubrication interval, depth and optimal sequence of re-profiling, and so on).

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