

Inference for the Wiener process with random initiation time

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- 1 Introduction and model
- 2 Parameters estimation
- 3 Time-to-failure estimation
- 4 Application to a dataset
- 5 Bibliography



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Introduction

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- ▶ **Degradation models vs. Lifetime models?** highly reliable components, use of complex preventive maintenance policies, etc.
- ▶ **Current models:** component degradation initiated when put in service!
- ▶ **Need of some new models:** models with an initiation period (deterministic or random)
See Guo *et al.* (13), Nelson (10)

Degradation model

Degradation model with random initiation period $(X(t))_{t \geq 0}$:

$$X(t) = [\mu(t - S) + \sigma B(t - S)] \mathbb{I}_{t \geq S}$$

where

- ▶ $t = 0$ is the instant where the component is put in service
- ▶ $(B(t))_{t \geq 0}$ is a standard Brownian motion
- ▶ S is an absolutely continuous and positive random variable, independent of $(B(t))_{t \geq 0}$

Time-to-failure

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$$T_c = \inf\{t \geq 0; X(t) \geq c\}$$

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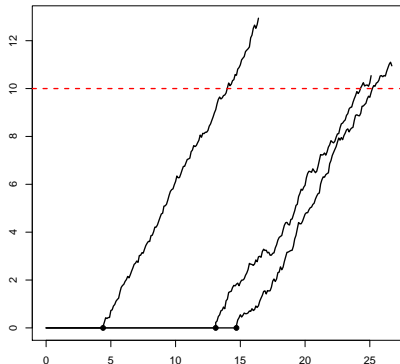
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Special case: S exponentially distributed, see Schwarz (01, 02) with an application in psychology

Simulations

Simulation of three sample paths:
 black circles = degradation initiations
 red dash line = critical level.





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Model assumptions? **Parametric model** for the distribution of S ,
with unknown parameter $\theta \in \Theta \subseteq \mathbb{R}^p$

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Information on θ (interval-censoring), μ and σ^2



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- ▶ \mathcal{N}_{2+} : set of individuals with exactly at least two degradation measures:

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- ▶ Random number Q_n of non-null increments: if Q_n non empty set,

$$Q_n = \sum_{i \in \mathcal{N}_{2+}} (m - R_i) = \sum_{j=1}^{m-1} (m - j) K_j$$

taking values in $\{1, \dots, (m-1)n\}$

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Lemma

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- 3 $\mathbb{E}[Q_n^{-1} | Q_n > 0] \xrightarrow[n \rightarrow \infty]{} 0$

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- ▶ Maximum likelihood estimator:

$$\hat{\theta}_n = \operatorname{argmax}_{\theta \in \Theta} \ell(\theta|\text{data}).$$

No closed-form expression in general

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- ▶ Closed expression for the Fisher information

Example: exponential distribution

- ▶ Closed expression for the MLE:

$$\widehat{\lambda}_n = \frac{1}{\delta} \log \left(\frac{N_0 \tau + \delta \sum_{r=1}^m r K_r}{N_0 \tau + \delta \sum_{r=1}^m (r-1) K_r} \right)$$

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Remark: $\rho^2 \xrightarrow{\delta \rightarrow 0} \frac{\lambda^2}{1 - e^{-\lambda \tau}}$

Estimation of μ and σ^2 (1/2)

- Natural estimator of μ :

$$\hat{\mu}_n = \frac{\sum_{i \in \mathcal{N}_{2+}} \sum_{j=1}^{m-R_i} \Delta X_{i,j}}{\delta \sum_{i \in \mathcal{N}_{2+}} (m-R_i)} = \frac{1}{\delta Q_n} \sum_{h=1}^{Q_n} Z_h,$$

where Z_1, \dots, Z_{Q_n} are the increments between two non-null degradation measures: random number of iid Gaussian random variables with mean $\mu\delta$ and variance $\sigma^2\delta$

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- ▶ Natural estimator of σ^2 :

$$\widehat{\sigma}_n^2 = \frac{1}{\delta(Q_n-1)} \sum_{h=1}^{Q_n} (Z_h - \delta\widehat{\mu}_n)^2.$$

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Proposition

1 $\hat{\mu}_n$ is asymptotically normal:

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- 2 $\hat{\sigma}_n^2$ is asymptotically normal:

$$\sqrt{Q_n}(\hat{\sigma}_n^2 - \sigma^2) \xrightarrow[n \rightarrow \infty]{d} N(0, 2\sigma^4)$$



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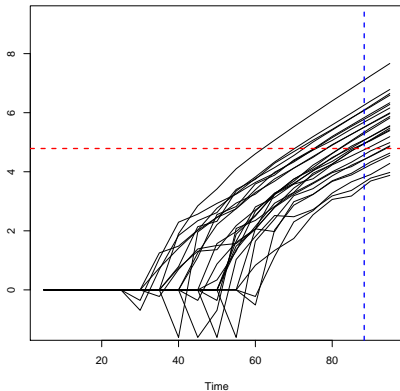
$$I(\theta)^{-1} \left(\int_0^{\infty} \partial_{\theta} \bar{F}_S(u; \theta) du \right)^2 + \frac{c^2 \sigma^2}{\mu^4 \tau \alpha(m, \tau)}$$

Guo *et al.* data

Black lines: observed degradation paths

Red dashed line: critical level

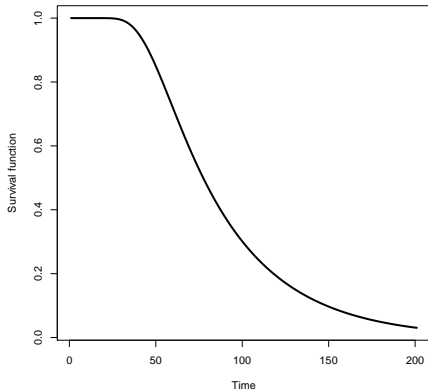
Blue dashed line: MTTF estimation



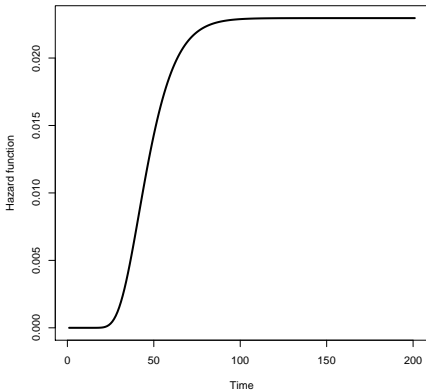
Fitted parameters

Parameter	Estimation	95% confidence interval
λ	0.023	[0.013,0.032]
μ	0.108	[0.097,0.119]
σ^2	0.041	[0.033,0.048]
<i>MTTF</i>	88.332	[69.438,107.227]

Estimated survival function





Estimated hazard function





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Some references

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