AMORE-MIO

Advanced MethOds for Reliability and maintenance Evaluation: Models, Inference, Optimization

Equipe action PERSYVAL-Lab 2020-2023

Journée département DATA 2022

23 juin 2022

Context

Strategic industrial issue

Maintaining repairable equipment in working conditions in accordance with safety, availability and cost constraints.

Recent advances "change the game" in reliability

Wide access to information and data on systems

- Reliability database: description of successive events (failures, maintenances, inspections) for the different sub-systems.
- Sensors and modern monitoring: record specific working and usage conditions, measure health indicators, ...

Aim of the project (both theoretical and applied results)

Develop integrated approaches to optimally manage the health state of deteriorating systems based on all available information.

Related to **CDP RISK@UGA -> CD Tools** and project of **RISK Institute -> ARIMA**

Consortium

2 research teams & 2 industrial partners

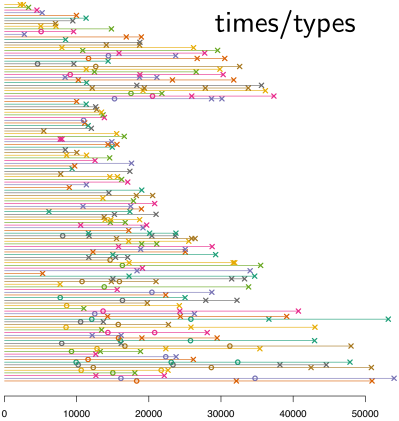
- **LJK - ASAR team:** stochastic modelling and statistical inference in reliability and maintenance

- **GIPSA-lab - SAFE team:** state health monitoring, control and prognosis, post-prognosis decision making

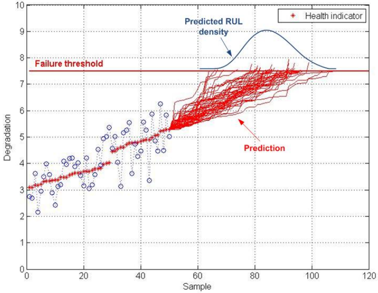
- **EDF R&D and GRTgaz:** challenging industrial open issues, motivating examples, end-users of the methods

Two classically disconnected mathematical tools

- **Recurrent events models:** stochastic discrete event times/types



- **Stochastic degradation processes:** continuous evolution of a wear-out phenomenon



Both approaches are considered.

Final Challenge

Closing the gap between these two "modelling worlds".

Research lines

Modelling

- multivariate wear-out phenomenons
- multiple maintenance effects
- environmental factors
- ...

Case Study

Inference

- different observation schemes
- censoring (left, interval censored data, ...)
- observed/unobserved heterogeneity
- ...

Descision Making

- optimize maintenance times and types
- optimize health indicator measurements
- control system health
- ...

Resources

Researchers funded on the project

- **1 PhD:** M Leroy (2020-)$\rightarrow$ degradation models
- **1 year PostDoc:** Centered on adaptive monitoring for optimal inference/prediction & decision-making (from september Xiaopeng Xi from Tsinghua Univ.)
- **2 Master internships** A Haytam (2021) $\rightarrow$ Descision Making with recurrent events models
- **Invitations of researcher (partly funded)** : ML Bautista Barcena, PhD Extremadura Univ (3 months 2022) $\rightarrow$ degradation models

External resources (seeked leverage effect)

- **1 CIFRE PhD with GRT-Gaz** (+ 2 prior collaboration contracts): T. Cousino (2022-) $\rightarrow$ recurrent events
- **Visiting researchers** : I. Castro, Prof and ML Bautista Barcena, Extremadura Univ. $\rightarrow$ degradation models

Dissemination

- Common seminars with regional working group FIMA (3 labs + 3 companies) of the IMdR
- Organisation of ENBIS spring meeting (19-20 mai 2022)
  - 2 invited + 21 contributed papers
  - 42 delegates (24 from France)
  - 1 special issue in Applied Stochastic Models in Business and Industry
- Organisation of the 43th school of automatic in Grenoble (september 2022)

Focus on the research works of T. Cousino, GRT-Gaz PhD student

Maintenance effects in recurrent events models:

- inference
- modelling
- decision making

Recurrent events context

- Successive failure times: $T_1 < T_2 < \ldots.$
- Associated counting process N : $t \mapsto N(t) = \sum_{j \geq 1} \mathbb{1}_{\{T_j \leq t\}}$.
  Filtration $\mathbb{H} = (\mathcal{H}_t)_{t \geq 0}$
- N is characterized by its intensity:

$$\lambda(t) = \lim_{\Delta \to 0} \frac{1}{\Delta} P(N((t+\Delta)^-) - N(t^-) = 1 | \mathcal{H}_{t^-}).$$

  Interpretation:
  $P(N((t+\Delta)^-) - N(t^-) = 1 | \mathcal{H}_{t^-}) = \lambda(t)\Delta + o(\Delta).$

Modelling maintenance effect in recurrent events models

Behaviour of the new unmaintained system :

$h(t) = \lim_{\Delta \to 0} \frac{1}{\Delta} P(T_1 < t + \Delta | T_1 \geq t)$
Weibull distribution example $h(t) = \alpha \beta t^{\beta - 1}$

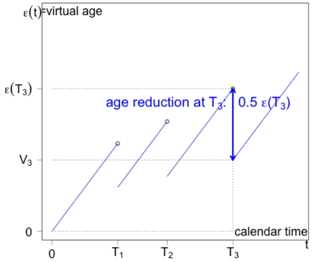
Virtual age models *[Kijima 89]*:

Maintenance effect rejuvenates the system: $\lambda(t) = h(\varepsilon(t))$

ARA_1 model:

- $\varepsilon(t) = t - T_{N(t^-)} + V_{N(t^-)}$
- $V_k = \varepsilon(T_k) - \rho(T_k - T_{k-1})$

$\lambda(t) = h(t - \rho T_{N(t^-)})$



Current developments and future works

- GRT-Gaz problematic: Failures are not online detected. System is detected to failed only when it is prevently maintained.
- Taking into account interval censoring in inference method.
- Developing new models in witch corrective maintenance effect is postponed at the next preventive maintenance times.
- Taking into account left censoring.
- Integrating categorical covariates.
- Developing Bayesian estimation methods.

Focus on the research works of M. Leroy, PERSYVAL-lab PhD student

Maintenance effects on degradation process:

- inference
- modelling
- decision making

Modelling maintenance effect in degradation models

Wiener underlying degradation process

$X(t)$: underlying degradation level at time t.

- $X(t) = \mu t + \sigma B(t) \Longrightarrow X(t+\Delta t) - X(t) \sim \mathcal{N}(\mu \Delta t, \sigma^2 \Delta t)$
- Degradation increments are independent on disjoints time intervals

ARD1 degradation process [Mercier-Castro19]

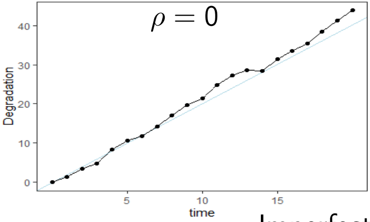
Successive maintenance times are denoted by $\{\tau_i\}_{i\geq 1}$, $\tau_0 = 0$
$\forall i \in \mathbb{N}$, $\forall t \in]\tau_i, \tau_{i+1}]$, the degradation process $Y(t)$ integrating maintenance effects verifies

- $Y(t) = Y(\tau_i) + X(t) - X(\tau_i)$
- $Y(\tau_{i+1}+) - Y(\tau_{i+1}-) = -\rho(Y(\tau_{i+1}-) - Y(\tau_i)+)$

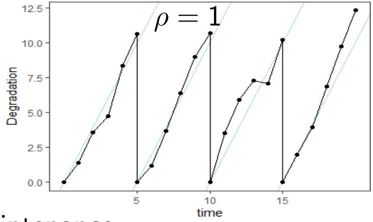
$Y(t) = X(t) - \rho X(\tau_i)$

Modelling maintenance effect in degradation models (2)

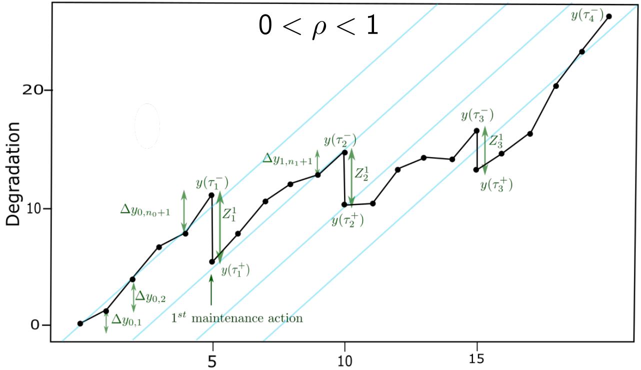
Minimal maintenance (ABAO) ,



Perfect maintenance (AGAN) ,

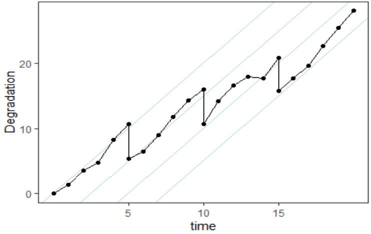


Imperfect maintenance

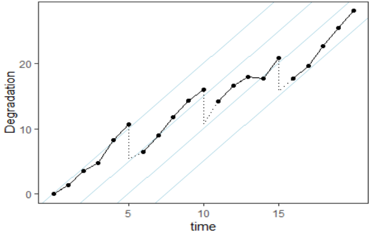


Inference in ARD1 model depending on observations scheme

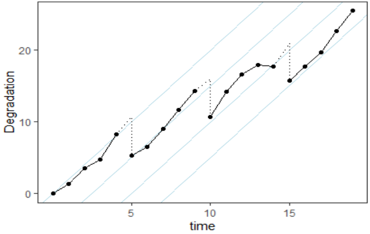
Case 1: Obs. before and after maintenance



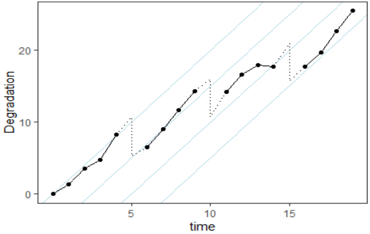
Case 2: Obs. before but not after maintenance



Casee 3: Obs. after but not before maintenance



Case 4: Obs. neither before nor after maintenance



Maximum likelihood estimation: case 4

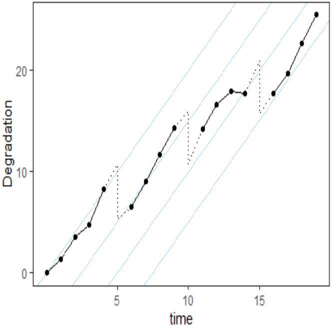
$$L_4\left(\mu,\sigma^2,\rho\right) = g_{(Z_1^4,Z_2^4,\ldots,Z_k^4)}\left(z_1^4,z_2^4,\ldots,z_k^4\right) \times \prod_{j=0}^{k}\prod_{i=1+\mathbb{1}_{j>1}}^{n_j} f_{\Delta Y_{j,i}}\left(\Delta y_{j,i}\right)$$

Where $\forall j \in \{1,\ldots,k\}$, Z_j^4 are the jumps observed between two successive maintenance actions.
$Z^4 = (Z_1^4, Z_2^4, \ldots, Z_k^4)$ is a Gaussian vector and g is the joint density of the jumps conditionally to the previous observed increments

Variance-covariance Matrix Σ :

$$\begin{pmatrix} s_1 & -\rho\Delta t_{1,1} & 0 & \cdots & 0 \\ -\rho\Delta t_{1,1} & s_2 & -\rho\Delta t_{2,1} & \cdots & 0 \\ \vdots & \ddots & \ddots & \ddots & \vdots \\ \vdots & & \cdots & & 0 \\ 0 & \cdots\ 0 & -\rho\Delta t_{k-3,1} & s_{k-2} & -\rho\Delta t_{k-2,1} \\ 0 & \cdots & 0 & -\rho\Delta t_{k-2,1} & s_{k-1} \end{pmatrix}$$

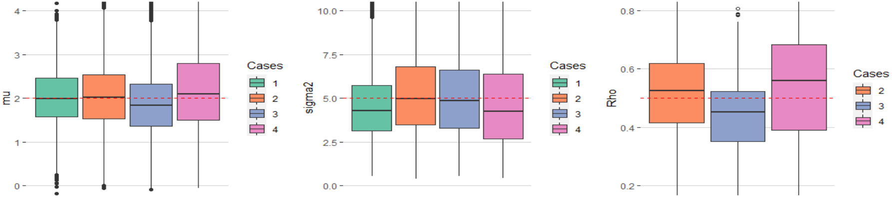
Where $s_j =$
$\left[\Delta t_{j,1} + (1-\rho)^2\Delta t_{j-1,n_{j-1}+1} + \rho^2\Delta t_{j-1,1}\mathbb{1}_{j>1}\right]$



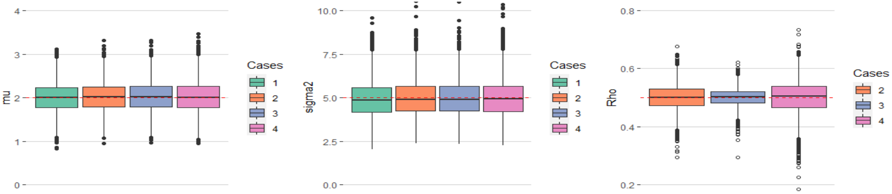
Estimation quality depending on observation scheme

3 maintenance actions, $\mu = 2$, $\sigma^2 = 5$, $\rho = 0.5$

2 obs. between two successive maintenances



11 obs. between two successive maintenances



Current developments and future works

- Originality of the approach: considering different observation schemes for the inference in the ARD1 degradation model
- Highlight drawback of ARD1 model: deterministic maintenance effects for the first observation scheme (not realistic from a practical point of view)
- Current work: propose new maintenance effects models for degradation processes (study of their probabilistic properties, development of corresponding inference methods)
- Future work: optimize maintenance times and observation scheme
- Long run works: considering multivariate degradation and system heterogeneity

Publications

Journal papers

- **Virtual age models with time-dependent covariates: A framework for simulation, parametric inference and quality of estimation.** L. Brenière, L. Doyen, C. Bérenguer; *Reliability Engineering and System Safety*; 203 (2020).
- **Optimization of Preventive Replacements Dates and Covariates Inspections for Repairable Systems in Varying Environments.** L. Brenière, L. Doyen, C. Bérenguer *(submitted)*.
- **Statistical inference for a Wiener-based degradation model with imperfect maintenances under different observation.** M. Leroy, C. Bérenguer, O. Gaudoin *(submitted)*.

Conference presentations

- **Inference statistique pour un processus de dégradation en présence de maintenances : le modèle ARD 1.** M. Leroy; *52 ème JDS* (2021).
- **Estimation of industrial assets ageing and maintenance efficiency with interval censored data.** T. Cousino, F. Brissaud, L. Marle, L. Doyen, O. Gaudoin, *ESREL 2022*.
- **Parameter estimation for a degradation-based imperfect maintenance model with different information levels.** M. Leroy, L. Doyen, C. Bérenguer, O. Gaudoin, *ESREL 2022*.