Simultaneous assessment of the efficiency of preventive and corrective maintenances for repairable systems in a competing risk framework

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All along their life, complex industrial systems are subjected to two kinds of maintenance tasks.

- **Corrective Maintenance (CM, repair)**:
carried out after a failure, intends to put the system into a state in which it can perform its function again.

- **Preventive Maintenance (PM)**:
carried out when the system is in operational conditions, intends to slow down the wear process and reduce the frequency of occurrence of failures.

  - Planned PM: occur at predetermined times (deterministic PM).
  - Condition-based PM: occur at times which are determined according to the results of inspections and degradation or operation controls (random PM).

**Aim of the talk**: Present a general framework for the stochastic modelling of the maintenance process and the assessment of the efficiency of CM and condition-based PM.
Contents

1. Only corrective maintenance
   • Stochastic modelling of the failure process
   • Usual models: ABAO, AGAN, Brown-Proshan, Virtual age models

2. Corrective and preventive maintenance
   • Stochastic modelling of the PM-CM process
   • Classical competing risk models
   • Generalized competing risk models
   • Generalized virtual age models

3. An application to real data

4. Conclusion and future work
1. Models with only corrective maintenances
Notations

- Failure times: $\{T_i\}_{i \geq 1}$
- Inter failure times: $X_i = T_i - T_{i-1}$, $i \geq 1$
- Counting failure process: $\{N_t\}_{t \geq 0}$, $N_t =$ number of failures occurred at time $t$

- A CM is performed after each failure.
- Repair times are negligible or not taken into account.
- Two failures cannot occur at the same time.
Stochastic modelling of the failure process

the failure intensity : $\lambda_t$

$$\lambda_t = \lim_{dt \to 0} \frac{1}{dt} P(N_{t+dt} - N_t = 1 | \mathcal{H}_t)$$

where $\mathcal{H}_t$ is the history of the failure process at time $t$.

Self-excited point process : $\mathcal{H}_t = \sigma (\{N_s\}_{0 \leq s \leq t})$.

$\Rightarrow \lambda_t$ completely defines the failure process.

the likelihood function

The likelihood function for an observation of the failure process with $n$ failures on $[0, t]$:

$$L_t(\theta) = \left[ \prod_{i=1}^{n} \lambda_{t_i}(i-1; t_1, \ldots, t_{i-1}) \right] \exp \left( - \sum_{i=1}^{n} \int_{t_{i-1}}^{t_i} \lambda_u(i-1; t_1, \ldots, t_{i-1}) du \right)$$
**Stochastic modelling of the failure process**

**the initial failure intensity** $\lambda(t)$

Before the first failure, the failure intensity is a deterministic and continuous function of time $\lambda(t)$, the failure rate of $T_1$.

$$\lambda(t) = \lim_{\Delta t \to 0} \frac{1}{\Delta t} P(t < T_1 \leq t + \Delta t | T_1 > t)$$

Wearing systems: $\lambda(t)$ is strictly increasing.

**example of initial intensity**

$$\lambda(t) = \alpha \beta t^{\beta-1} \quad \alpha > 0, \beta > 0$$

$$\Rightarrow \begin{cases} 
\beta > 1 : \text{wear out (industrial systems).} \\
\beta < 1 : \text{improvement (software).} \\
\beta = 1 : \text{no ageing (PPH).}
\end{cases}$$
Each maintenance leaves the system in the same state as it was before failure.

**Statistical modelling** : a Non Homogeneous Poisson Process (NHPP).

\[ \lambda_t = \lambda(t) \]
Perfect repair or As Good As New Model AGAN

Each maintenance perfectly repairs the system and leaves it as if it were new.

**Statistical modelling**: the Renewal Process (RP).

$$\lambda_t = \lambda(t - T_{N_t})$$

Reality is between the case ABAO and AGAN
The Brown-Proschan model [1983]

Each maintenance is perfect (AGAN) with probability $p$ and minimal (ABAO) with probability $1 - p$.

**Statistical modelling**:

\[
\begin{cases}
B_i = 1 &: \text{$i^{th}$ repair AGAN} \\
B_i = 0 &: \text{$i^{th}$ repair ABAO}
\end{cases}
\]

, $B_i \sim iid \mathcal{B}(p)$

\[
\lambda_t = \lambda(t - T_{N_t}) + \sum_{j=1}^{N_t} \left(\prod_{k=j}^{N_t} (1 - B_k)\right) X_j
\]
Virtual age models

After the $i^{th}$ repair, the system performs as a new one having survived until $A_i$.

$$\forall i \geq 0, \forall t \geq 0 P(X_{i+1} > t | X_1, .. X_i) = P(X_1 > A_i + t | X_1 > A_i) = \frac{S(A_i + t)}{S(A_i)}$$

where $S$ is the survival function associated to $X_1$.

$$\lambda_t = \lambda(t - T_{N_t} + A_{N_t})$$

The $A_i$ are called the **effective ages**. $A_0 = 0$.

**Properties** : Virtual age models are a generalization of previous models:

- **ABAO** : $A_i = T_i$
- **AGAN** : $A_i = 0$
- **BP** : $A_i = \sum_{j=1}^{i} \prod_{k=j}^{i} (1 - B_k) X_j$ = time elapsed since last perfect repair
The Arithmetic Reduction of Age model $ARA_1$

After a repair, the system have an age age proportional to his true age:

$$A_i = (1 - \rho)T_i$$

$\rho$ is called the **improvement factor** or **repair efficiency**:

- $\rho = 0 \Rightarrow ABAO$
- $\rho = 1 \Rightarrow AGAN$

$$\lambda_t = \lambda(t - \rho T_{N_t})$$
2. Models with two kind of maintenances
Notations

- maintenances times (CM+PM) : \( \{C_i\}_{i \geq 1} \)
- inter-maintenance times (CM+PM) : \( W_i = C_i - C_{i-1}, \ i \geq 1 \)
- The counting maintenance process :
  \[
  \begin{align*}
  \{K_t\}_{t \geq 0} & : \text{PM+CM} \\
  \{N_t\}_{t \geq 0} & : \text{CM} \\
  \{M_t\}_{t \geq 0} & : \text{PM}
  \end{align*}
  \]
- the types of maintenances : \( U_i = \begin{cases} 
  1 & \text{if the } i^{\text{th}} \text{ maintenance is preventive} \\
  0 & \text{if the } i^{\text{th}} \text{ maintenance is corrective}
 \end{cases} \)
The maintenance intensities:

- The global maintenance intensity: \( \lambda^K_t(K, U) = \lim_{dt \to 0} \frac{1}{dt} P(K_{t+dt} - K_t = 1 | H_t) \)

- The CM intensity: \( \lambda^N_t(K, U) = \lim_{dt \to 0} \frac{1}{dt} P(N_{t+dt} - N_t = 1 | H_t) \)

- The PM intensity: \( \lambda^M_t(K, U) = \lim_{dt \to 0} \frac{1}{dt} P(M_{t+dt} - M_t = 1 | H_t) \)

where \( H_t \) is the history of the maintenance process at time \( t \).

Typically, \( H_t = \sigma \{ K_s, U_{K_s} \}_{0 \leq s \leq t} \).

- \( \lambda^K_t(K, U) = \lambda^N_t(K, U) + \lambda^M_t(K, U) \)

- The PM and CM intensities completely define the maintenance process.
Main results

Jacod’s formulae: \[ P(W_{k+1} > w, U_{k+1} = 0| W_1 = w_1, \ldots, U_k = u_k) = \]
\[ \int_{w}^{+\infty} \lambda_c^N(k, w_1, \ldots, u_k) P(W_{k+1} > u| w_1, \ldots, u_k) du \]
\[ P(W_{k+1} > w| W_1 = w_1, \ldots, U_k = u_k) = \exp \left( - \int_0^w \lambda_c^K(k, w_1, \ldots, u_k) ds \right) \]
\[ P(U_{k+1} = 0| W_{k+1} = w, W_1 = w_1, \ldots, U_k = u_k) = \frac{\lambda_c^N(k, w_1, \ldots, u_k)}{\lambda_c^K(k, w_1, \ldots, u_k)} \]

The likelihood function associated to an observation of the PM-CM process with \( k \) maintenances on \([0, t]\): \[ L_t(\theta) = \exp \left( - \sum_{j=1}^{k+1} \int_{c_{j-1}}^{c_j} \lambda_s^K(j - 1, w_1, \ldots, u_{j-1}) ds \right) \]
\[ \prod_{i=1}^{k} \lambda_c^N(i - 1, w_1, \ldots, u_{i-1})^{1-u_i} \lambda_c^M(i - 1, w_1, \ldots, u_{i-1})^{u_i} \] where \( c_0 = 0, \ c_{k+1} = t \).
Classical competing risk models


After the \((k - 1)^{th}\) maintenance, the **risk variables** are :

- \(Y_k\) = potential time to the next PM if no CM occur before (risk of PM)
- \(Z_k\) = potential time to the next CM if no PM occur before (risk of CM)

**Observations**

In practice, \(Y_i\) and \(Z_i\) are not observed. The observations are :

- The time to next maintenance : \(W_i = \min(Y_i, Z_i)\)
- The type of next maintenance : \(U_i = \begin{cases} 1 & \text{if } Y_i < Z_i \quad \text{(PM)} \\ 0 & \text{if } Z_i < Y_i \quad \text{(CM)} \end{cases}\)
Main aspects of the classical competing risk model

Examples of CR models:

- Independent competing risks: $Y_i \perp Z_i$
  
  Drawback: non realistic model.

- Random time censoring:
  
  $Z_i$ independent from $\text{sign}(Z_i - Y_i) \Rightarrow Z_i$ independent from $U_i$

Main drawbacks of the classical approach:

- By definition, the maintenance are supposed AGAN.
- The joint distribution $S_1(y, z) = P(Y_1 > y, Z_1 > z)$ is generally not identifiable. Indeed, we can estimate the sub-survival functions:

$$
S^*_{Z_1}(z) = P(Z_1 > z, Z_1 < Y_1) = P(W_1 > z, U_1 = 0) \\
S^*_{Y_1}(y) = P(Y_1 > y, Y_1 \leq Z_1) = P(W_1 > y, U_1 = 1)
$$

Idea: Define identifiable models taking into account of the past of the process in order to estimate a maintenance effect.
Generalized competing risk models

PM-CM (conditional) survival function:

\[ S_{k+1}(y, z; w_1, \ldots, u_k) = P(Y_{k+1} > y, Z_{k+1} > z | W_1 = w_1, \ldots, U_k = u_k) \]

Generalized sub-survival functions:

\[ S^*_{z_{k+1}}(z; w_1, \ldots, u_k) = P(Z_{k+1} > z, Z_{k+1} < Y_{k+1} | W_1 = w_1, \ldots, U_k = u_k) \]

\[ = \int_{z}^{+\infty} \left[ -\frac{\partial}{\partial z} S_{k+1}(y, z; w_1, \ldots, u_k) \right]_{(s,s)} ds \]

\[ S^*_{y_{k+1}}(y; w_1, \ldots, u_k) = P(Y_{k+1} > y, Y_{k+1} < Z_{k+1} | W_1 = w_1, \ldots, U_k = u_k) \]

\[ = \int_{y}^{+\infty} \left[ -\frac{\partial}{\partial y} S_{k+1}(y, z; w_1, \ldots, u_k) \right]_{(s,s)} ds \]
Generalized competing risk models (2)

Link with the colored point process approach:

\[ S_{k+1}(w, w; w_1, \ldots, u_k) = P(W_{k+1} > w|w_1, \ldots, u_k) \]

\[ S_{Z_{k+1}}^*(w; w_1, \ldots, u_k) = P(W_{k+1} > w, U_{k+1} = 0|w_1, \ldots, u_k) \]

\[ S_{Y_{k+1}}^*(w; w_1, \ldots, u_k) = P(W_{k+1} > w, U_{k+1} = 1|w_1, \ldots, u_k) \]

\[ \lambda^N_t(K, U) = \left[ -\frac{\partial}{\partial z} S_{K_{t+1}}(y, z; w_1, \ldots, u_{K_t}) \right]_{(t-c_{K_t}, t-c_{K_t})} \]

\[ \lambda^M_t(K, U) = \left[ -\frac{\partial}{\partial y} S_{K_{t+1}}(y, z; w_1, \ldots, u_{K_t}) \right]_{(t-c_{K_t}, t-c_{K_t})} \]

\[ \lambda^K_t(K, U) = -\frac{d}{dt} \ln S_{K_{t+1}}(t-c_{K_t}, t-c_{K_t}; w_1, \ldots, u_{K_t}) \]
Generalized competing risk models (3)

Ex: Conditionnally independent generalized competing risks

∀k, Y_{k+1} and Z_{k+1} are independent conditionnally to W_1, \ldots, U_k.

The intensities depend only on the values of the PM-CM survival function around the first diagonal

⇒ same identifiability problem as in classical competing risks: for any GCR model, there exists a conditionnally independent GCR model with the same PM and CM intensities.

Likelihood:

\[
L_t(\theta) = S_{k+1}(t - c_k, t - c_k; w_1, \ldots, u_k)
\]

\[
\prod_{i=1}^{k} \left[ \left( -\frac{\partial}{\partial y} S_i(y, z; w_1, \ldots, u_{i-1}) \right)_{(w_i, w_i)} \right]^{u_i} \left[ \left( -\frac{\partial}{\partial z} S_i(y, z; w_1, \ldots, u_{i-1}) \right)_{(w_i, w_i)} \right]^{1-u_i}
\]
Generalized virtual age models

**Idea of the model**: there exist a sequence of effective ages \( \{A_k\}_{k \geq 1} \), with \( A_0 = 0 \), such that after \( k^{th} \) maintenance, the risk variables \( Y_{k+1} \) and \( Z_{k+1} \) behave as the risk variables of a new system with no maintenance before \( A_k \):

\[
P(Y_{k+1} > y, Z_{k+1} > z \mid w_1, \ldots, u_k, A_k) = P(Y > A_k + y, Z > A_k + z \mid Y > A_k, Z > A_k, A_k)
\]

where \((Y, Z)\) is a random couple with the same distribution as \((Y_1, Z_1)\).

The effect of maintenance is symmetrical on both risks.

**PM-CM Survival function**: \( S_{k+1}(y, z; w_1, \ldots, u_k) = \frac{S_1(A_k + y, A_k + z)}{S_1(A_k, A_k)} \)

**Virtual age property on the times between maintenances**: \( P(W_{k+1} > w \mid w_1, \ldots, u_k, A_k) = P(W_1 > w + A_k \mid W_1 > A_k, A_k) \)
Main results in the virtual ages approach

The complete maintenance intensities

\[
\lambda^N_t(K, U) = \lambda_c(t - C_{K_t} + A_{K_t}) \quad (3)
\]
\[
\lambda^M_t(K, U) = \lambda_p(t - C_{K_t} + A_{K_t}) \quad (4)
\]
\[
\lambda^K_t(K, U) = \lambda(t - C_{K_t} + A_{K_t}) \quad (5)
\]

where:

\[
\lambda_c(t) = -\frac{\partial}{\partial z} S_1(y, z) \left[ z, t, t \right] \left( t, t \right) \quad (6)
\]
\[
\lambda_p(t) = -\frac{\partial}{\partial y} S_1(y, z) \left[ z, t, t \right] \left( t, t \right) \quad (7)
\]

\[
\lambda(t) = \lambda_c(t) + \lambda_p(t)
\]

The generalized sub-survival functions

\[
S^*_Z_{k+1}(z; w_1, \ldots, u_k) = \int_z^{+\infty} \lambda_c(s + A_k) \exp \left( - \int_0^s \lambda(u + A_k) du \right) ds \quad (6)
\]
\[
S^*_Y_{k+1}(y; w_1, \ldots, u_k) = \int_y^{+\infty} \lambda_p(s + A_k) \exp \left( - \int_0^s \lambda(u + A_k) du \right) ds \quad (7)
\]
How to build a generalized virtual age model

1. Define the dependency between both kind of maintenances by characterizing the joint survival function $S_1$
2. Define the effective ages by characterizing the both maintenances effects.
3. Derive $\lambda_c$ and $\lambda_p$ from $S_1$.

**Assumptions on maintenance efficiency**:
- PM and CM AGAN : each maintenance restores the system as new (RP) : $A_k = C_k$
  \[
  \lambda^N_t(K, U) = \lambda_c(t - C_{K_t})
  \]
- PM and CM ABAO : each maintenance is minimal (NHPP) : $A_k = C_k$
  \[
  \lambda^N_t(K, U) = \lambda_c(t)
  \]
- PM and CM BP
  \[
  \begin{cases}
    B_i = 1 : i^{th} \text{ maintenance AGAN} & \quad B_i \sim \mathcal{B}(p_p) \text{ if } U_i = 1 \\
    B_i = 0 : i^{th} \text{ maintenance ABAO} & \quad B_i \sim \mathcal{B}(p_c) \text{ if } U_i = 0
  \end{cases}
  \]

  \[
  \lambda^N_t(K, U) = \lambda_c \left( t - C_{K_t} + \sum_{j=1}^{K_t} \sum_{k=j}^{K_t} (1 - B_k)W_k \right)
  \] (8)
Generalized $ARA_1$ model

The effect of PM is to reduce the virtual age of $\rho_p$ times the time elapsed since last maintenance, and the effect of CM is similar with a different parameter $\rho_c$:

$$A_k = \begin{cases} 
A_{k-1} + W_k - \rho_p W_k & \text{if } U_k = 1 \\
A_{k-1} + W_k - \rho_c W_k & \text{if } U_k = 0 
\end{cases} \Rightarrow A_k = C_k - \sum_{i=1}^{k} \rho_p^U_i \rho_c^{1-U_i} W_i$$

$$\lambda^N_t(K, U) = \lambda_c \left( t - \sum_{i=1}^{K_t} \rho_p^U_i \rho_c^{1-U_i} W_i \right)$$

- $\rho_p = 0 \Rightarrow$ PM are ABAO. $\rho_c = 0 \Rightarrow$ CM are ABAO.

- $\rho_p = 1 \Rightarrow$ PM are not AGAN but “As Good As Previous”: PM restores the system in the state it was just after previous CM ($A_k = A_{k-1}$, not 0). Then, PM cannot prevent the ageing due to CM.

- $\rho_p = 1$ and $\rho_c = 1 \Rightarrow$ PM and CM are AGAN.
Dependency between PM and CM (1)

**Independent Risks Model**: \( Z_1 \) and \( Y_1 \) are independent

\[ \Rightarrow \lambda_c \text{ and } \lambda_p \text{ are respectively the hazard rates of } Z_1 \text{ and } Y_1 \]

\[
\lambda_c(t) = \frac{-S'_{Z_1}(t)}{S_{Z_1}(t)} \quad \lambda_p(t) = \frac{-S'_{Y_1}(t)}{S_{Y_1}(t)}
\]

**Example with Weibull distributions for** \( Z_1 \) and \( Y_1 \):

\[
\lambda_t^N(K, U) = \alpha_c \beta_c (t - C_{K_t} + A_{K_t})^{\beta_c - 1} \quad \lambda_t^M(K, U) = \alpha_p \beta_p (t - C_{K_t} + A_{K_t})^{\beta_p - 1}
\]

Not realistic for condition-based PM.
Dependency between PM and CM (2)

**A non independent Risks Model**: the maintenance type $U_1$ is independent of the maintenance time $W_1$.

$$\Rightarrow S_{Z_1}^*(z) = (1 - q)S_1(y, y) \quad \text{and} \quad S_{Y_1}^*(y) = qS_1(y, y)$$

where $q = P(U_1 = 1)$.

$$\lambda_c(t) = (1 - q)\lambda_{W_1}(t) \quad \lambda_p(t) = q\lambda_{W_1}(t)$$

**Example with Weibull distributions for $W_1$**:

$$\lambda^N_t(K, U) = (1 - q)\alpha\beta(t - C_{Kt} + A_{Kt})^{\beta-1} \quad \lambda^M_t(K, U) = q\alpha\beta(t - C_{Kt} + A_{Kt})^{\beta-1}$$

Very simple model.
The Langseth & Lindqvist model [LL,2003]

**LL assumptions:**
1. Random sign model: $U_1 \perp Z_1$

2. PM and CM are of the BP type.

3. The hazard rate of $Z_1$ is $\lambda(t)$.

4. The link between the two kind of risks $Y_1$ and $Z_1$ are defined as follows:
   \[ P(Y_1 \leq y | Z_1 = z, Y_1 < Z_1) = \frac{\Lambda(y)}{\Lambda(z)}, \Lambda(t) = \int_0^t \lambda(x)dx \]
   This hypothesis allows to perform PM just before a CM occurs.

5. $q = P(Y_1 < Z_1) = P(U_1 = 1)$

**Problem**: In practice, the maintenance effects ($B_k$) are not observed.

⇒ the likelihood function has a recursive expression, difficult to use.

⇒ we prefer using another virtual age model, e.g. $ARA_1$. 
Main results of the LL model with $ARA_1$ assumptions

**The survival and sub-survival functions:**

- $S^*_Y(y) = P(W_1 > y, U_1 = 1) = q(e^{-\Lambda(y)} - \Lambda(y)Ie(\Lambda(y)))$
- $S^*_Z(z) = P(W_1 > z, U_1 = 0) = (1 - q)e^{-\Lambda(z)}$
- $S(t) = P(W_1 > t) = e^{-\Lambda(t)} - q\Lambda(t)Ie(\Lambda(t))$

**The initial maintenance intensities:**

\[
\lambda_c(t) = \frac{\left(1 - q\right)\lambda(t) \exp(-\Lambda(t))}{\exp(-\Lambda(t)) - q\Lambda(t)Ie(\Lambda(t))}
\]
\[
\lambda_p(t) = \frac{q\lambda(t)Ie(\Lambda(t))}{\exp(-\Lambda(t)) - q\Lambda(t)Ie(\Lambda(t))}
\]

with $Ie(t) = \int_t^{+\infty} e^{-s}/s \, ds$

**The likelihood function:**

\[
\mathcal{L}_t = \prod_{i=1}^{n} \frac{\lambda(y_{ci}^{i-1})(1 - q)^{1-u_i}q^{u_i}e^{-\Lambda(y_{ci}^{i-1})(1-u_i)}Ie^{u_i}(\Lambda(y_{ci}^{i-1}))}{e^{-\Lambda(y_{ci}^{i-1})} - q\Lambda(y_{ci}^{i-1})Ie(\Lambda(y_{ci}^{i-1}))} \cdot \frac{e^{-\Lambda(y^n_t)} - q\Lambda(y^n_t)Ie(\Lambda(y^n_t))}{e^{-\Lambda(y^n_{cn})} - q\Lambda(y^n_{cn})Ie(\Lambda(y^n_{cn}))}
\]

with $y^k_s = s - \sum_{j=1}^{k} \rho_p^{u_i} \rho_c^{1-u_i}w_j$
3. An application to real data
Data and assumptions

Data:

- Data of specific systems used in power plants issued from the French Electricity company EDF.
- 17 similar and independent production units with times of maintenances and right censored.
- 15 years of observation, 16 PM and 12 CM observed.

Assumptions of the model:

- The LL model with ARA maintenance effects.
- $Z_1$ has a Weibull distribution:
  \[ \lambda(t) = \alpha \beta t^{\beta-1} \]
- the 17 systems are iid.

$\Rightarrow$ Estimate $\theta = (\alpha, \beta, \rho_p, \rho_c, q)$
Estimation of the parameters

\[ \hat{\alpha} = 0.00045 \]
\[ \hat{\beta} = 0.95 \Rightarrow \text{global improvement.} \]
\[ \hat{\rho}_c = 0.95 \Rightarrow \text{harmful CM.} \]
\[ \hat{\rho}_p = 0.01 \Rightarrow \text{minimal PM (ABAO).} \]
\[ \hat{q} = 0.55 \Rightarrow \hat{q} \approx \text{proportion of PM (57 \%).} \]

⇒ Remove the burn-in period (3 years) : 10 PM and 9 CM remain.
Estimation of the parameters without the burn-in period

\[ \hat{\alpha} = 5 \times 10^{-7} \]
\[ \hat{\beta} = 1.70 \implies \text{global ageing.} \]
\[ \hat{\rho}_0 = 0.03 \implies \text{nearly minimal CM.} \]
\[ \hat{\rho}_1 = 0.99 \implies \text{PM nearly optimal but not AGAN} \]
\[ \hat{q} = 0.47 \implies \hat{q} \approx \text{proportion of PM(52 \%)}. \]
Conclusions and Prospects

Conclusions

• General modelling of the effect of PM and CM, with possibly dependent PM and CM times

• Simultaneous estimation of parameters linked to the wear-out process and maintenance efficiency

• Great help for the monitoring of the reliability centered maintenance process

Prospects

• Take into account the burn-in period of the systems:
  – Add a risk variable specific to this period.
  – Choose fitted failure intensities like bathtub shaped intensities.
  – Adapt the maintenances effects to burn-in period.

• Change the dependency between CM and PM.

• Study the conditionally independent generalized competing risks.
References


