Challenges and opportunities in reliability engineering: the big KID (Knowledge, Information and Data)

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Problem statement

Failures

Prevented by

Design for Reliability

Maintenance

Redundancy  Training  Safety Reviews

No Hazard

Hazard

Normal  Degraded  ...  Failure

Time
INDUSTRY
The 4th Industrial Revolution - "Industry 4.0"

**Drivers**
- Quality of life
- Engineering Sciences

**1st Industrial Revolution**
- 1782: Steam engine
- 1813: Industrialization
- Power generation, Mechanical automation

**2nd Industrial Revolution**
- 1913: Conveyor belt

**3rd Industrial Revolution**
- 1954: Electronic Automation
- Computer, NC, PLC

**4th Industrial Revolution**
- 2015: Smart Automation
- Cyber Physical Systems
- ICT

**From Industry 1.0 to Industry 4.0**

- **First Industrial Revolution**
  - Based on the introduction of mechanical production equipment driven by water and steam power
  - First mechanical loom, 1784

- **Second Industrial Revolution**
  - Based on mass production achieved by division of labor concept and the use of electrical energy
  - First conveyor belt, Cincinnati slaughterhouse, 1870

- **Third Industrial Revolution**
  - Based on the use of electronics and IT to further automate production
  - First programmable logic controller (PLC) Modicon D64, 1969

- **Fourth Industrial Revolution**
  - Based on the use of cyber-physical systems

**Degree of complexity**

**CentraleSupélec**

**Fondation EDF**

Science - Enseignement en partenariat avec l’Institut de France
(SMART) Reliability Engineering
The Big KID
\begin{align*}
v_q &= -r_s i_q + \frac{\omega_c}{\omega_b} \Psi_d + \frac{p}{\omega_b} \Psi_q, \\
v_d &= -r_s i_d - \frac{\omega_c}{\omega_b} \Psi_q + \frac{p}{\omega_b} \Psi_d, \\
v_o &= -r_s i_o + \frac{p}{\omega_b} \Psi_o, \\
0 &= v_{aq} i_{aq} + \frac{p}{\omega_b} \Psi_{aq}, \\
v_f &= v_{lf} + \frac{p}{\omega_b} \Psi_f, \\
0 &= v_{ad} i_{ad} + \frac{p}{\omega_b} \Psi_{ad}, \\
T_e &= \frac{3}{2} \frac{P}{\omega_b} \left( \Psi_d i_q - \Psi_q i_d \right), \\
p \omega_r &= \frac{P}{2f} (T_a - T_e),
\end{align*}

\text{Real World Problem} \quad \text{Mathematical Problem} \quad \text{Real World Solution} \quad \text{Mathematical Solution} \quad \text{interpretation} \quad \text{formulation}
Big (K)Information(D)
Can the Big KID become SMART for Reliability Engineering?
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Reliability analysis for Design for Reliability:

From failure modeling to degradation-to-failure modeling
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Integrating physics-of-failure knowledge in reliability models

- Multi-State Physic-Based Models
Reliability?

KID
(Knowledge, Information, Data)

Model

Sufficient failure data

Statistical models of time to failure

Stochastic process models

Physics-based models

Multi-state models

Physics knowledge
Expert judgment

Field data

Highly reliable
Alloy 82/182 dissimilar metal weld of piping in a PWR primary coolant system

Physical laws

Multi-state physics model of crack development in Alloy 82/182 dissimilar metal weld

\[ \varphi_1 = \int \left( \frac{b}{T} \right) \cdot \left( \frac{t}{T} \right)^{b-1} \cdot f_{PDF}(\tau, b) \, d\tau \, db \]

\[ \varphi_2 = \begin{cases} \frac{adP_D}{a_Mu^2(1-P_D(1-a_D/(u\hat{a}_M)))}, & \text{if } u > a_D/\hat{a}_M \\ 0, & \text{else} \end{cases} \]

\[ \varphi_3 = \begin{cases} \frac{acPC}{a_Mu^2(1-P_C(1-a_C/(u\hat{a}_M)))}, & \text{if } u > a_C/\hat{a}_M \\ 0, & \text{else} \end{cases} \]

\[ \varphi_4 = \begin{cases} \frac{1}{w}, & \text{if } w > (a_L - a_D)/\hat{a}_M \\ 0, & \text{else} \end{cases} \]
Random shocks

Degradation process

Random shock process

Dependences in degradation processes

Internal leak

Initial state

Failure state

\[ \dot{D}_b(t) = \omega_b (1 + \beta_{Y_p(t)}) \]

\[ Z(t) = \left( \begin{array}{c} D_b(t) \\ Y_p(t) \end{array} \right) \]

\[ \begin{align*}
Y_p(t) & \xrightarrow{\lambda_{32}} 2 \\
2 & \xrightarrow{\lambda_{21}} 1 \\
1 & \xrightarrow{\lambda_{10}} 0
\end{align*} \]
Maintenance

Degradation process

Preventive maintenance (a)
Corrective maintenance (b)
Uncertainty

Uncertain parameters in degradation models

Initial state

Failure state

Uncertainty

Internal leak

$D_b(t)$

$Y_p(t)$

$\dot{D}_b(t) = \omega_b (1 + \rho \dot{Y}_p(t))$
Degradation processes

Internal leak

$D_b(t)$

$\dot{D}_b(t) = \omega_b (1 + \beta Y_p(t))$

$Z(t) = \begin{pmatrix} D_b(t) \\ Y_p(t) \end{pmatrix}$

Initial state

Failure state

$Y_p(t)$

$\lambda_{32}$

$\lambda_{21}$

$\lambda_{10}$

$3 \rightarrow 2 \rightarrow 1 \rightarrow 0$

Piecewise-deterministic Markov process (PDMP)

$X(t)$

$\dot{X}(t) = \begin{pmatrix} X_{L_1}'(t) \\ \vdots \\ X_{L_M}'(t) \end{pmatrix}$

$= f_L^{Y(t)}(X(t), t | \theta_L)$

$Y(t)$

$\lim_{\Delta t \rightarrow 0} P(Y(t + \Delta t) = j | X(t), Y(t) = i, \theta_K) / \Delta t$

$= \lambda_i(j | X(t), \theta_K), \forall t \geq 0, i, j \in S, i \neq j$
MC Simulation

While \( k < N_{\text{max}} \)

1. Initialize the system by setting \( Z' = (X'(0), Y'(0)) \) (initial state), and the time \( T = 0 \) (initial system time).
2. Set \( t' = 0 \) (state holding time).
3. While \( T < T_{\text{max}} \)
   - Sample a \( t' \) by using the probability density function (3.7).
   - Sample an arrival state \( Y' \) for stochastic process \( Y(t) \) from all the possible states by using the conditional probability distribution (3.8).
   - Set \( T = T + t' \).
   - Calculate \( X(T) \) by using the physics eq. (3.3).
   - Set \( Z' = (X(T'), Y') \).
   - If \( T \leq T_{\text{max}} \)
     - If \( Z' \in \mathcal{F} \)
       - Set \( k' = k' + 1 \)
       - Break
     - Else (when \( T > T_{\text{max}} \))
       - Calculate \( Z(T_{\text{max}}) \)
       - If \( Z(T_{\text{max}}) \in \mathcal{F} \)
         - Set \( k' = k' + 1 \)
         - Break
   - End if
   - End if
End While

Finite-volume scheme

\[
P_{n+1}(A, i \mid \theta) = \frac{1}{1 + \Delta t b_A^i} \overline{P}_{n+1}(A, i \mid \theta) + \Delta t \sum_{j \in S} \frac{a_{A}^{j,i}}{1 + \Delta t b_{A}^j} \overline{P}_{n+1}(A, j \mid \theta)
\]
Reliability analysis for Design for Reliability:

From failure modeling to degradation-to-failure modeling

Integrating physics-of-failure knowledge in reliability models

- Multi-State Physic-Based Models

And the data?
**ADT Procedure**

**Degradation Model:**
Degradation VS Time

Stochastic process or degradation-path:

Wiener process: \( Y(t) = \sigma B(t) + d(S)t \)

**Acceleration Model:**
Stress VS Time

Physical or empirical models:

Arrhenius: \( d(S) = Ae^{-Ea/kS} \)
Data Analysis

Trend analysis & Accelerability Verification:

- Degradation Process Model
- Maximum Likelihood
- Degradation Fitting
- Parameter Estimation

Parameter estimation:

<table>
<thead>
<tr>
<th>$\hat{a}$</th>
<th>$\hat{b}$</th>
<th>$\hat{\sigma}^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>-36.961</td>
<td>13.112</td>
<td>8.278e-07</td>
</tr>
</tbody>
</table>

Reliability Prediction:
Challenges in ADT

- **Degradation trend**
  - The whole trend is defined (linear, exponential, etc.)

- **Aleatory uncertainty**
  - Inherent randomness
  - Probability

- **Epistemic uncertainty**
  - Incomplete knowledge due to limited information
  - Interval, possibility, etc.

### Challenges:

- Traditional methods mainly model degradation trend and aleatory uncertainty.

- Failing to consider epistemic uncertainty may cause serious reliability evaluation problems.

### Stochastic Process – some revised models:

1. **DBM model**
   \[ Y(t) = d(S) \cdot t + \sigma_B B(t) \]

2. **Revised model I**
   \[ Y(t) = d(S)t + \sigma_B B(t) \]

3. **Revised model II**
   \[ Y(t) = d(S)t + \sigma_B B(t) \]

- \( d(S) \): a definite value
- \( d(S) \sim N(\mu, \sigma^2) \)
- \( \overline{d(S)} \sim N(\mu, \sigma^2) \)
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No Hazard  Hazard

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Time
Maintenance:

Integrating physics knowledge and data:

- Prognostics and Health Management (PHM)
Maintenance

- Corrective Maintenance
- Planned Periodic Maintenance
- Condition Based Maintenance (CBM)
- Predictive Maintenance (PrM)

Prognostics and Health Management (PHM)

PHM is fostered by advancements in:

- Sensor
- Algorithm
- Computation power
PHM for what?

PHM in support to CBM and PrM

- Fault Detection
  - Normal Conditions
  - Abnormal Conditions
- Fault Diagnostics
  - Anomaly of Type 1
  - Anomaly of Type 2
  - Anomaly of Type 3
- Fault Prognostics
  - Remaining Useful Life (RUL)

Equipment Maintenance Decision
Abnormal Conditions
Normal Conditions

Vibration
Temperature

Sensors measurements

Maintenance
Decision
No Maintenance
Maintenance
- **Increase** maintainability, availability, safety, operating performance and productivity

- **Reduce** downtime, number and severity of failure and life-time cost
PHM: how? (Fault detection)

MODEL OF PLANT BEHAVIOR IN NORMAL OPERATION

- Nominal Range-based
- Physics-based
- Data-Driven (AAKR, PCA, RNN, …)

Signal reconstructions ≠ Real measurements

Abnormal Condition
PHM: how? (Fault diagnostics)

- Signal measurements representative of the fault classes: $\langle x_1, x_2, ..., x_n, \text{class} \rangle$

- Empirical classification methods:
  - Support Vector Machines
  - K-Nearest Neighbours
  - Multilayer Perceptron Neural Networks
  - Supervised clustering algorithms
  - Ensemble of classifiers

- $C_1 = \text{Inner race}$
- $C_2 = \text{Balls}$
- $C_3 = \text{Outer race}$
PHM: how? (Fault prognostics)

Model-Based
- Physics-based model of the degradation process
- Measurement equation

Data-Driven
- Current degradation trajectory
- A threshold of failure
- External/operational conditions

- Degradation trajectories of similar components
- Life durations of a set of similar components

Kalman Filter
- Monte Carlo Simulation
- Hidden Semi-Markov Models
- Artificial Neural Networks
- Neuro-fuzzy systems

Particle filter
- Autoregressive (AR) models
- Similarity-based methods

Degrading component

Similar components
PHM: performance?

- Accuracy
• Accuracy
  ➢ Fault Detection:
    - Low rate of False Alarms
    - Low rate of Missing Alarms

Example:

<table>
<thead>
<tr>
<th>False Alarm Rates</th>
<th>Missing Alarm Rates</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.54%</td>
<td>0.98%</td>
</tr>
</tbody>
</table>
• Accuracy
  ➢ Fault diagnostics:
    ❑ Low Misclassifcation rate

\[
\text{Misclassification rate} = 2.58\%
\]
• Accuracy
  ➢ Prognostics
PHM &

1) Context changing
2) Uncertainty management
3) Fleet
4) Return of Investment
5) Safety
Context changing: concept

Present time

Changes

Context Changes
Monitoring components of a (e.g. nuclear power) plant

The detection model should be able to follow the process changes:

- Incremental learning of the new data that gradually becomes available
- No necessity of human intervention for:
  - selecting recent normal operation data
  - building the new model

New data are coming

Automatic updating of the model
Context changing (fault prognostics)

Degradation indicator vs. time (t)

Failure threshold
Context changing (prognostics)

Degradation indicator

![Graph showing the degradation indicator over time](image)
Context changing (fault prognostics)

- New FV: 13
- Changed FV: 57
1) Context Changing
2) Uncertainty management
3) Fleet
4) Return Of Investment
5) Safety

PHM &
Uncertainty management (prognostics)

Sources of uncertainty:
1) noise on the observations (measurements)

- **True leakage**
- **Leakage measurement**
Sources of uncertainty:
1) noise on the observations (measurements)
2) intrinsic stochasticity of the degradation process
Sources of uncertainty:
1) noise on the observations (measurements)
2) intrinsic stochasticity of the degradation process
3) unknown future external/operational conditions
4) Modeling errors, i.e. inaccuracy of the prognostic model used to perform the prediction

Uncertainty on the RUL prediction?

Maximum acceptable failure probability is 5%

Probability to have a failure in this interval is lower than 5%

Time for maintenance
1) Context Changing
2) Uncertainty management
3) Fleet
4) Return of Investment
5) Safety
Fleet (fault diagnostics)

• Can we use data from similar industrial plants of the same fleet to build diagnostic systems?

Plant A
(near the sea)

Temperature

Failure of Class 1

Failure of Class 2

Failure of Class 3

Plant B
(near a river)

Temperature

Plant Z
(in a very rainy region)

Temperature
SMART Reliability Engineering – component Challenges (PHM)

PHM &

1) Context Changing
2) Uncertainty management
3) Fleet
4) Return of Investment
5) Safety
Return Of Investment (ROI)

- Most frequently used measure to estimate the economic benefit of PHM:

\[ ROI = \frac{\text{Cost avoidance}}{\text{Investment}} - 1 \]

Questions:
1- How to reformulate the ROI based on these economic benefits and make the ROI framework general?
2- How the performance indicators will affect the ROI?
1) Context Changing
2) Uncertainty management
3) Fleet
4) Return of Investment
5) Safety
Risk $\rightarrow (p_i, c_i | k)_{i=1,\ldots,N}$

**PHM**

- Avoided failures thanks to PHM
- Reduction of unnecessary maintenance interventions (< human errors in maintenance)
- ...
- Management of abnormal conditions
- Missing alarms of the fault detection system
- Late RUL predictions of the prognostic system
- Unexpected scenarios
- ...

$\rightarrow (p_i^*, c_i^* | k^*)_{i=1,\ldots,N^*}$

(Terje Aven, ESRA Webinar, What is Risk, March 17, 2016)
PHM & safety

+ PHM System

Safety?
Conclusions: Big KID and Smart KID
Conclusions: Smart KID for Reliability Engineering

SMART KID

Knowledge

Information

Data

Simulation, Modeling, Analysis, Research for Treasuring Knowledge, Information and Data

(for Reliability Engineering)
Conclusions: Smart KID for Reliability Engineering

Some challenges and opportunities in reliability engineering
Thanks…

…for your outstanding contributions
Thanks…

…for your attention