Online reliability-adaptive decision making for predictive maintenance and system remaining useful life control

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Outline

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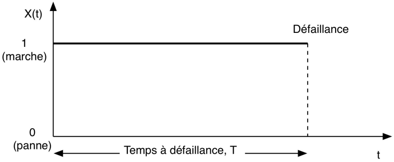
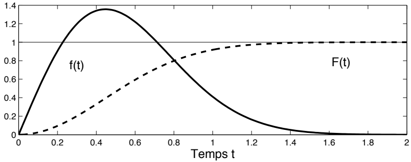
"Classical reliability"





- Use mainly failure data
- Population-based statistical approaches: average system (all systems are equal), identical usage, average static environment, ...
- Blind on the system behavior between "new" and "failed"
- Static approaches in decision-making : maintenance, ...
- Difficult to take into account dynamically the item-to-item variability, different usages, changes in the environment and operating load ... to perform dynamic decision-making in maintenance, control, operation, ...
- Not fully adapted to new needs for dynamic reliability assessment, centered on a given system, using online information

A new technological paradigm for reliability evaluation

- Monitoring data of different nature are largely available

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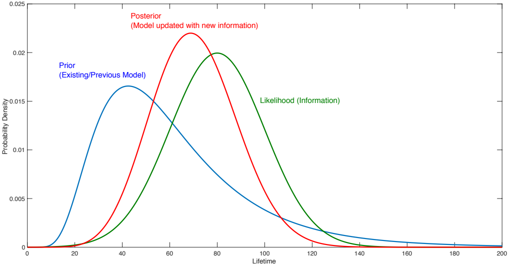
- Condition Monitoring Systems (CMS), Health and Usage Monitoring Systems and Operational Data Recording (HUMS-ODR) or Supervisory Control And Data Acquisition Systems (SCADA)... and even projects of "Digital Twins"
- New reliability data with (hopefully) richer information for dynamic evaluation and prediction, at the item level

A new technological paradigm for reliability evaluation & maintenance decision-making

- Monitoring data of different nature are largely available : examples of monitored systems
  - Vehicles : aircraft systems and structures, locomotives, automobiles, ...
  - Energy production and conversion systems : offshore/onshore wind turbines & farms, solar energy systems, NPP, ...
  - Critical infrastructures : power grids, transportation infrastructures, ...
  - Industrial installations and manufacturing systems
- Smart systems : use information to optimize their operation (closed-loop), but have to use it in a smart way to capture all the "value of information"
- General requirements for reliability of smart systems or smart reliable systems : methods and models for dynamic online reliability evaluation and prediction, for an individual item, based on monitoring information

Monitoring information + reliability = conditional updated reliability

- Monitoring data & online information help to reduce uncertainty, which translates in an updated "conditional" reliability
- Bayesian analysis and bayesian decision-making : provides a formal approach to use the information and assess its effect on the system operation and evolution
- Information in reliability within the bayesian framework : consistent way of incorporating new information into existing models
- Sequential learning ; sequential decision-making



Dynamic condition-based or predictive maintenance / Conditional reliability

- “Production engineers want to know if plant will run “until the end of the week”, not that a stoppage is necessary now because “component X is due for replacement” ” (Scarf 2007)
- What is the reliability gain achieved by the use of a health monitoring system?
- From a psychological point of view, condition monitoring can reduce the uncertainty operators feel about the current state of plant (Scarf 2007)

Condition monitoring and dynamic maintenance approaches can help

- But, dynamic maintenance can be expensive to implement and returns on investment has to be studied (cost-benefits analysis)
- Need for practice-oriented performance models that can help to go from static (but robust) preventive maintenance policies to dynamic condition-based maintenance polices

Dynamic condition-based or predictive maintenance

- Maintenance : a privileged area for the use of dynamic reliability implementation
- Strong interest in the use of the monitoring information in "health management" : predictive maintenance, PHM, SHM, ...

Role of prognostic in maintenance decision-making : still to be explored and thoroughly assessed

Applying the prognostic in decision-making can avoid inopportune maintenance spending. But...

- Prognostic is always associated with unavoidable inaccuracy and uncertainty problem
- How to integrate the prognostic in maintenance strategies and in the decision process, knowing the existence of this uncertainty?

Remaining useful life estimation: a key step

Why prognostics ?

- Prognostics can enable:
  - Adopting condition-based maintenance strategies, instead of time-based maintenance

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  - Prolonging component life by modifying how the component is used (e.g., load shedding)

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  - Prolonging component life by modifying how the component is used (e.g., load shedding)
  - Optimally plan or replan a mission
- System operations can be optimized in a variety of ways

Remaining useful life

Prognosis defined in the standard ISO 13381-1 as a "technical process resulting in determination of remaining useful life".
Two main prediction types in a prognosis procedure :

1. To predict how much time is left before a failure occurs, given the current system state and past operation profile (and the associated "uncertainty" quantification, e.g. a probability density function of this time)

$$F_R(t|t_1) = \mathbb{P}(T_R \leq t | T > t_1 \cap \Theta_{t_1} \cap \mathcal{O}(t_1) \cap \mathcal{E}(t_1))$$

2. To evaluate the probability that the system operates without failure up to a given future time, given the current system state and past operation profile:

$$\mathbb{P}(T > t_2 | T > t_1 \cap \Theta_{t_1} \cap \mathcal{O}(t_1) \cap \mathcal{E}(t_1))$$

Remaining useful life prediction

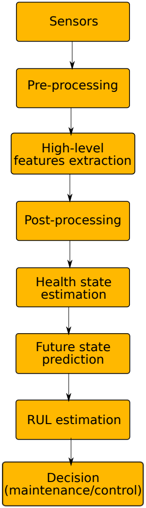
Uncertainty assessment and propagation for RUL prediction

- Probabilistic characterization of the RUL: necessary to weigh the benefits and the costs of a decision + framework to integrate quantitative and qualitative information
- Strong arguments for probabilistic rather than point prediction : this indicates the degree of uncertainty and enables comparisons under different assumptions about costs and benefits for maintenance/safety decision-making
- Sources of uncertainty ?? : intrinsic aleatory uncertainty (item-to-item variability, environment/operation variation) vs modelling (epistemic) or even "technical" (from the prediction process) uncertainty. Subjective vs objective probabilities ? Bayesian framework ?

RUL prognosis is not a prediction, but rather the characterization, quantification and propagation of the uncertainty we have on the system state and failure time, based on our knowledge of its deterioration behavior, of its past operational (usage, environment, maintenance, ...) history and assuming future operational scenarios

Remaining useful life prediction

RUL prediction : a complex and complicated process



- Resort to different competencies, disciplines and complementary methodologies, sometimes difficult to integrate into a comprehensive framework
- Iterative design process, too often sketched as a linear one (misleading)
- How to determine the quality of a RUL prediction : trueness, accuracy, precision, predictive power, ...?

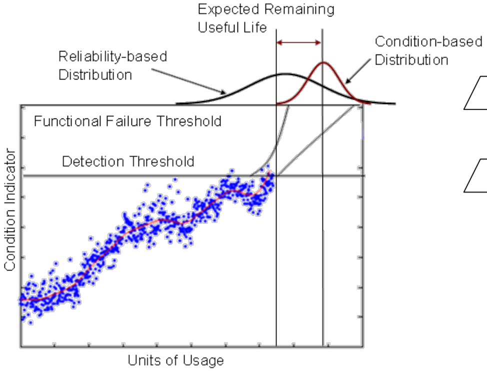
For maintenance purposes, the quality of RUL estimation can be measured by the performance of the maintenance policy

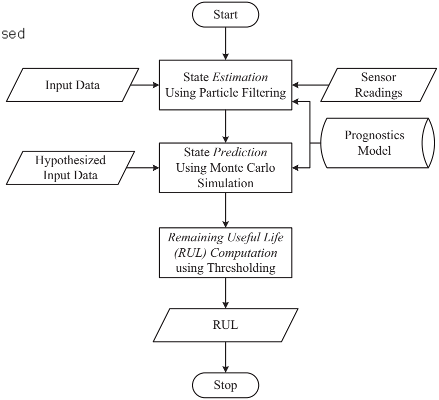
What is the added value of monitoring information through prognosis ?

$\Downarrow$

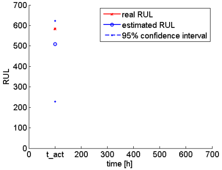
Joint prognosis/maintenance assessment
Joint prognosis/decision-making assessment

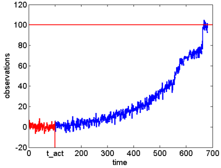
Deterioration-based failure prognosis

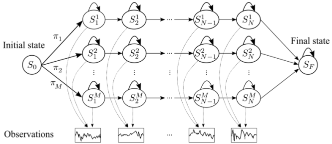


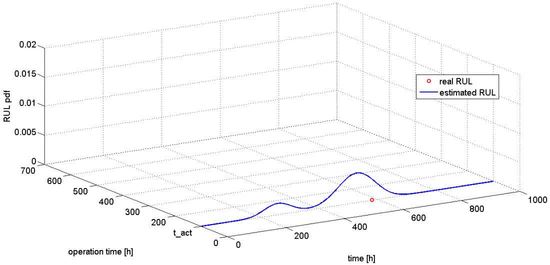


Example of RUL estimation



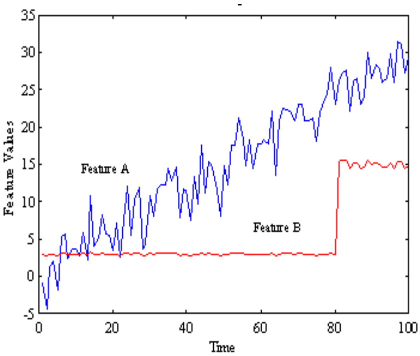






High-level deterioration feature for prognosis

- Feature A : Useful for both diagnostics and prognostics since it exhibits a predictable trend
- Feature B : Useful for diagnostics only since it provides wide separation in feature space but difficult to predict the abrupt change



PHM Approaches / Prognostics Algorithms Classification

Classification proposed by (Celaya Galvan & Saxena, 2014) and extended by (Rakowksy & Bertsche, 2015)

- Type 1- Reliability data-based
  - Use population-based statistical model
  - Consider historical time to failure data to model the failure distribution. Estimate the life of an average component operating under historically average usage conditions
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- Type 2 - Stress-based
  - Use population based fault growth modelÑlearned from accumulated knowledge
  - Consider environmental stresses (e.g. temperature, load, vibration, etc.) on the component. Estimate the life for an average component under the given usage conditions
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  - Proportional hazards model
- Type 3 - Effects-based, condition-based or deterioration-based
  - Use individual component based data-driven model
  - Consider the way in which a specific component responds to its specific usage, the measured or inferred component degradation. Estimate the life of a specific component under specific usage and degradation conditions
  - General Path Model, cumulative damage model, filtering and state estimation.

PHM Approaches / Prognostics Algorithms Classification

- Type 4 - Predictive analytics
  - Data-mine information from large datasets and identify complex patterns that have been shown to lead towards anomalies of failures through collected history data
  - high dimensional large time-series datasets

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- Type 5 - Reliability adaptive systems
  - Feedback from system-individual remaining useful life information on the system operation.
  - Item derating
  - Maintenance optimisation
  - System control
  - System reconfiguration

Outline

Maintenance & imperfect monitoring

Imperfect monitoring information

+

Stochastic dependencies between components

$\Rightarrow$ Taking into account information "quality"
in the decision-making procedure

Objectives :

- Robust maintenance performance
- Design/choice of the monitoring device performance
- Joint optimization of maintenance and monitoring

Maintenance and imperfect monitoring

Condition-based replacement policy

- Observed failure rate

$$\Lambda_t^o = \lim_{h \to 0} \frac{1}{h} \mathbb{P}(t < T_{panne} \le t + h | \mathcal{F}_t)$$

where $\mathcal{F}_t$ contains all the imperfect monitoring information $[0, t]$.

Λ_t^o deterioration or condition "index"

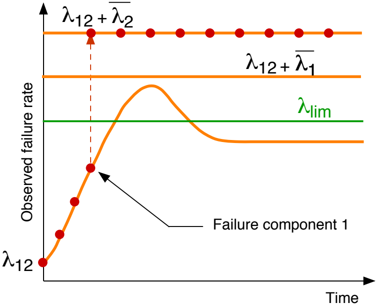
- Maintenance decision rule

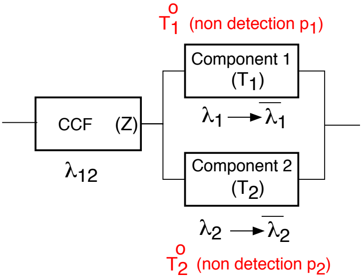
$$\text{Replacement at } \tau = \min\{\inf_{t>0}\{\Lambda_t^o > \lambda_{lim}\}, T_{failure}\}$$

Control limit condition-based maintenance policy

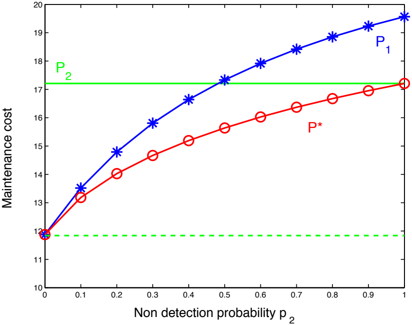
Observed failure rate

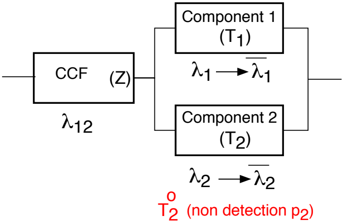
$$\Lambda_t^o = \lim_{h \to 0} \frac{1}{h} \mathbb{P}(t < T_{failure} \leq t + h | \mathcal{F}_t)$$





Policy performance





Decision rule :

$$\tau^* = \min\{T_1^o, T_2^o, b^*, Z, T_{failure}\}$$

Maintenance and imperfect monitoring (cont'd)

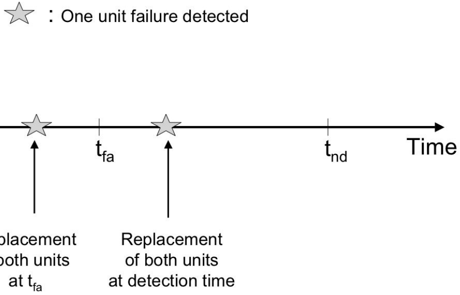
- Consider a system made of monitored components (failed ? running ?)
- Imperfect monitoring characterized by p_{fa} (false alarm) and p_{nd} (non detection): ROC curves
- For component i, the available information is T_i^o instead of T_i (true failure time).

How do we integrate "optimally" this imperfect monitoring information in maintenance decisions, e.g. replacement policy for the monitored components ?

Maintenance and imperfect monitoring (cont'd)

For example, for a 2 components parallel system, it can be shown that the optimal replacement policy for the system has the following structure

$$\tau = \min\{t_{\mathsf{nd}}, \max\{T_1^o, t_{\mathsf{fa}}\}, \max\{T_2^o, t_{\mathsf{fa}}\}, T\}$$



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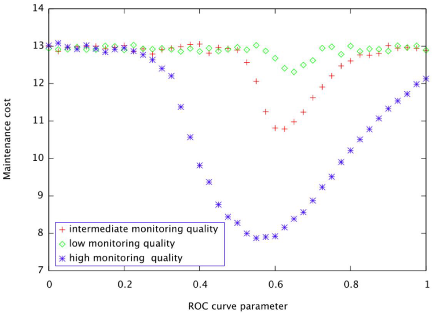

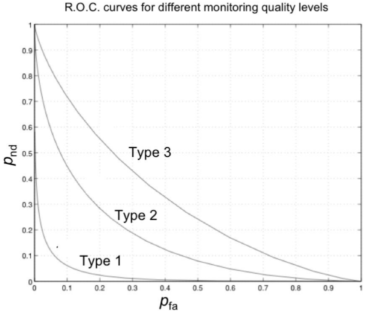

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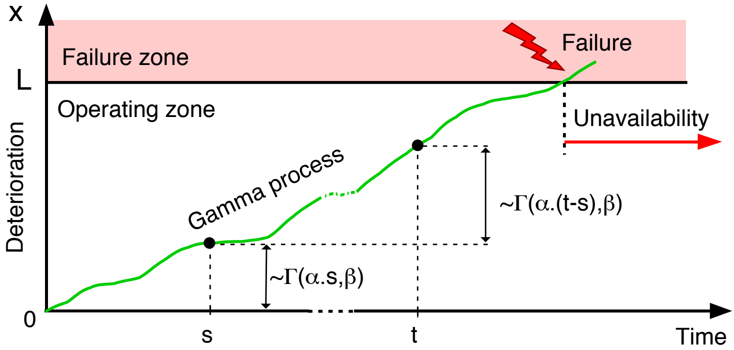
Continuously deteriorating system

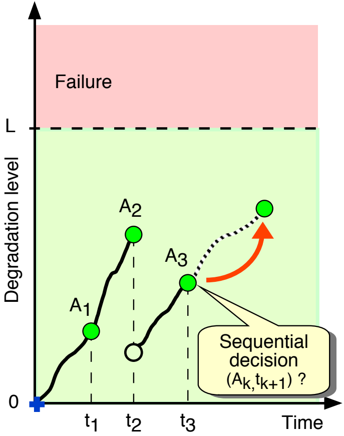
E.g. Gamma process : a generic stochastic model (see survey by Van Noortwijk, 2009)



Physical phenomena : erosion, corrosion, crack propagation, mechanical wear, ...

Condition-based maintenance problem

Sequential condition-based policy

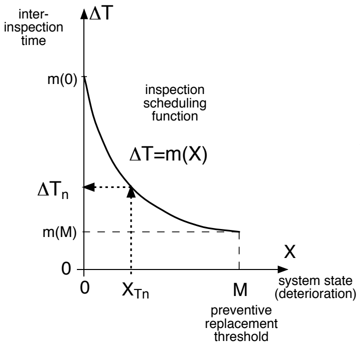


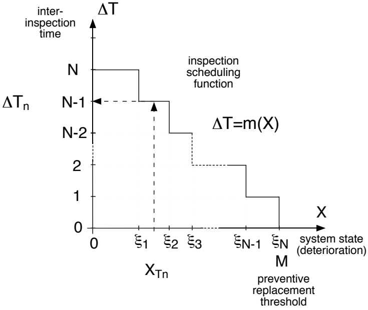
- Inspection/replacement policy
- General maintenance policy (partial repair)
- Stochastic deterioration model

2 main characteristics :

- Joint optimization of the nature and of the time of the maintenance action
- Non periodic inspection/maintenance (time dynamic intervals)

Parametric maintenance policy





Deterioration vs RUL based decision

- Deterioration based decision-making:
  maintenance decision rule = function of the degradation level of the system (health state estimation)
- RUL based decision-making:
  maintenance decision rule = function of the remaining time before failure (prognosis - which depends on the current system deterioration level)
- Both are conditioned by the past observations, but use and process the information differently

Deterioration based decision

Aperiodic condition-based policy

At inspection time t_i, degradation level x_i

- if $x_i \geq L$ (failure) then: corrective replacement
- if $L > x_i \geq M$ (advanced deterioration) then: preventive replacement
- if $M > x_i$ then: next inspection planned at time t s.t.

$$t - t_i = m(x_i)$$

where m is a linear function of x (simplest case)

Decision "parameters"

- Preventive replacement threshold M
- Slope of function m and $m(0)$

RUL based decision

Remaining Useful Lifetime

$$\text{RUL}_t = \inf\{s \geq t, \text{ system ``failed'' at time s}\} - t$$

Quantity of interest: distribution given the observations

$$\mathcal{L}(\text{RUL}_t | X_{t_i} = x_i)$$

Dynamic time based policy

- Inspection schedule built dynamically - RUL update after each inspection
- At inspection time t_i, degradation level x_i
  - Next inspection such that the probability of failure does not exceed $1 - Q$

$$P(t_i + \Delta T > \text{RUL}_{t_i} | X(t_i) = x_i) = 1 - Q$$

  - if $\Delta T < \Delta T_{\mathbf{min}}$ then: preventive replacement.

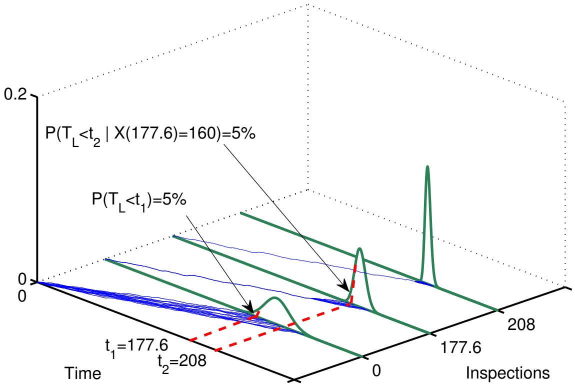
Decision "parameters"

- Preventive replacement threshold ΔT_{min}
- Decision parameter for inter-inspection time.

RUL based decision

Dynamic time based decision rule: example of successive decisions

Probability of failure before next inspection ≤ 0.05 ($Q = 0.95$)

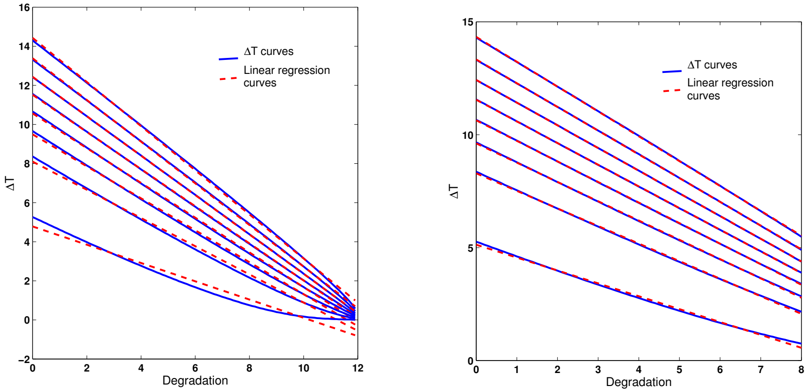


Degradation level at last inspection time close to failure limit $\Rightarrow$ Peaky RUL distribution

Inter-inspection time evolution

ΔT as a function of the degradation level

Example: $Ga(t, 1)$, $L = 12$ and $1 - Q = 0.01 : 0.1 : 0.71$ (curves from bottom to top)



ΔT functions are almost linear for homogenous Gamma process

Comparison based on cost

Long-run cost per time unit

$$\lim_{t\to\infty} \frac{C(t)}{t} \text{ with } C(t) = N_i \cdot C_i + N_p \cdot C_p + N_c \cdot C_c + T_d \cdot C_d$$

Acronyms

- N_i: Nb of inspections (cost C_i)
- T_d: downtime duration (cost C_d)
- N_c: Nb of corrective replacements (cost C_c)
- N_p: Nb of preventive replacements (cost C_p)

Numerical example

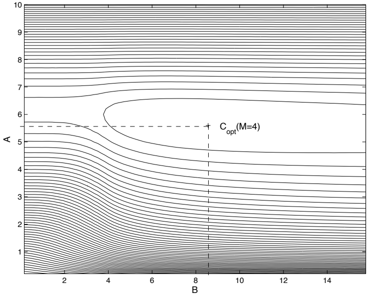
$Ga(t,1)$, $L = 12$, $C_i = 25$, $C_p = 50$, $C_c = 100$ and $C_d = 250$

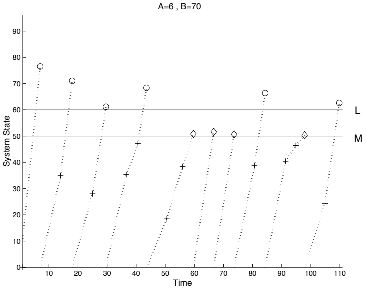
Numerical result

C^*_{RUL}	C^*_{Degrad}	Gain
12.21	12.75	4.4%

- Is the cost gain significant? (linear inspection function)
- Is it a relevant indicator? implementation modalities, complexity level of the decision rule, number of parameters to optimize, **robustness** ...

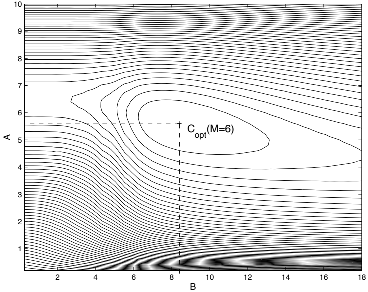
Numerical results

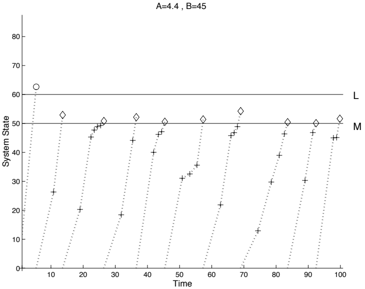




Linear inspection scheduling function $m(x) = 1 + \max(n(x), 0)$ with $n(x) = a - (a/b)x$ - M=4

Numerical results





Linear inspection scheduling function $m(x) = 1 + \max(n(x), 0)$ with $n(x) = a - (a/b)x$ - M=6

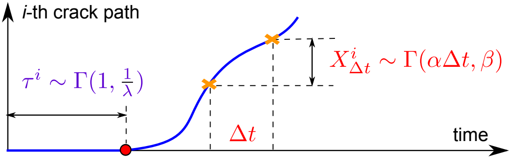
Outline

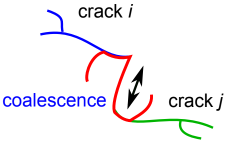
Deterioration vs RUL based decision: robustness analysis

Example of multiple degradation paths of stress corrosion cracking

Modeling of crack behavior (e.g., i-th crack), traditional model again

- Arrival: homogeneous Poisson process $\{N_t^i\}_{t\geq 0}$ with parameter λ
- Propagation: homogeneous gamma process $\{X_t^i\}_{t\geq 0}$ with parameters α and β





Modeling of system failure

- Coalescence phenomenon $\Rightarrow$ System fails due to multiple crack paths
- Failure: {sum of crack sizes X_t^S exceeds L} or {cracks number N_t reaches N}

Degradation based maintenance decision rules

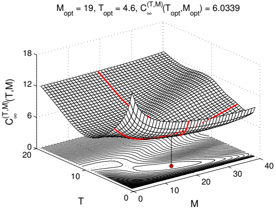
Periodic inspections every T

(T, M) strategy {crack size}

- Preventive replacement is performed when

$$M \leq X^S_{T_k} < L$$

- Decision parameters: T, M

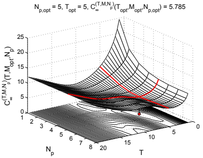


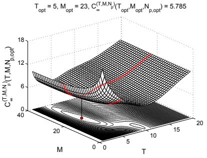
(T, M, N_P) strategy {crack size, crack number}

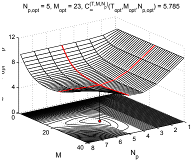
- Preventive replacement is performed when

$$M \leq X^S_{T_k} < L \text{ or } N_p \leq N_{T_k} < N$$

- Decision parameters: T, M, N_p







RUL based maintenance decision rules

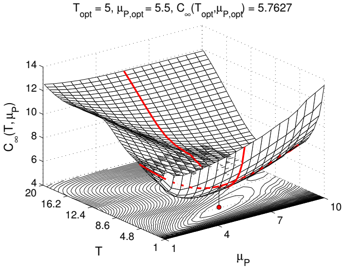
Periodic inspections every T
($\text{RUL}_t = \inf\{s \geq t, \text{ system "failed" at time } s\} - t$)

(T, μ_P) strategy {MRL}

- Preventive replacement is performed when

$$0 < E\left(\text{RUL}_{T_k} \mid X^S_{T_k}, N_{T_k}\right) \leq \mu_P$$

- Decision parameters: T, μ_P

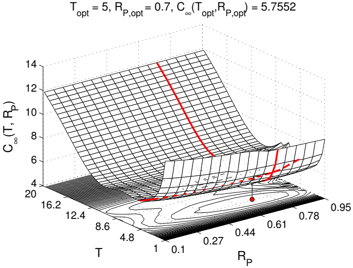


(T, R_P) strategy {RUL law}

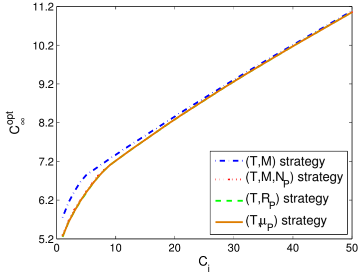
- Preventive replacement is performed when

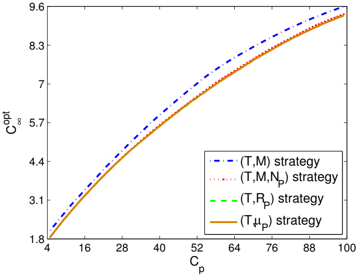
$$P\left(\text{RUL}_{T_k} < T \mid X^S_{T_k}, N_{T_k}\right) \leq R_P$$

- Decision parameters: T, R_P



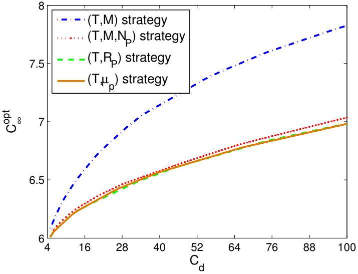
Performance analysis - Cost





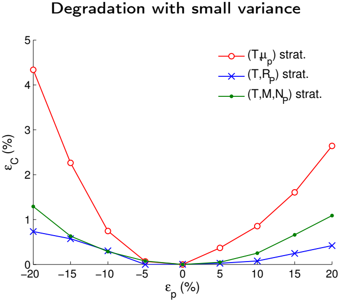
Remarks

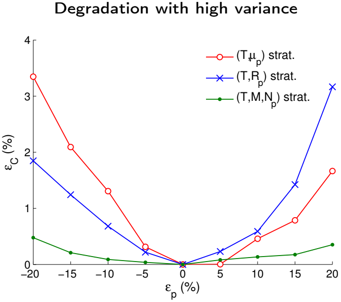
- (T, M) strategy is less profitable
- Other strategies have the same profit
- Perfect parameters estimation



Performance analysis - Robustness

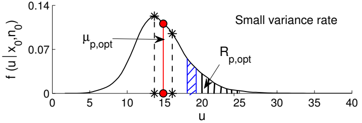
Variation of the decision parameters μ_p, R_p, M:

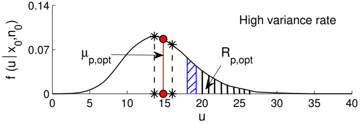




Remarks

- Imperfect parameters estimation
- (T, R_P) strategy $>$ (T, μ_P) strategy
- Increasing variance in degradation process
  $\Rightarrow$ Increasing robustness



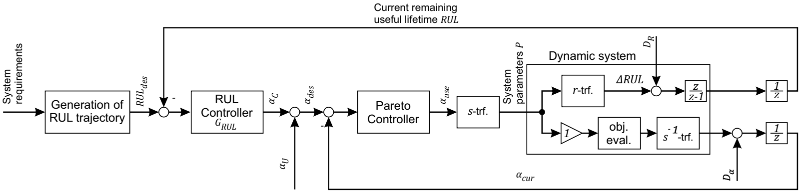


Outline

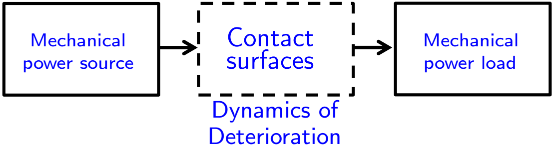
Reliability adaptive systems

[Taken from Meyer & Sextro, 2014]

Controlling the remaining useful life using control approaches



Problem & work motivation



Tire-road contact

Clutch system

Friction drive system

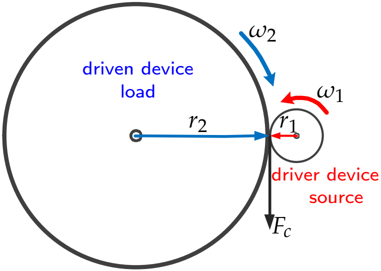
Applications

PHM - Prognostics and Health Management
RAS - Reliability-Adaptive Systems

Problem: Modeling and on-line estimating the deterioration of a friction drive system with respect to the operating conditions

Friction Drive System Modelling

Roller-on-tire system



Friction drive

Type of transmission that uses 2 circular devices to transfer power by friction.

Roller-on-tire basic system

- Is a friction drive composed by a wheel (driven device) and a motor (driver device).
- Both contact surfaces (rotor of the motor and the tire) deteriorate
- Deterioration reaches eventually a threshold above which the system is considered failed

Friction Drive System Modelling

Motion equations

$$J_1\dot{\omega}_1(t) = -B_1\omega_1(t) + \underbrace{T_L(t)}_{F_c(t)r_1} + K_m I(t)$$

$$J_2\dot{\omega}_2(t) = -B_2\omega_2(t) + \underbrace{T_S(t)}_{F_c(t)r_2}$$

$$F_c = \alpha\Delta_v = \alpha(\underbrace{r_1\omega_1}_{v_1} - \underbrace{r_2\omega_2}_{v_2})$$

$\alpha \geq 0$ is the contact quality coefficient

$\rightarrow$ uncertain parameter, time varying

Dynamical model of deterioration

By assumption, $\alpha(t)$ decreases as deterioration $D(t)$ increases:

$$\alpha(t) = -mD(t) + b$$

where $m \geq 0$ and b are considered as **unknown and bounded** parameters.

Dissipation-energy based model of deterioration

The deterioration due to the dissipated energy in the contact $D(t)$is:

$$D(t) := \int_0^t \underbrace{F_c(t)\Delta_v}_{P_c(t)} dt = \int_0^t \alpha(r_1\omega_1 - r_2\omega_2)^2 dt$$

Where P_c is the dissipated power at the contact level.

Now we can compute the dynamics of the parameter $\alpha(t)$, as follows:

$$\dot{\alpha}(t) = -m \cdot \alpha \cdot p(x)$$

where the sliding factor $p(x) \geq 0$ is given by:

$$p(x) := (r_1\omega_1 - r_2\omega_2)^2 = {\Delta_v}^2$$

Dynamical model of deterioration

Remark that the contact quality deterioration-rate $\dot{\alpha}(t)$, depends on the relative tangential speed, which could be controlled if the uncertain system is **controllable**.

In terms of the deterioration index D, equation (1) can be rewritten in a relative form as follows:

$$\frac{\alpha(t)}{\alpha(0)} = -\bar{D}(t) + 1 \qquad (1)$$

where $0 \leq \bar{D}(t) \leq 1$ denotes the **normalized deterioration**. That is:

$$\bar{D}(t) = \frac{m}{\alpha(0)} D(t) \qquad (2)$$

Dynamical model of deterioration

Using Equation $\alpha(t) = -mD(t) + b$, the deterioration $\hat{D}$ can be estimated by:

$$D = (\alpha(0) - \alpha)/m \quad (3)$$

$$\hat{D} = (\alpha(0) - \hat{\alpha})/m \quad (4)$$

From $\dot{D} = c\alpha\Delta_v^2$ and

$$\dot{D} = -m \underbrace{c\Delta_v^2}_{d(t)} D + b \underbrace{c\Delta_v^2}_{d(t)}$$

Let us consider

$$D_{max} \triangleq \lim_{t \to +\infty} D(t)$$

This can be calculated with $\dot{D} = 0$, thus:

$$-mD_{max} + b = 0 \quad (5)$$

And

$$D_{max} = b/m = \alpha(0)/m \quad (6)$$

Consequently, using equations (2), (4) and (6), it is obtained the normalized estimation of deterioration $\hat{\bar{D}}$:

$$\hat{\bar{D}} = \hat{D}/D_{max} = (\alpha(0) - \hat{\alpha})/\alpha(0) \quad (7)$$

Uncertain linear system modelling

Defining the system state as $x := [\omega_1(t)\ \omega_2(t)]^T$ (the angular speeds), the control input $u = I(t)$ (the electrical motor current) the state space representation of the uncertain linear system will be

$$\begin{aligned} \dot{x} &= A(\alpha)x + Bu \\ y &= x \end{aligned}$$

where α stands for the uncertain parameter, with matrices:

$$A(\alpha) = \begin{bmatrix} \left(-\alpha r_1^2 - B_1\right)/J_1 & \alpha r_1 r_2 / J_1 \\ \alpha r_2 r_1 / J_2 & \left(-\alpha r_2^2 - B_2\right)/J_2 \end{bmatrix},$$

$$B = \begin{bmatrix} K_m / J_1 \\ 0 \end{bmatrix}$$

α affects the matrix $A_d(\alpha)$ in an **affine** way

Estimating the state of deterioration

Consider the augmented system:

$$\begin{aligned} \dot{x} &= A(\alpha)\ x + B\ u \\ \dot{\alpha} &= -m \cdot \alpha \cdot p(x) \\ \dot{m} &= 0 \\ y &= x \end{aligned}$$

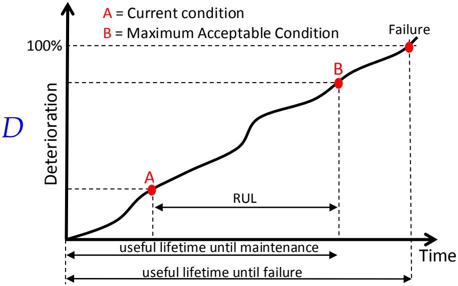
$\rightarrow$ If we assume that this augmented system is **observable**[1], then, it is possible to design an **Extended Kalman filter** to estimate the states x, the contact quality coefficient α and the constant m.
$\rightarrow$ The availability of the estimations of α and m means that, the state of deterioration D can be evaluated as well at every time instant.

$$\dot{D} = -(1/m)\dot{\alpha} \rightarrow \text{Deterioration current condition}$$

Remaining Useful Life (RUL)

Remaining Useful Life RUL

The Remaining Useful Life (RUL) of an asset or system is defined as the time left from the current time to the end of the useful life, where this end can be defined according a threshold acceptable condition.



The problem on RUL is:

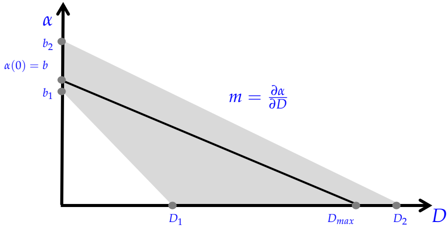
For a given predefined scenario and/or protocol (fixed duty cycles, minimal and maximal electrical motor current, etc), at every time instant, estimate the RUL of the actuator with a certain precision.

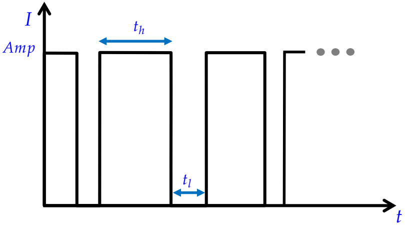
Introducing randomness in the model

Due that the estimation of Remaining Useful Life (RUL) is not deterministic, we try to estimate it using stochastic simulation.

There are two kind of uncertainties that have to be treated here:

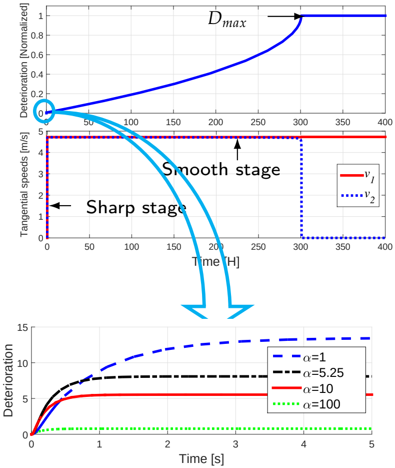
Internal mode	External mode
Uncertain/random parameters	Uncertain operating conditions



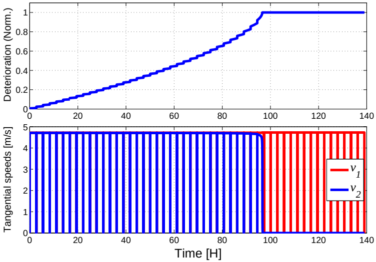


Deterministic operational analysis

Constant behavior of input



Variable behavior of input



Stochastic operational analysis

Scenario A

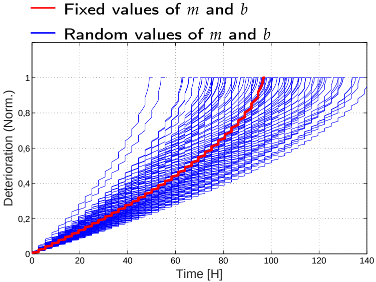
Internal mode

Uncertain/random parameters

Ramdom value for parameters m and b in each simulation

Input $I(t)$ - square wave with constant values in duty cycle

$$m \sim \mathcal{N}(m_m, \sigma_m^2), \quad m_m > 0$$
$$b \sim \mathcal{N}(b_m, \sigma_b^2), \quad b_m > 0$$



100 simulations

Stochastic operational analysis

Scenario B

External mode

⇩

Uncertain operating conditions

Input $I(t)$ - square wave with random values in duty cycle

Constant parameters m and b

$$t_l \sim Exp(1/\mu_{tl}), \quad 0 < \mu_{tl}$$
$$t_h \sim Exp(1/\mu_{th}), \quad 0 < \mu_{tl} < \mu_{th}$$

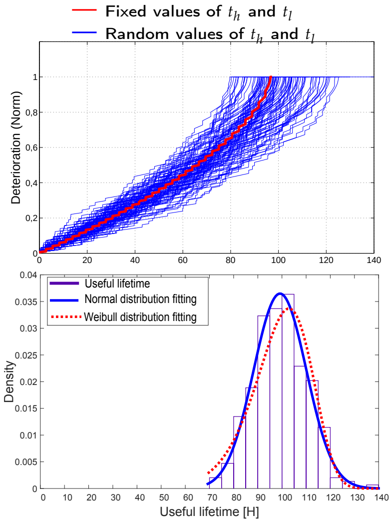


Figure: Useful lifetime. Histogram with normal and Weibull distribution fitting.

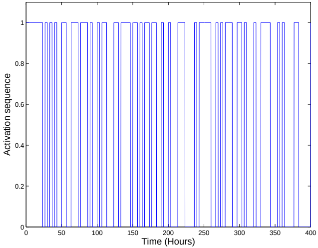
Stochastic operational analysis

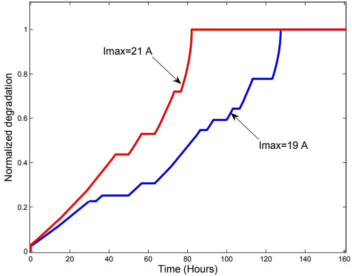
Scenario C

External mode

Uncertain operating conditions

Input $I(t)$ - square wave with random values in duty cycle





Deterioration obtained with 2 different maximal values of $I(t)$

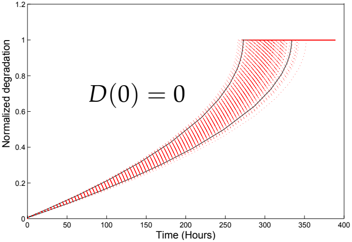
Stochastic operational analysis

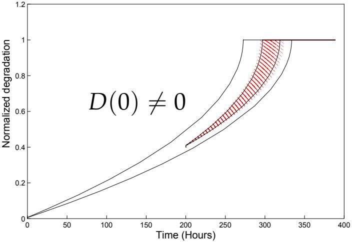
Scenario D

External mode

Uncertain operating conditions

Input $I(t)$ - step with random amplitude





Stochastic operational analysis

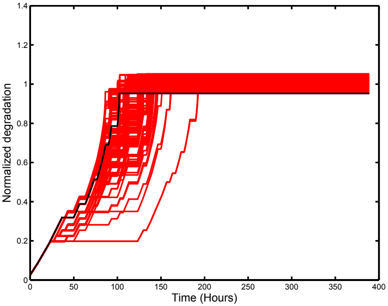
Scenario E

Internal/external mode

Uncertain/random
parameters and operational conditions

Input $I(t)$ - square wave with random values in duty cycle

Ramdom value for parameters m in each simulation



— Curve with the maximal value of m

Condition monitoring and prognosis

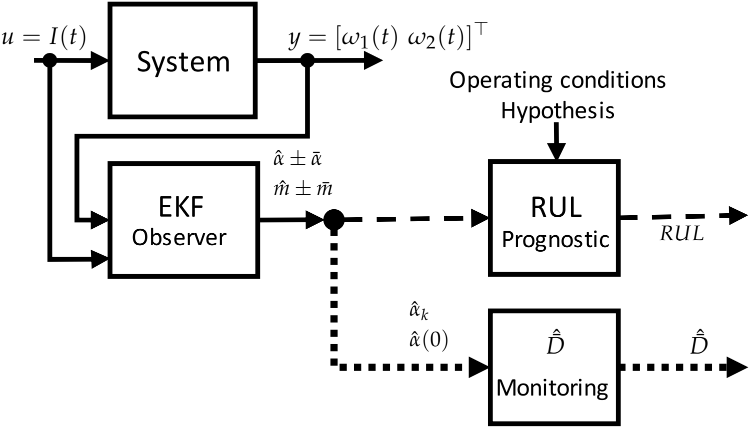


Figure: Condition monitoring and RUL prognosis architecture.

Synthesis of an Extended Kalman Filter - EKF

Defining the vector state of the augmented system as $\boldsymbol{x} := [\omega_1(t)\ \omega_2(t)\ \alpha(t)\ m]^\top$, the control input $u = I(t)$, and assuming that at every time instant $\omega_1(t)$ and $\omega_2(t)$ are available from the sensors, the state transition and the system output in continuous time are respectively:

$$\dot{\boldsymbol{x}} = f(\boldsymbol{x}) + Bu + \boldsymbol{w} \tag{8}$$

$$\boldsymbol{y} = \boldsymbol{C}\boldsymbol{x} + \boldsymbol{v} \tag{9}$$

with

$$\boldsymbol{C} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \tag{10}$$

and where $\boldsymbol{w}$ and $\boldsymbol{v}$ are the process and measurement noises which are both assumed to be Gaussian noises with zero mean and covariance Q and R respectively.

Synthesis of an Extended Kalman Filter - EKF

In order to synthesize an Extended Kalman filter, the following covariance matrices are selected:

$$Q = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \sigma_m^2 \end{bmatrix}, \; R = \begin{bmatrix} \sigma_1^2 & 0 \\ 0 & \sigma_2^2 \end{bmatrix} \tag{11}$$

where σ_m^2 stands by the disturbance variance affecting the behavior of the state m. The symbols σ_1^2 and σ_2^2 represent the sensor noise variances in speed sensors measuring ω_1 and ω_2, respectively.

Evaluation of the observer performance

Three different assumptions on the dynamics of m are presented:

1. $\dot{m} = 0$ the parameter m is always constant,
2. $\dot{m} = \delta(t^*)$ the parameter m is piece-wise constant, and an abrupt change in the value of m can appears at the instant $k = t^*$ (a Dirac delta function models this aspect)
3. $\dot{m} = \varepsilon$ the parameter m can suffer a progressive change with a rate of change equal to ε (a possible random but *a priori* bounded input).

Evaluation of the observer performance

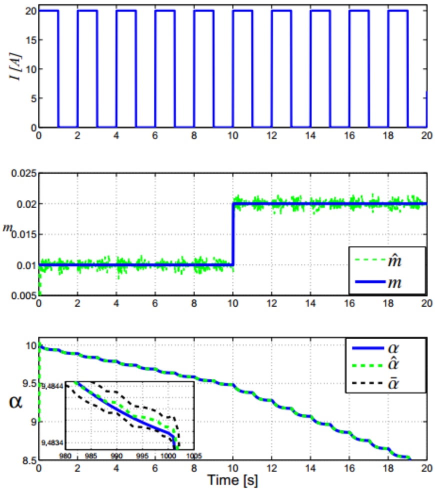


Figure: Input sequence and estimation of the current state of $\hat{m}$ and $\hat{\alpha}$ with an abrupt variation of m

Evaluation of the observer performance

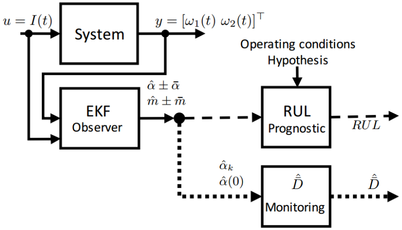


Figure: Condition monitoring and RUL prognosis architecture.

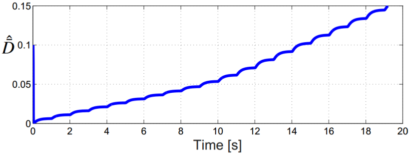


Figure: Condition monitoring of $\hat{\bar{D}}$

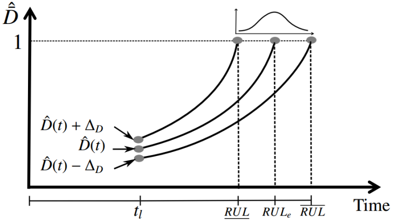


Figure: Uncertainty of $\bar{D}$ (Confidence interval) used in the prognostic of RUL.

Evaluation of the observer performance

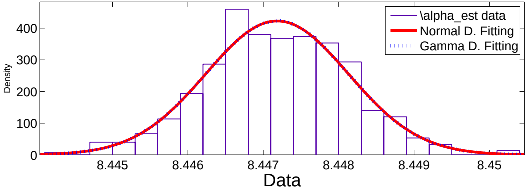


Figure: Distribution of α for 500 trials. $\hat{\alpha}_{mean} = 8.44, \sigma_{\alpha} = 9.43x10^{-4}$

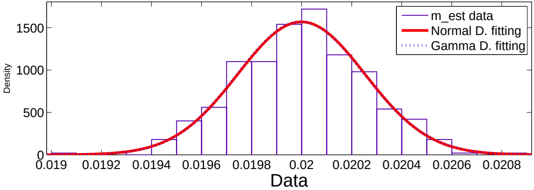


Figure: Distribution of m for 500 trials. $\hat{m}_{mean} = 0.02, \sigma_m = 2.54x10^{-4}$

Evaluation of the observer performance

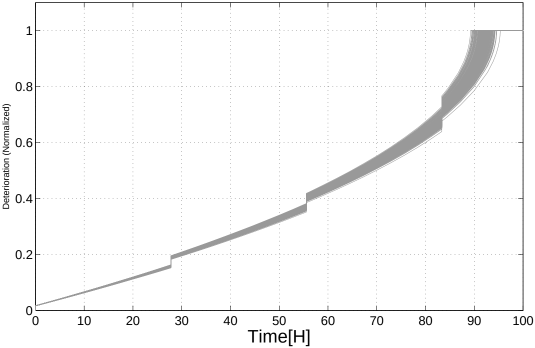
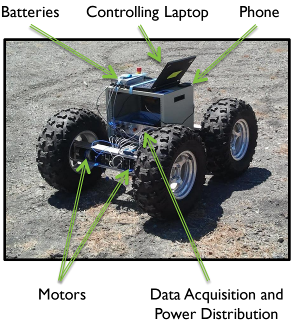


Figure: Several simulations of deterioration. Example.

NASA Ames Center Rover Testbed

[Taken from Daigle, 2014 - PHM 2014]

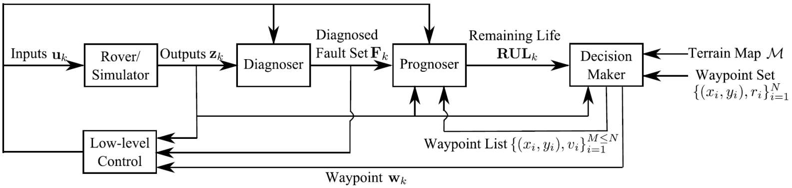
- Developed rover testbed for hardware-in-the-loop testing and validation of control, diagnosis, prognosis, and decision-making algorithms
- Skid-steered rover (1.4x1.1x0.63 m) with each wheel independently driven by a DC motor
- Two parallel lithium-ion battery packs (12 cells in series) provide power to the wheels
- Separate battery pack powers the data acquisition system
- Onboard laptop implements control software
- Flexible publish/subscribe network architecture allows diagnosis, prognosis, decision-making to be implemented in a distributed fashion



Integrated prognostics architecture

[Taken from Daigle, 2014 - PHM 2014]

- Rover receives control inputs (individual wheel speeds) and sensors produce outputs
- Low-level control modifies wheel speed commands to move towards a given waypoint in the presence of diagnosed faults
- Diagnoser receives rover inputs and outputs and produces fault candidates
- Prognoser receives rover inputs and outputs and predicts remaining useful life (RUL) or rover and/or its components (eg, batteries, motors)
- Decision maker plans the order to visit the waypoints (science objectives) given diagnostic and prognostic information. It can also selectively eliminate some of the waypoints if all of them are not achievable due to vehicle health or energy constraints.



Outline

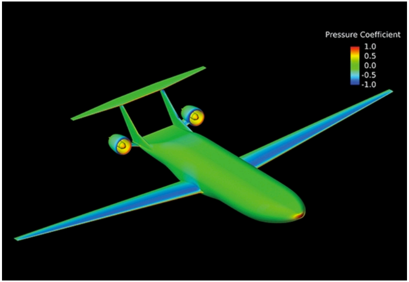
Technical needs for effective RUL prediction and management

As usual a good mix of engineering expertise, physics of failure knowledge and data analytics for robust decision-making

- Well understood failure mode(s)
- Model the link between the reliability of a unit (and failure time data) and its deterioration/usage/environment history
- Ability to model and predict deterioration/usage/environment covariates for individual units
- Empirical modeling vs physics of failure and knowledge based models
- System State Awareness (SSA) for a more resilient control and operation of the system

Example of a tool for SSA : Digital Twin

- A concept from NASA which combines as-built vehicle components, as-experienced loads and environments, and other vehicle-specific characteristics to enable ultrahigh fidelity modeling of aircraft and spacecraft or their components throughout their service lives.



Credit : MIT

- Aviation week, 2014 - " It is 2035, and a customer is taking delivery of not only a new aircraft but also a highly detailed digital model specific to that aircraft's tail number-its airframe, engines and systems."
- "Built up over the course of design, development, testing and production, and ultra-realistic down to the level of unique manufacturing flaws, the model will accompany the aircraft throughout its service life. Mirroring its flights exactly, the model's simulations will be compared with data from the real aircraft to identify anomalies, predict maintenance needs and forecast remaining life."

Concluding remarks: Open Issues

Many open challenges :

- Multi-component systems prognosis & maintenance : scalability issues
- Distributed multi-level prognosis ; prognosis fusion for maintenance
- Further integration of the processing chain from sensors to maintenance decision : proof of concept still challenging
- Design to PHM and maintenance
- Integration of future operating conditions, environments, ...jointly in the prognosis, maintenance & operation decision
- Feedback from operation and maintenance decisions on the RUL (eg derating)
- ...