Multi-branch multi-state modeling for prognosis of systems under multiple deterioration mode

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Context

FP7 European project: SUPREME

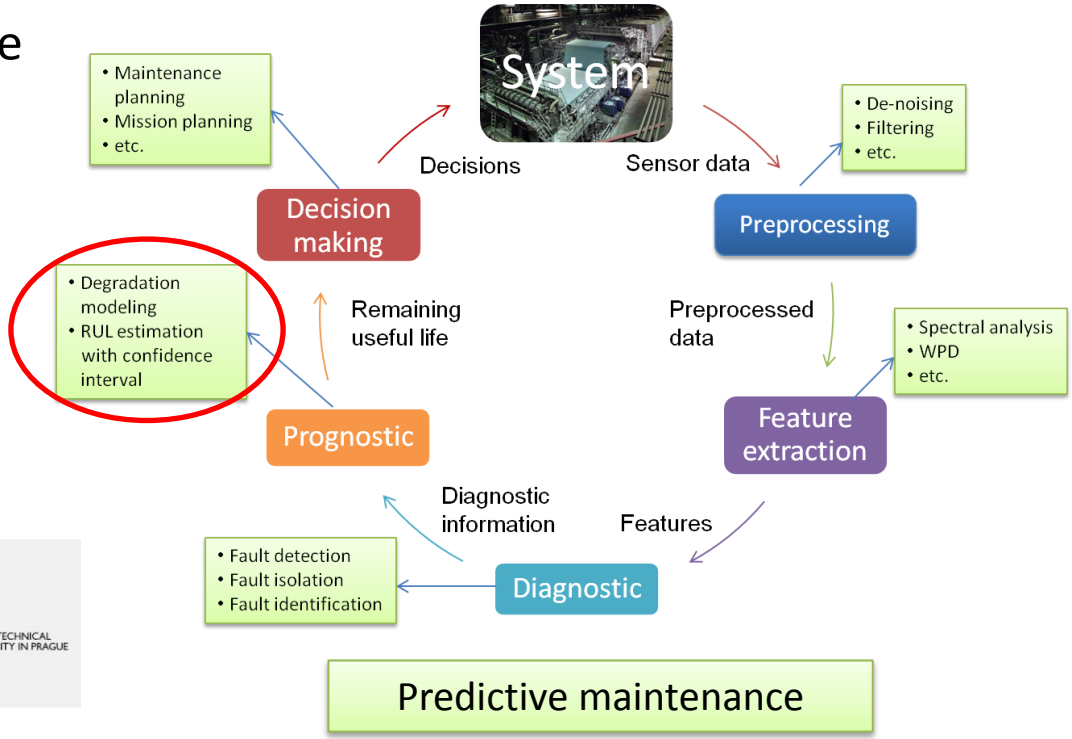
- "Sustainable Predictive Maintenance for manufacturing Equipment"
- Purpose: Development of new tools for predictive maintenance to improve productivity, reduce machine downtimes and increase energy efficiency.

⇒ Application case: Paper machine

⇒ **Main objectives:**

✓ **Deterioration modeling**

✓ **Remaining Useful Life (RUL) estimation**



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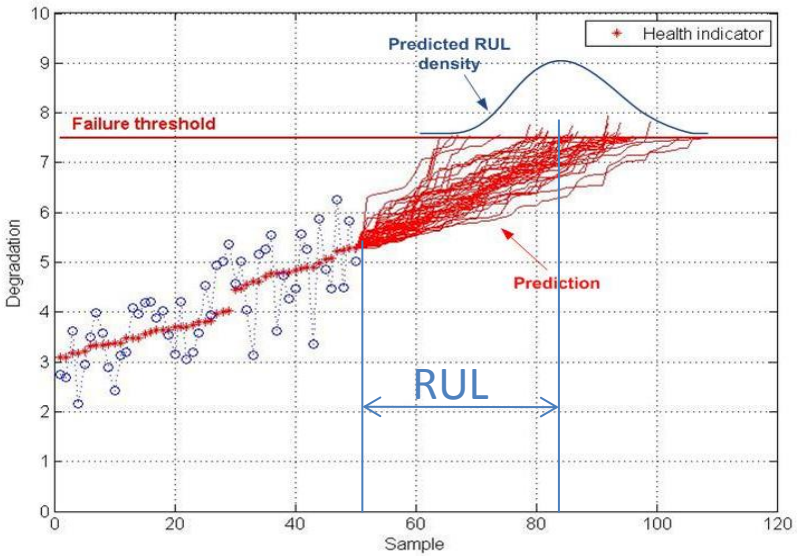
Deterioration modeling and RUL estimation

Deterioration modeling

- Synthesize health indicators from condition monitoring data
- Model its temporal evolution, e.g. by stochastic processes
- Assess component's current health



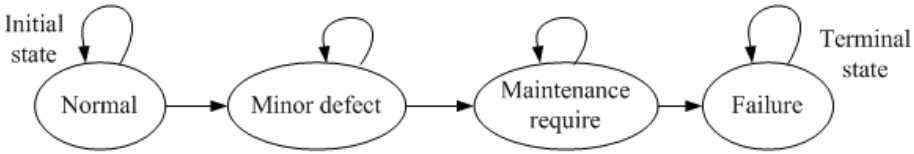
Remaining Useful Life (RUL)

- The time left before the failure
- Prediction uncertainties management

=> RUL: Conditional random variable

Two main methods

- Continuous states modeling
- Discrete or multi-state modeling

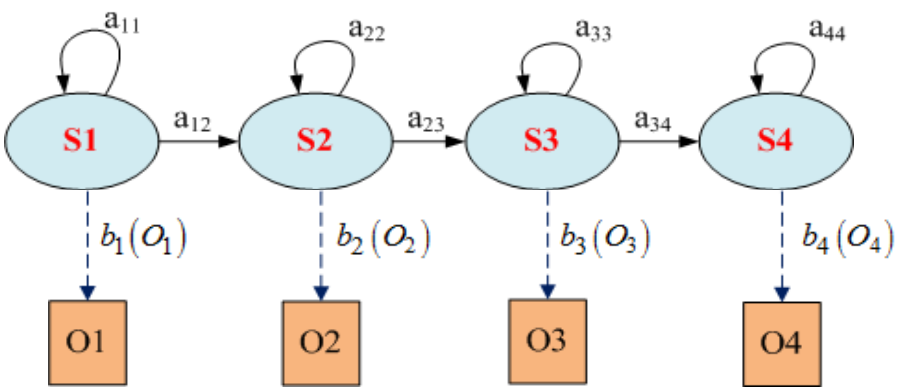


Hidden Markov Model

- Two-layer stochastic process
  - States: Hidden ~ Markov chain (propriété Markovienne)
  - Observations: emitted by states through some probabilistic links

Deterioration modeling

- States: System's health
- Observations: CM signals, high-level extracted features, etc.
- Left-right topology: irreversible deterioration

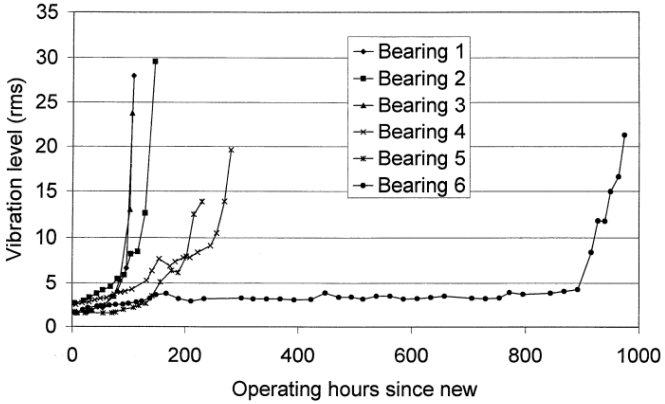


Hidden Markov Model

HMM modeling problems

- Model only one deterioration mechanism at one time

  Multiple deterioration modes could **co-exist in competition** in practice



Multi-branch Hidden Markov Model (MB-HMM)

- Markovian property: State sojourn time ~geometric or exponential distribution

  Can be extended to arbitrary distribution

Multi-branch Hidden semi-Markov Model (MB-HsMM)

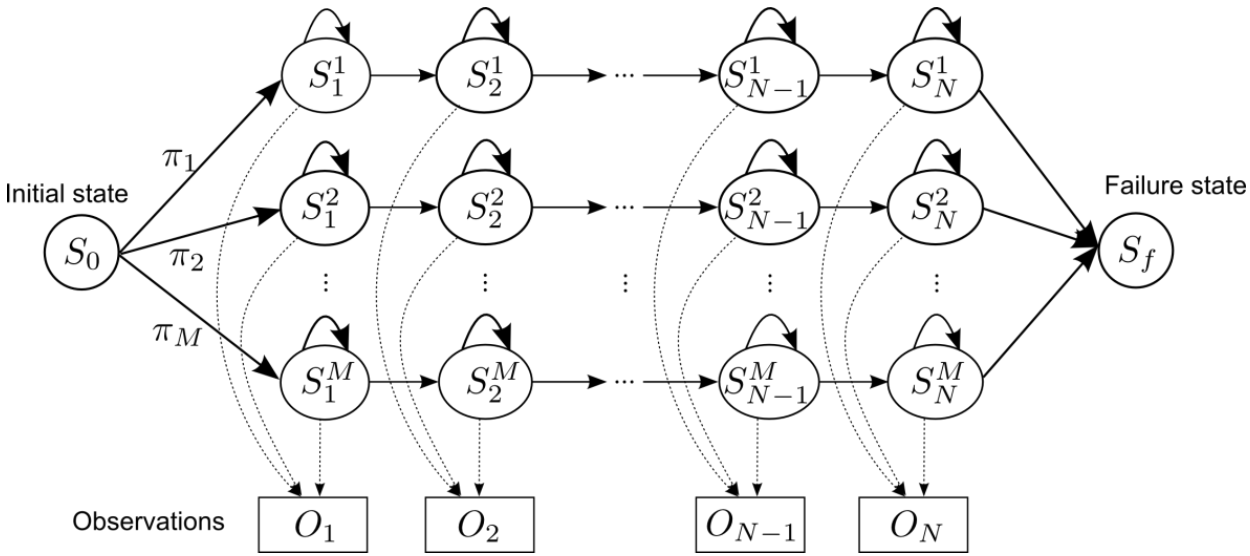
Outline

- Multi-branch multi-state model
  - Deterioration modeling
  - Remaining Useful Life estimation
- Numerical results
  - Simulated degradation data
  - A case study
- Conclusion & Perspectives

Multi-branch modeling

- Several branches with a common initial (normal) state
- Each branch ~ one deterioration mode
- Branch probability π_k

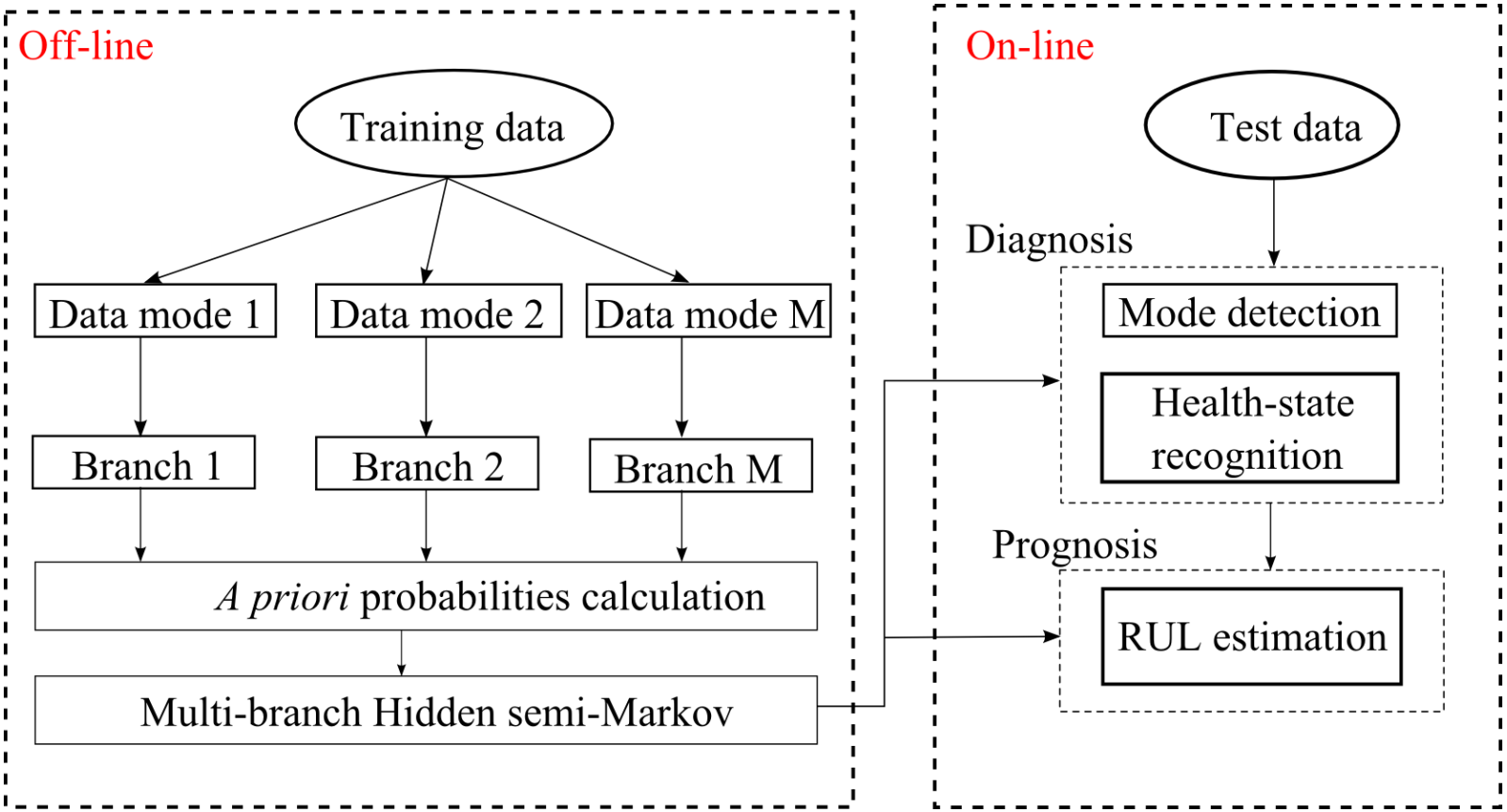
$$\sum_{k=1}^{M} \pi_k = 1$$



- Observations are continuous ~ Gaussian distributed
- **Semi-Markov**: State sojourn times ~ Gaussian distributed
- Corresponding states in different branches could emit the same observations

Multi-branch framework for diagnosis and prognosis

Two-phase implementation: offline & online



Off-line phase

Model training

- Train data: High-level features extracted from condition monitoring data (RMS, kurtosis, crest factor, etc.)
- Data classification => M groups => train M branches separately
- Parameters estimation:
  - HMM: Baum-Welch algorithm
  - HsMM: Adoption of the Forward-Backward procedure [Yu06]
- *A priori* probabilities calculation

$$\pi_k = P(\lambda_k) = K_k \Big/ \sum_{k=1}^{M} K_k$$

K_k : Number of training sequences corresponding to the mode *k*

*[Yu06]: Practical implementation of an efficient forward-backward algorithm for an explicit-duration hidden Markov model. *IEEE Transactions on Signal Processing*, *54*(5), 1947-1951.

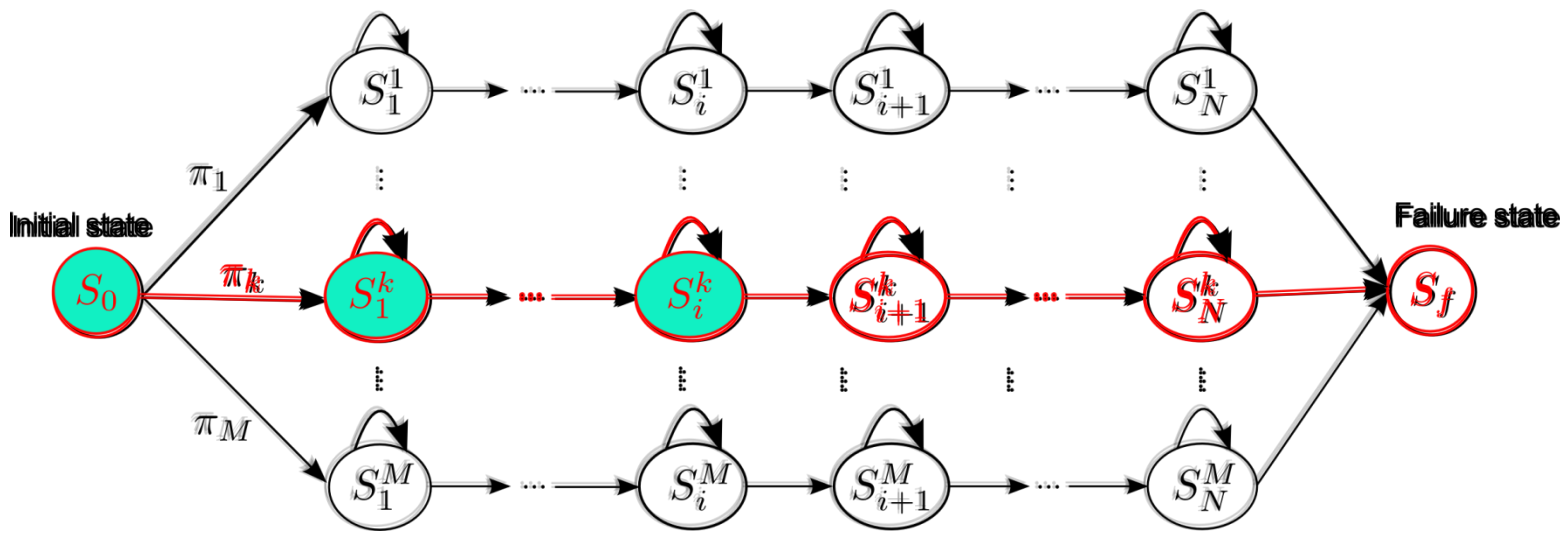
On-line phase

Diagnosis

– Mode detection: $\hat{k} = \arg\max_{k} P\left(\lambda_k \mid \mathbf{O}\right)$

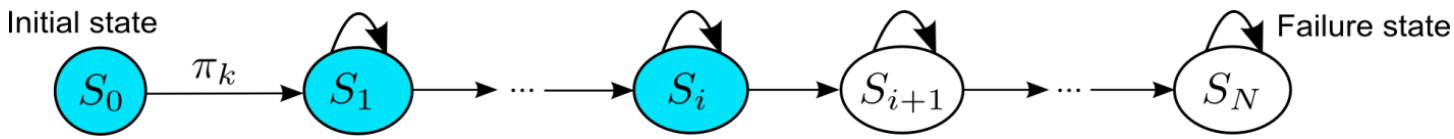
– Health-state assessment: Viterbi algorithm

- Determine of the "best" state sequence: $Q^* = \arg\max_{Q_{\hat{k}}} P\left(\mathbf{O}, Q_{\hat{k}} \mid \lambda_{\hat{k}}\right)$
- Consider the last state as the actual state



RUL estimation

One branch (HMM case)



- Suppose that the system is following the mode *k*
- RUL : number of transition steps to reach ***for the 1st time*** the failure state

$$RUL_i^{(l)} = P\left(RUL = l \mid q_t = S_i\right) = P\left(q_{t+l} = S_N, q_{t+l-1} \neq S_N, \ldots, q_{t+1} \neq S_N \mid q_t = S_i\right)$$

- Left-right HMM: Given the current state, the system can either stay in the same state or jump to the next one

$\Rightarrow$ ***Recursive computation***

RUL estimation *(cont.)*

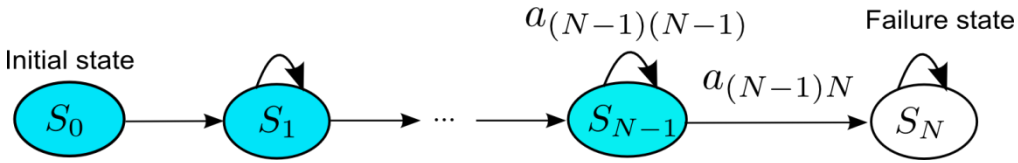
One branch (HMM case)

- At state S_{N-1}:

$$RUL_{N-1}^{(1)} = a_{(N-1)N}$$

$$\cdots$$

$$RUL_{N-1}^{(l)} = a_{(N-1)(N-1)} RUL_{N-1}^{(l-1)}$$

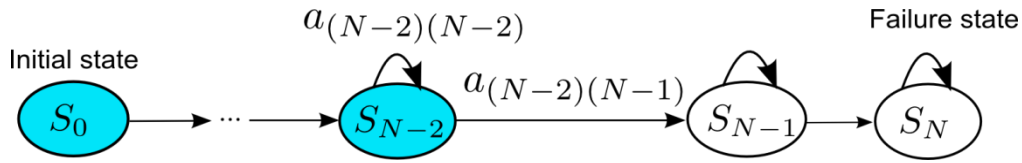


- At state S_{N-2}:

$$RUL_{N-2}^{(1)} = a_{(N-2)N} = 0$$

$$\cdots$$

$$RUL_{N-2}^{(l)} = a_{(N-2)(N-2)} RUL_{N-2}^{(l-1)} + a_{(N-2)(N-1)} RUL_{N-1}^{(l-1)}$$



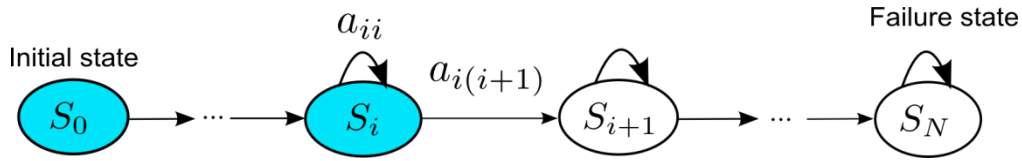
$\cdots \quad \cdots$

- At state S_i:

$$RUL_i^{(1)} = a_{iN}$$

$$\cdots$$

$$RUL_i^{(l)} = a_{ii} RUL_i^{(l-1)} + a_{i(i+1)} RUL_{i+1}^{(l-1)}$$

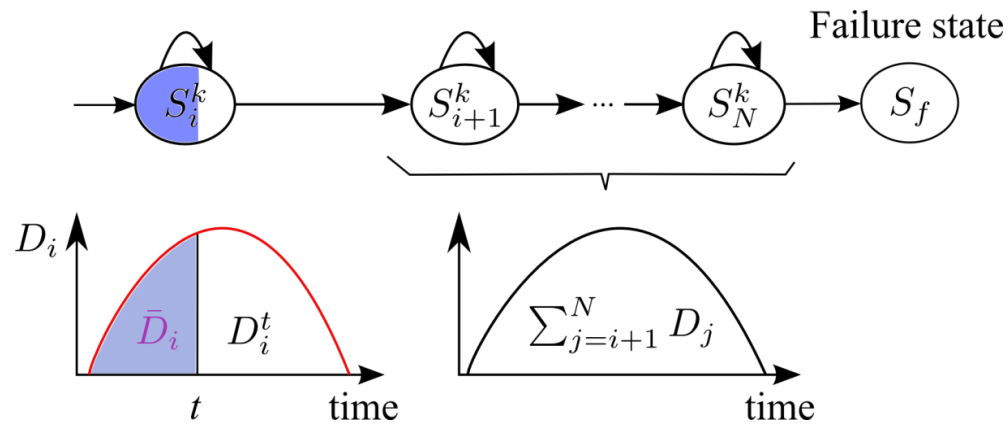


RUL estimation *(cont.)*

One branch (HsMM case)

- Strictly left-right model:

$$\mathrm{RUL}_i^t = D_i^t + \sum_{j=i+1}^{N} D_j$$



  - D_j : Sojourn time in states *j*
  - $D_i^t = D_i - \bar{D}_i \mid D_i > \bar{D}_i$ ~ truncated Normal distribution
  - $\sum_{j=i+1}^{N} D_j$ ~ Normal distribution

Bayesian Model Averaging

- Take into account model uncertainty: $P(\mathrm{RUL} \mid \mathbf{O}) = \sum_{k=1}^{M} P(\mathrm{RUL} \mid \lambda_k, \mathbf{O}) P(\lambda_k \mid \mathbf{O})$

Numerical examples

Simulated deterioration data

- **Fatigue Crack Growth (FCG)** model to represent the evolution of a crack depth

$$x_{t_i} = x_{t_{i-1}} + e^{w_{t_i}} C\left(\beta_b e^{\gamma_e} \sqrt{x_{t_{i-1}}}\right)^n \Delta t$$

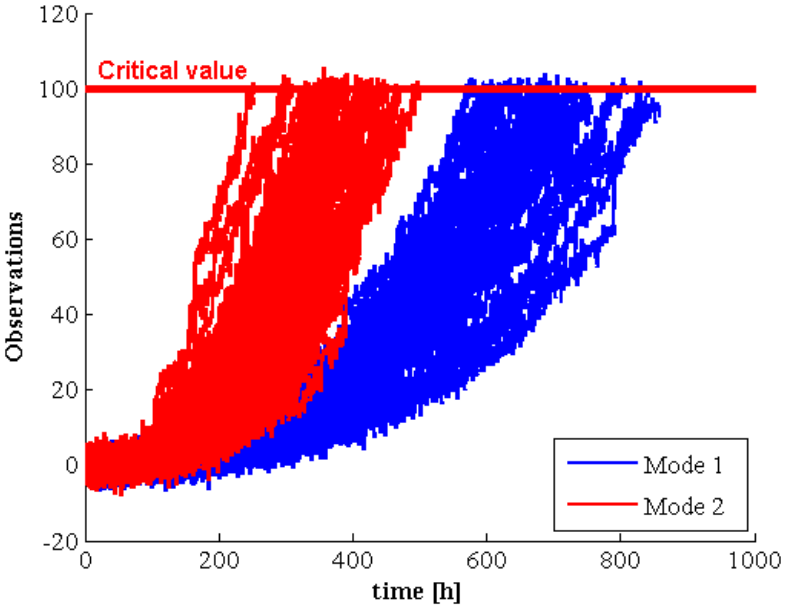
- Observation model: $y_{t_i} = x_{t_i} + \xi_{t_i}$

- Multi-mode: Two propagation rates
  - Crack depth is proportional with γ_e

$$\gamma_e = [0 \;\; 0.75]^T$$

$$C = 0.005, \quad n = 1.3, \quad \sigma_w = 1.7$$

$$\sigma_\xi^2 = 10, \; L = 100, \quad \pi_1 = \pi_2 = 0.5$$



Two-mode training data

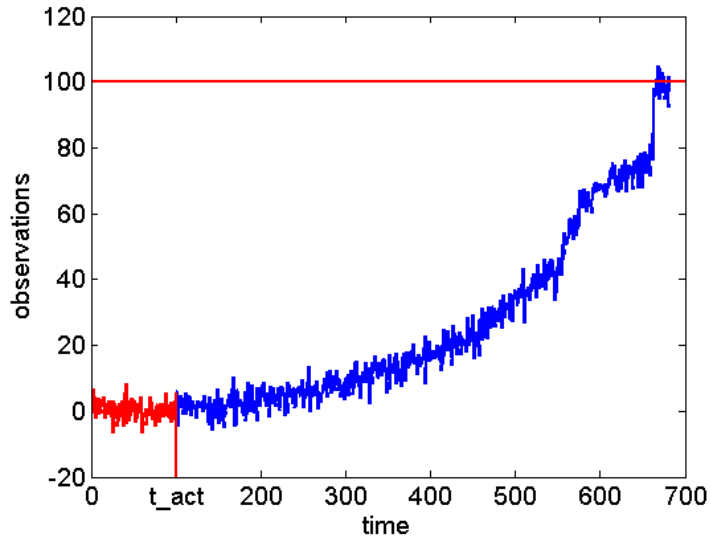
Numerical examples

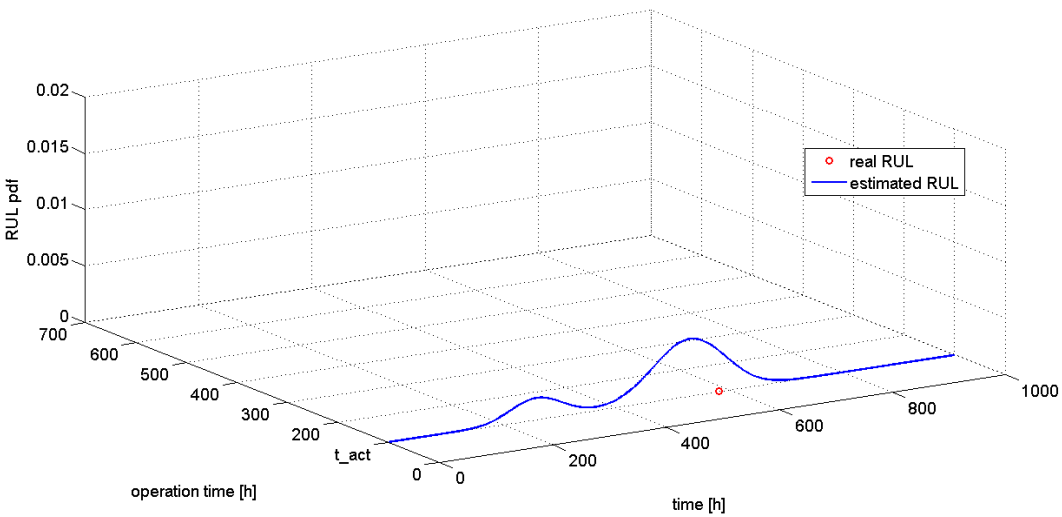
Test data

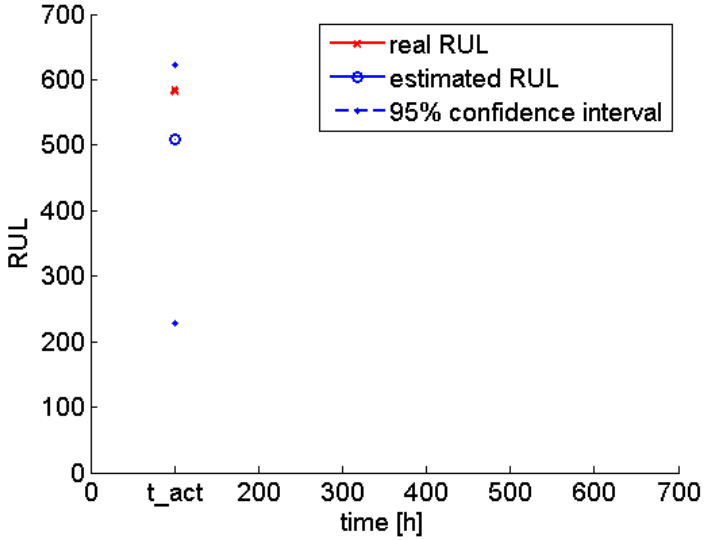
- Failure time: $T_f = 682h$

RUL estimation

- Online RUL estimation
  - Time replacement: 50h



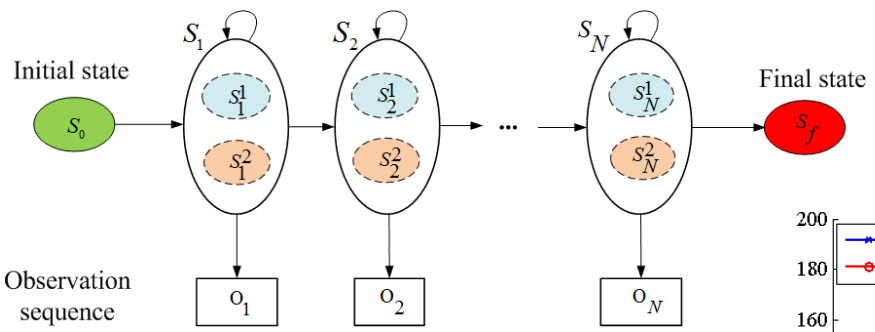




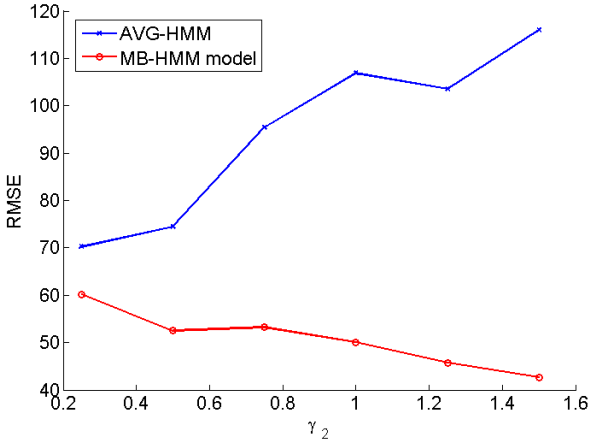
Numerical examples

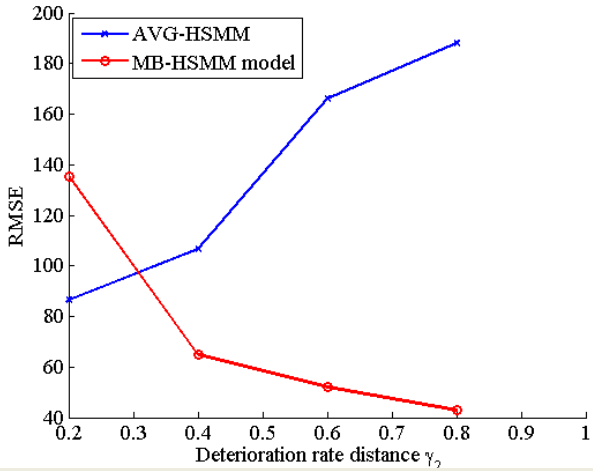
Multi-branch model vs. Average model

- Aims: Assess advantages of the proposed multi-branch models in case of multi-modes with different mode "distance"
- Mode "distance": proportional to γ_e
- Criterion: Root mean squared error (RMSE)



Average model





Case study:

PHM08 competition

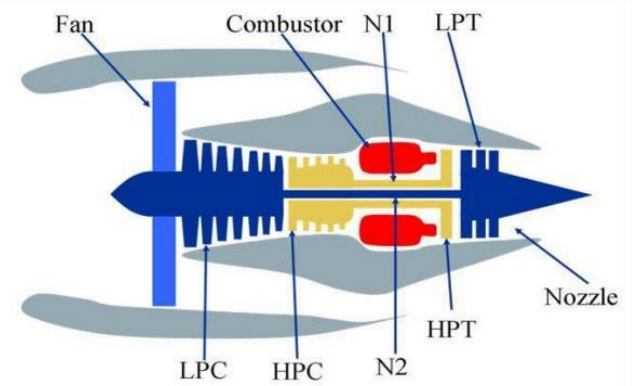
- C-MAPSS: Modeling a large realistic commercial turbofan engine
- 2 data set for training and test
- 218 identical and independent units
- Objective:
  - Construct a prognostic method basing on training data set
  - Use it to estimate the RUL of each unit in test data set
- Evaluation criterion:

$$S = \sum_{i=1}^{218} S_i$$

Where S_i is penalty score for unit *i*:

$$S_i = \begin{cases} e^{-d_i/13} - 1, & d_i \le 0 \\ e^{d_i/10} - 1, & d_i > 0 \end{cases} \quad \text{where } d_i = RUL_{est}^i - RUL_{real}^i$$

**C-MAPSS: Commercial Modular Aero-Propulsion System Simulation*



Simplified diagram of engine simulated in C-MAPSS

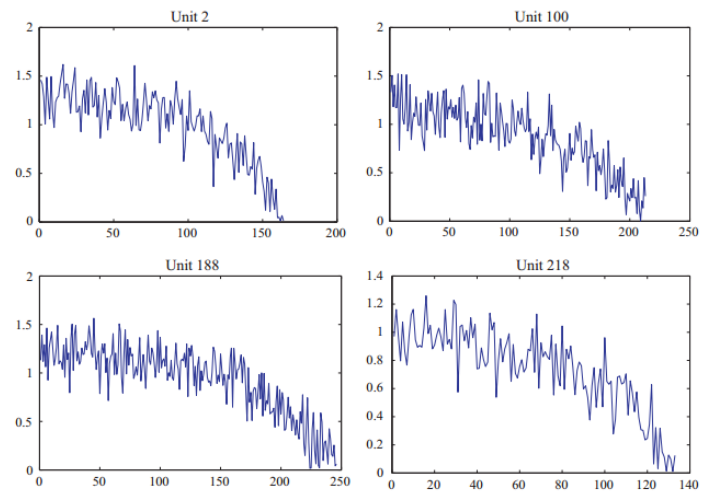
Case study *(cont.)*

Application of the MB-HsMM

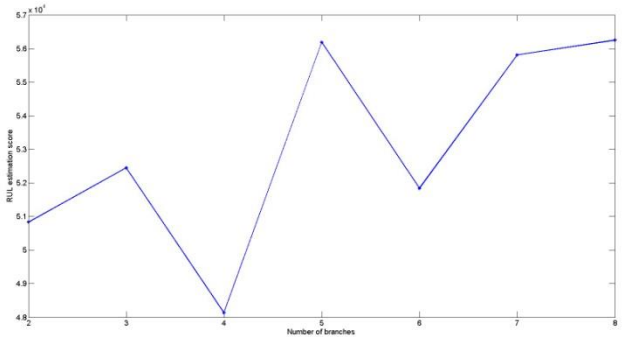
- Health indicator: From [Le Son *et al.* 2012]*
- Number of states determination
  - BIC criterion: N = 8 (fix M = 4)
- Number of branches determination:
  - K-fold cross validation with K = 10, N =8

  => M_opt = 4
- RUL estimation result

Method	Score	RSE	MSE
1-branch HsMM	12246	502	1157
2-branch HsMM	6456	451	936
3-branch HsMM	**5028**	**398**	**726**
4-branch HsMM	**4056**	**386**	**684**
Method in Le Son et al. (2012a)	5575	423	823
Method in Le Son et al. (2012b)	4107	434	864



Health indicator of some components



Cross-validation result

*Remaining useful life estimation based on stochastic deterioration models: A comparative study. *Reliability Engineering & System Safety 2012*

Conclusion & Perspectives

Conclusion

- Proposition of Multi-branch multi-state model to deal with:
  - Co-existing deterioration mechanisms
- Proposition of an multi-branch based framework for diagnosis & prognosis
  - Detection of actual deterioration mode
  - Assessment of current health status
  - Estimation of the RUL
- Evaluate the efficiency of the proposed models through numerical studies

Perspectives

- Development of multi-branch model for continuous states case
- Allowing transitions between different modes

Thank you for your attention!

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