Contribution to deterioration modeling and remaining useful life estimation based on condition monitoring data

PhD defense

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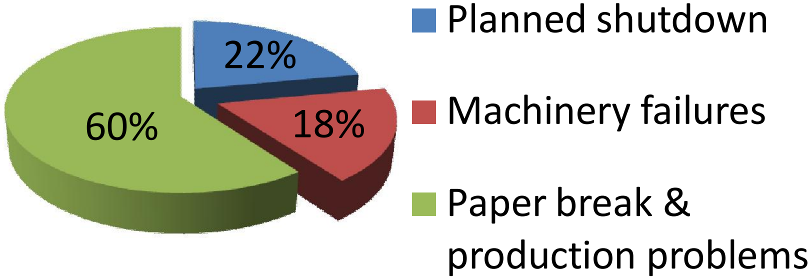
Industrial context

Continuous production systems

- Complex
- Continuity is a critical issue
- Can fail because of a defective componen
- Components deteriorate over time

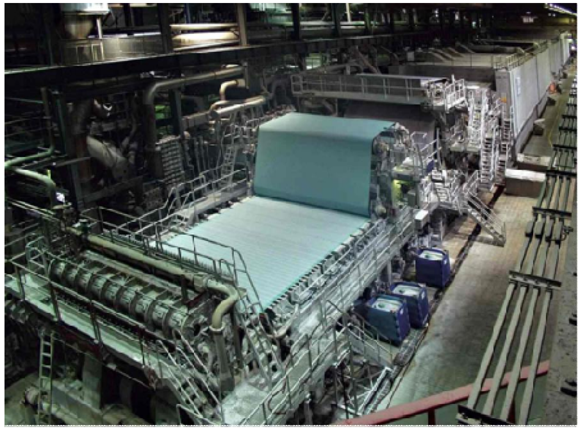
⇒ **Need of advanced maintenance programs**

Paper machine down time



Lost ~ **34 m€/year**

Critical components



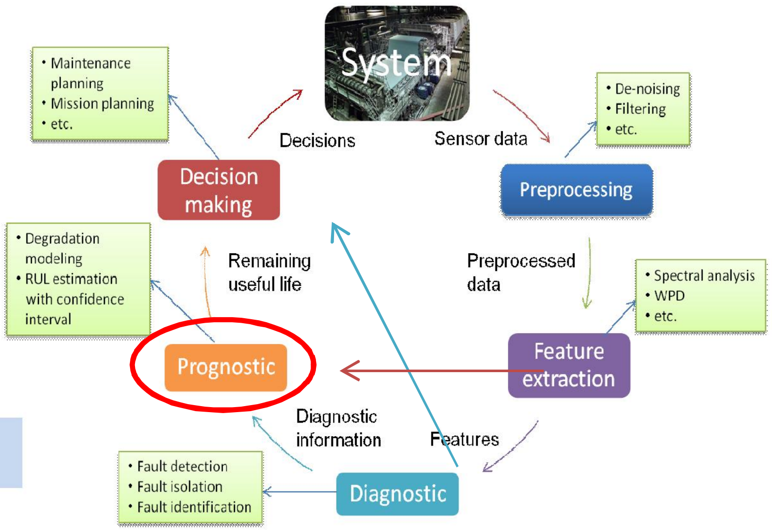
A paper machine

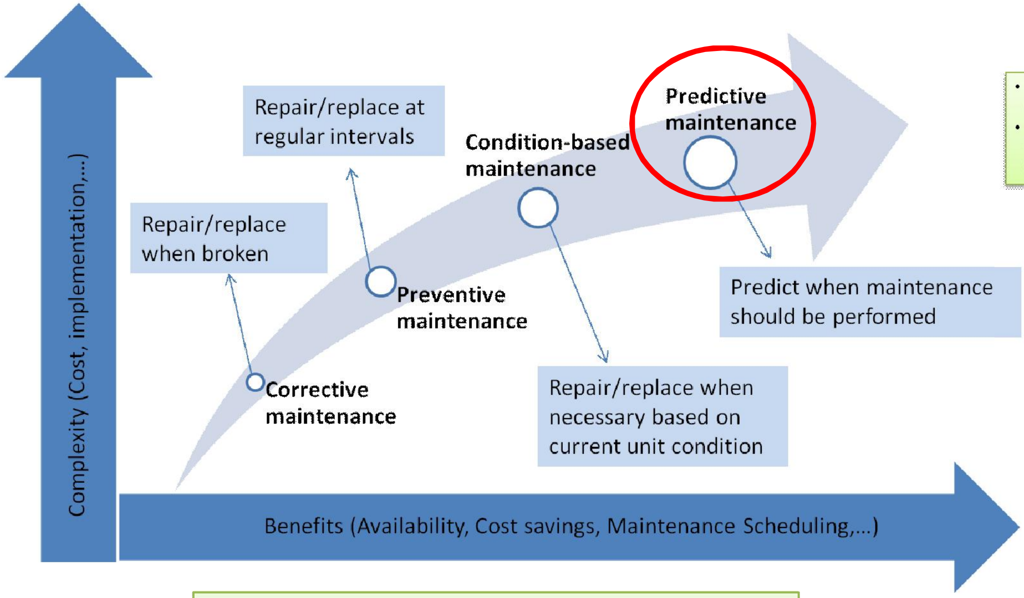
Predictive maintenance

Prognostics

➢ Anticipate the failure

Predictive maintenance program





Industrial maintenance methods

SUPREME project

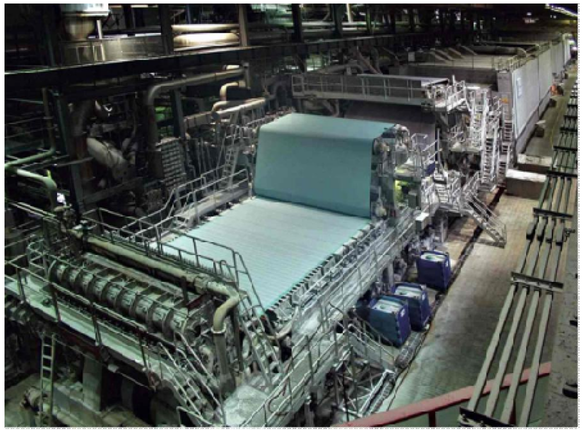
FP7 european project

- "SUstainable PREdictive Maintenance for manufacturing Equipment"
- 10 partners from both industry and academy
- **Purpose**: Development of new tools for predictive maintenance to improve productivity, reduce machine downtimes and increase energy efficiency.

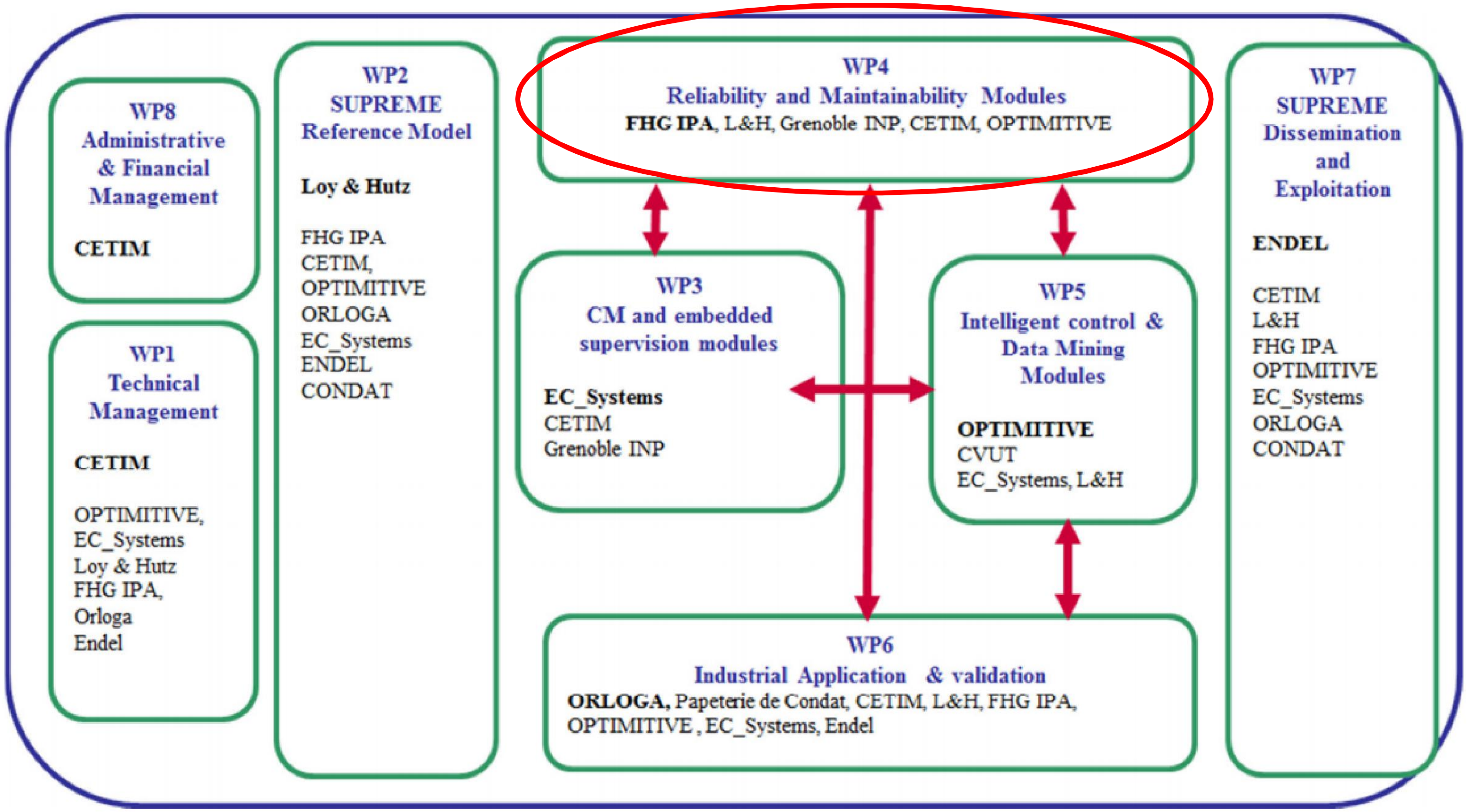
⇒ Application case: Paper machine

This project has received funding from the European Community's Seventh Framework Programme (FP7-2012-NMP-ICT-FoF) under grant agreement no 314311

SUPREME partners



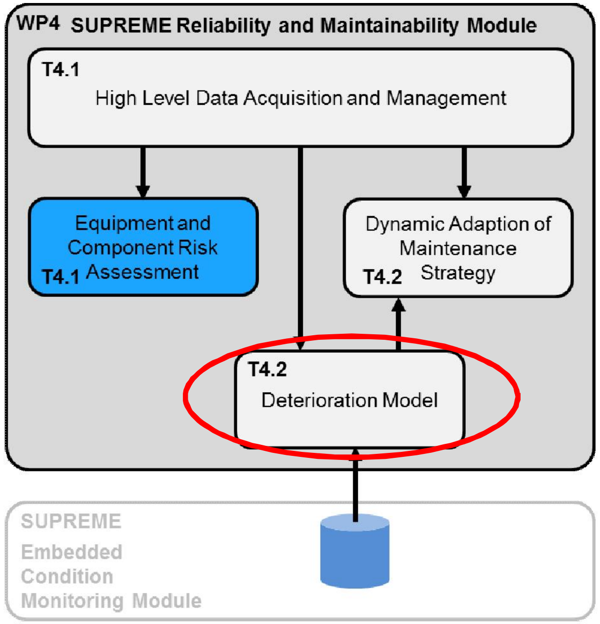
SUPREME work plan



Reliability and maintainability module

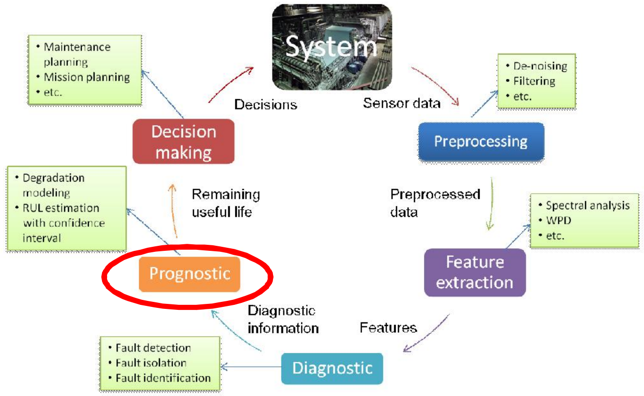
Four sub-modules

- Systematic critical component identification based on risk assessment
- Deterioration-based reliability
- Dynamic adaption of maintenance strategy



Objectives of the thesis

- ✓ **Deterioration modeling**
- ✓ **Remaining Useful Life (RUL) estimation**



Outline

- Problem statement
- Multi-branch discrete-state models
- Jump Markov linear systems
- Conclusion & Perspectives

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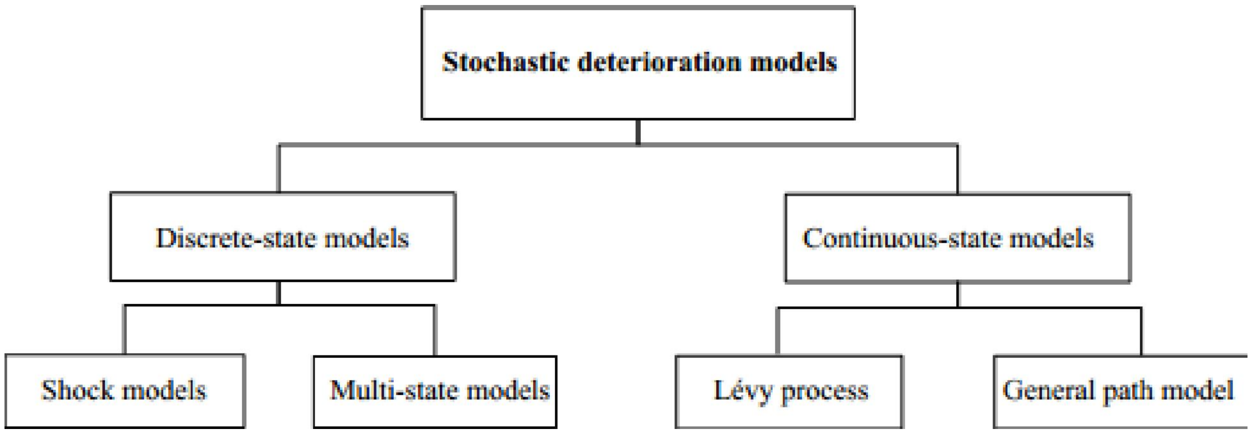
Deterioration modeling

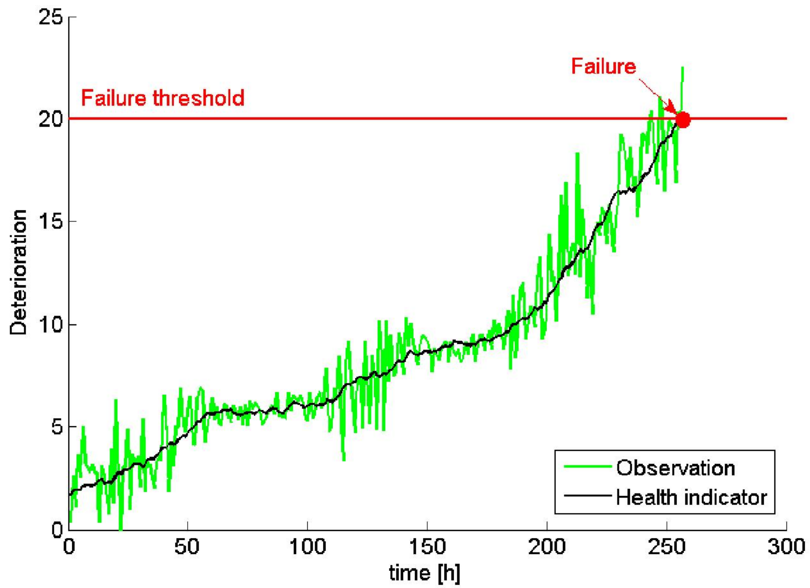
- Model the dynamic stochastic behavior of the deterioration
- Link the failure of an item to its deterioration level
- Allow health state assessment
- Basis for RUL prediction

Classification



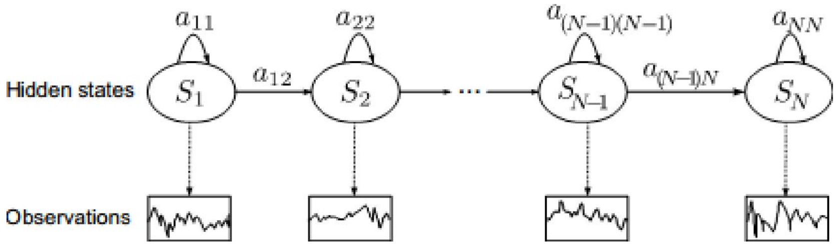
Continuous-state modeling

- Health states are continuous
- Continuous stochastic processes (Gamma, Wiener process,…)
- Stochastic filtering: Kalman, partical filters, etc.

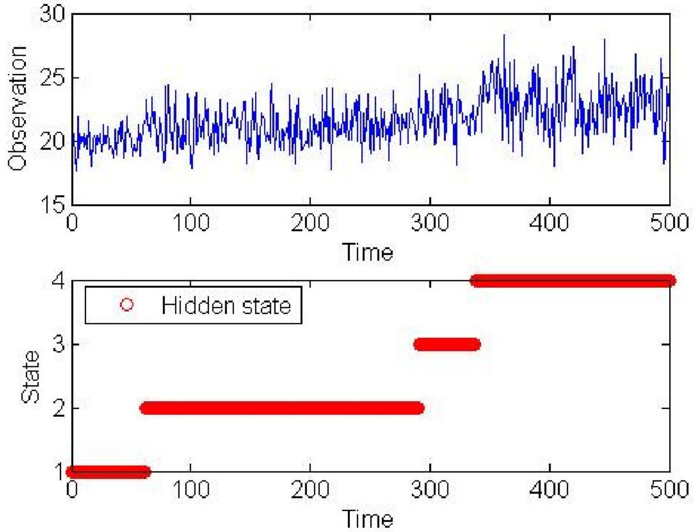


Discrete-state modeling

- Health states are discrete: normal, degraded level 1, degraded level 2, failure
- Power tools: Markov-based models
  - Hidden Markov Model (HMM)
  - Hidden semi-Markov Model (HsMM)



An HMM example



Remaining Useful Life (RUL)

- Residual time for accomplishing required functions
- Conditional random variable:

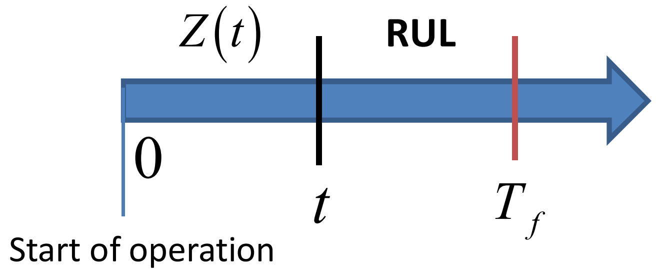
$$RUL = T_f - t \left| T_f > t, Z(t) \right.$$

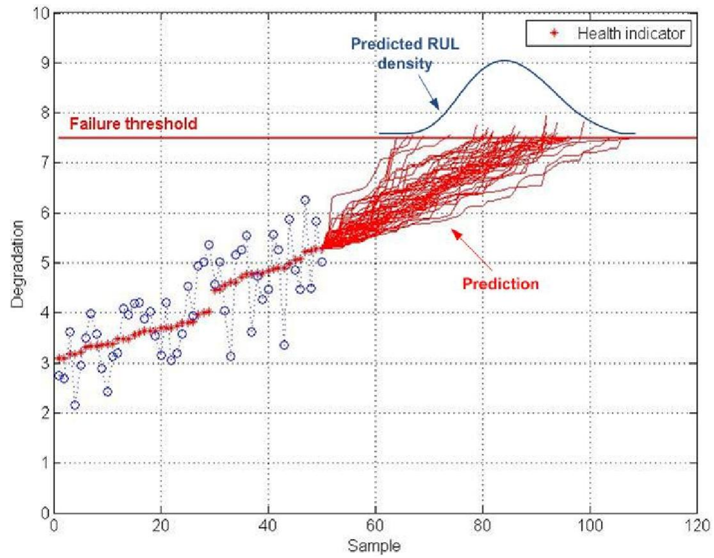
Z(t): information up to time *t* ;

T_f : time to failure

- Uncertainties assessment

=> characterized by probabilistic distributions

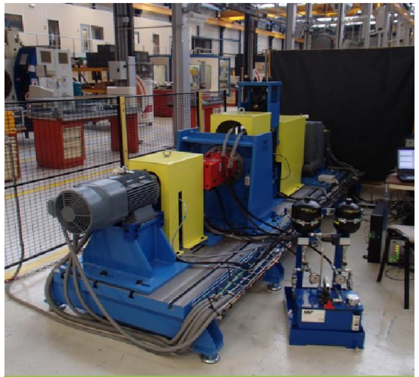




RUL = time to reach critical level

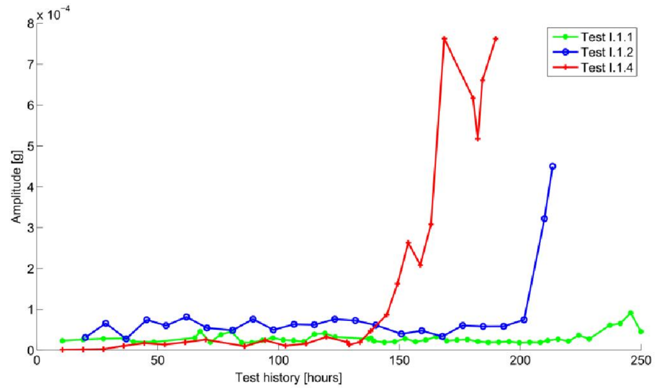
Problems

- CM data may not represent directly deterioration states
  - State-space representation
$$\begin{cases} x_t = f(x_{t-1}, \omega_t) & \text{: Hidden states} \\ y_t = g(x_t, v_t) & \text{: Observations} \end{cases}$$
- Multiple modes co-existence
  - Deterioration rates depend on initiation time
  - Deterioration behavior depend on applied loads



Test bench at CETIM

$\Rightarrow$ Proposed solution: Multi-branch modeling
  - Discrete-state: Multi-branch Hidden Markov models
  - Continuous-state: switching state space model



Bearing health index evolution

Outline

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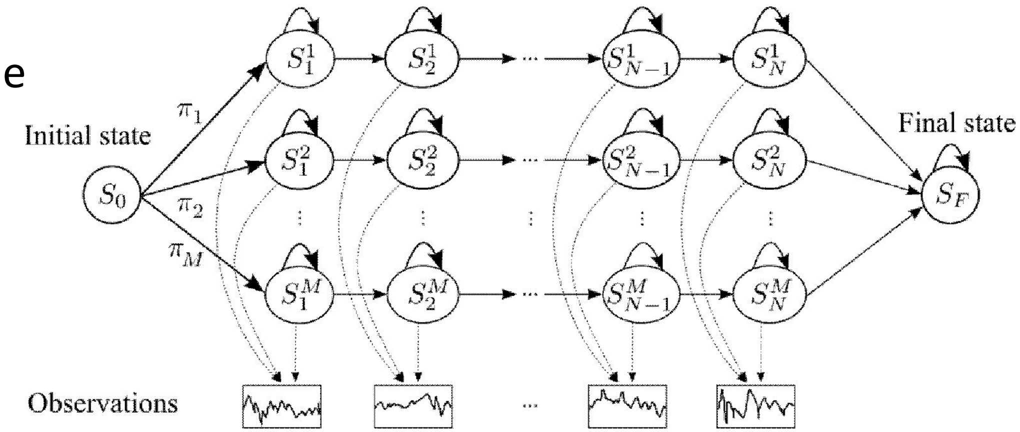
Multi-branch discrete-state modeling

Model construction

- Discrete states => Based on Markov models
- M deterioration modes => M branche
- Two common states:
  - Initial: normal condition
  - Final: failure state



Assumptions

- Monotonic deterioration: left-right topology
- Initial and final states: non-emitting states
- Exclusive deterioration modes once initiated => No branches switching

Multi-branch discrete-state modeling

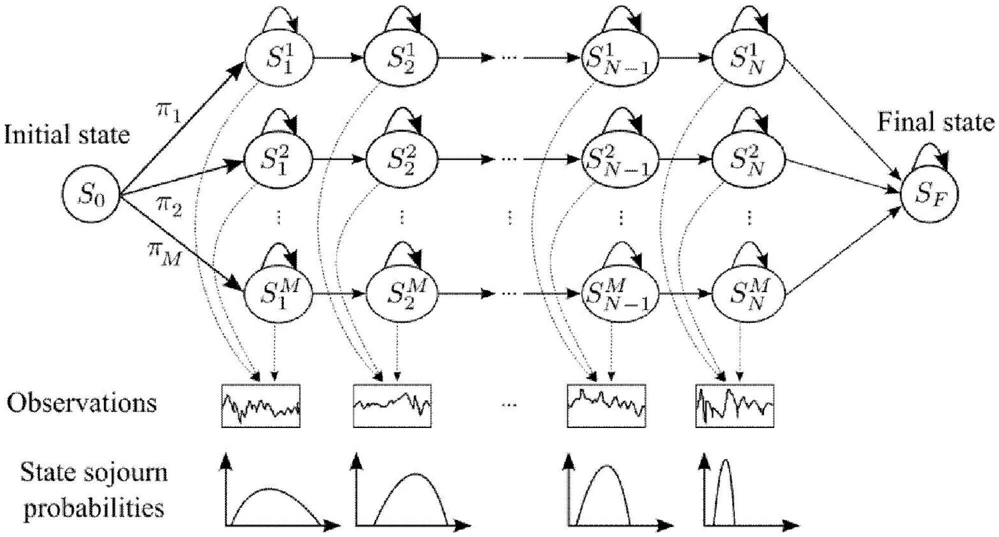
Multi-branch Hidden Markov Model

- Each branch ~ left-right HMM
- Markovian property

=> state sojourn time ~ exponential

or geometrical distributions

⇒ May not be true in practice



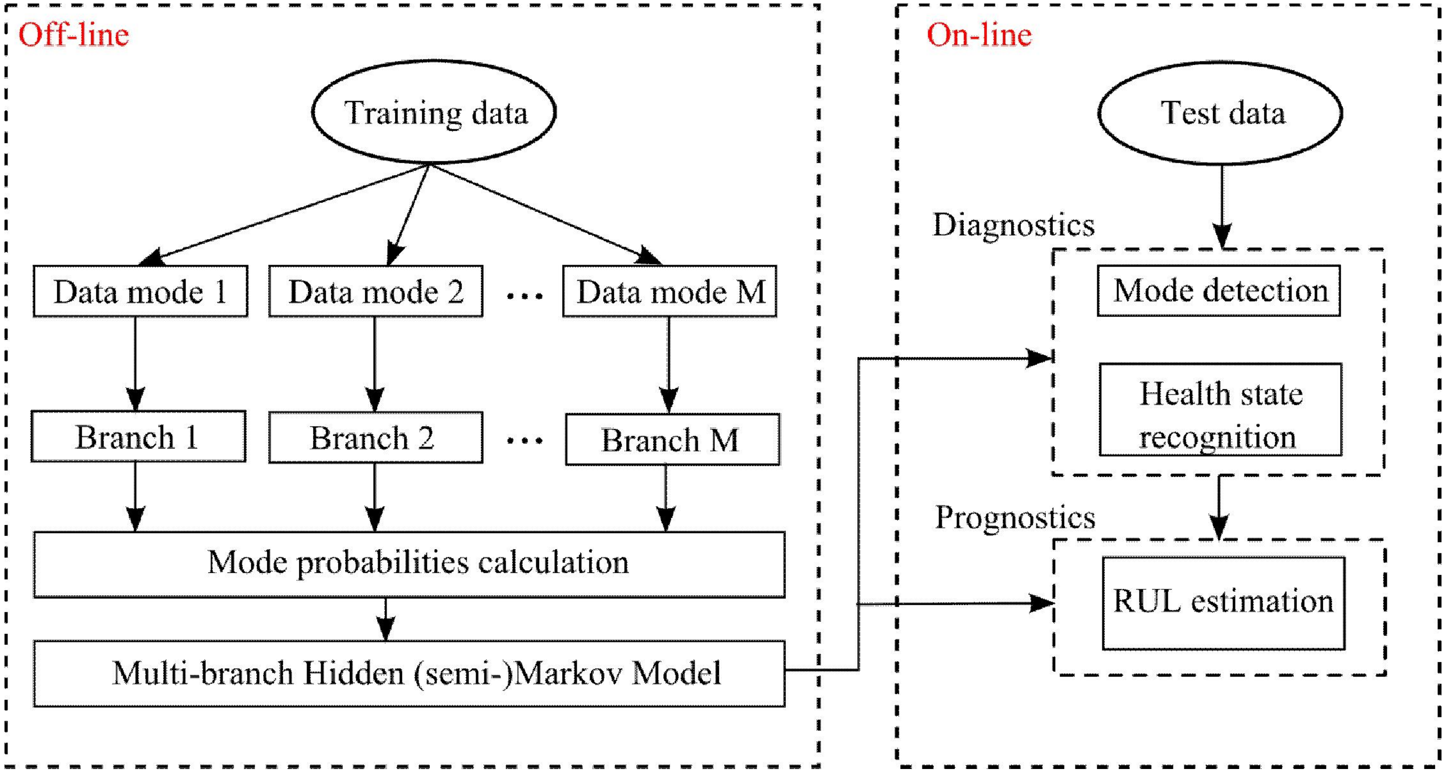
Multi-branch Hidden semi-Markov Model

- Each branch ~ left-right HsMM
- Semi-Markov property: relax the Markovian assumption

=> allow arbitrary distributions for state sojourn time: Gaussian, Weibull, …

Diagnostics and prognostics framework

Two-phase implementation: offline & online



Off-line phase

Model training

- Training data: high-level features
- Data classification => train each branch separately
  - MB-HMM: Baum-Welch algorithm adaption
  - MB-HsMM: Forward-Backward procedure adaption [Yu06]
- *A priori* mode probabilities

$$\pi_k = P(\lambda_k) = K_k / K \ , \quad k = 1 \dots M$$

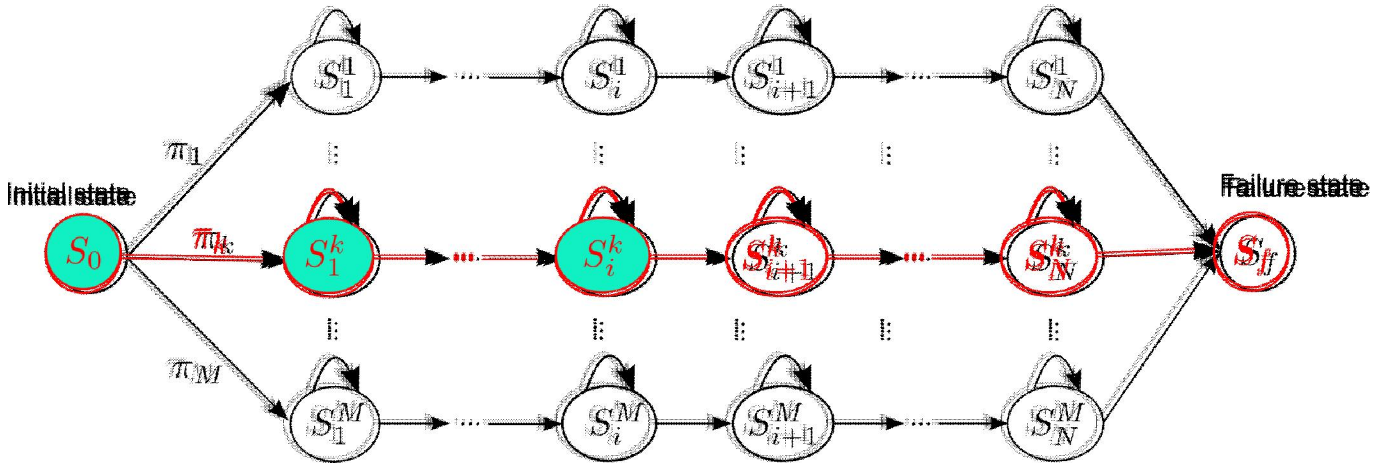
K_k : number of training sequences corresponding to the mode k

*[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

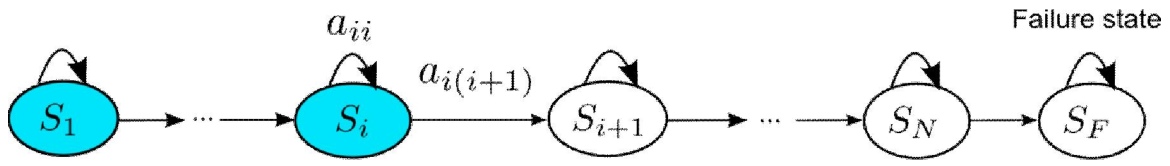
Diagnostics

- Mode detection: $\hat{k} = \arg\max_{k} P(\lambda_k \mid \mathbf{O})$
- Health-state assessment: Viterbi algorithm
  - Determine the "best" state sequence: $Q^* = \arg\max_{Q_{\hat{k}}} P(\mathbf{O}, Q_{\hat{k}} \mid \lambda_{\hat{k}})$
  - Actual health state = last state in Q^*



RUL estimation

One branch (HMM case)



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

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

- Strictly left-right: Given S_i, the system can either stay in S_i or jump to S_{i+1}

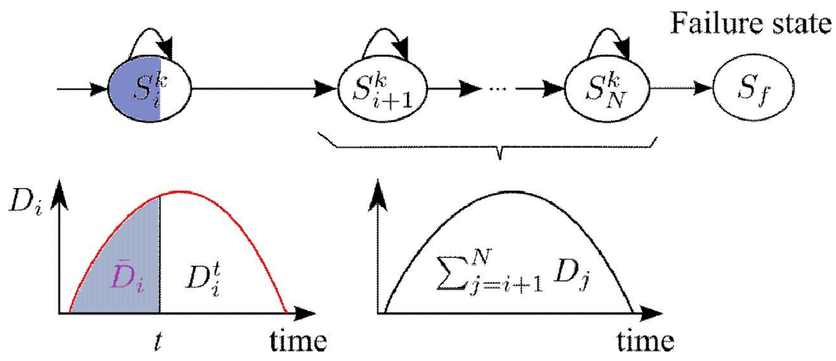
$$RUL_i^{(l)} = a_{ii} RUL_i^{(l-1)} + a_{i(i+1)} RUL_{i+1}^{(l-1)}$$

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

RUL estimation *(cont.)*

One branch (HsMM case)

- Strictly left-right:



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

D_j: sojourn time in states *j*

$D_i^t = D_i - \bar{D}_i \mid D_i > \bar{D}_i$ ~ truncated distribution

- Gaussian assumption: $\sum_{j=i+1}^{N} D_j$ ~ Normal distribution

Bayesian Model Averaging

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

where $P(\lambda_k \mid \mathbf{O}) = \dfrac{P(\mathbf{O} \mid \lambda_k) P(\lambda_k)}{\sum_{k=1}^{M} P(\mathbf{O} \mid \lambda_k) P(\lambda_k)}$

RUL estimation *(cont.)*

Bayesian Model Averaging

- Take into account model uncertainty

$$P(\text{RUL} \mid \mathbf{O}) = \sum_{k=1}^{M} P(\text{RUL} \mid \lambda_k, \mathbf{O}) P(\lambda_k \mid \mathbf{O})$$

where $P(\lambda_k \mid \mathbf{O}) = \dfrac{P(\mathbf{O} \mid \lambda_k) P(\lambda_k)}{\sum_{k=1}^{M} P(\mathbf{O} \mid \lambda_k) P(\lambda_k)}$: Posteriori mode probability

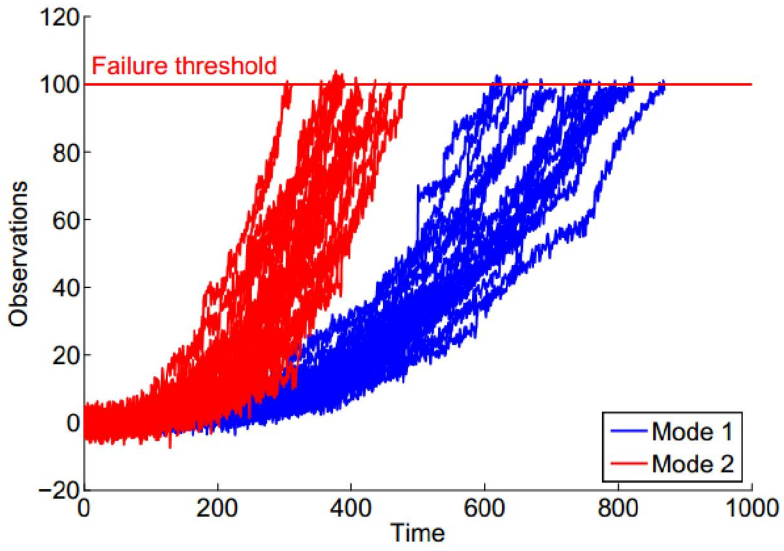
Numerical examples

Data generation

- Fatigue Crack Growth (FCG) model: temporal evolution of a crack
- Stochastic version: $x_{t_i} = x_{t_{i-1}} + e^{w_{t_i}} C\left(\beta\sqrt{x_{t_{i-1}}}\right)^n \Delta t$
- Observation model: $y_{t_i} = x_{t_i} + \xi_{t_i}$
- Multi modes: $\beta(\varepsilon) = \beta_b \cdot e^{\gamma_\varepsilon}$

  γ_ε : environment factor

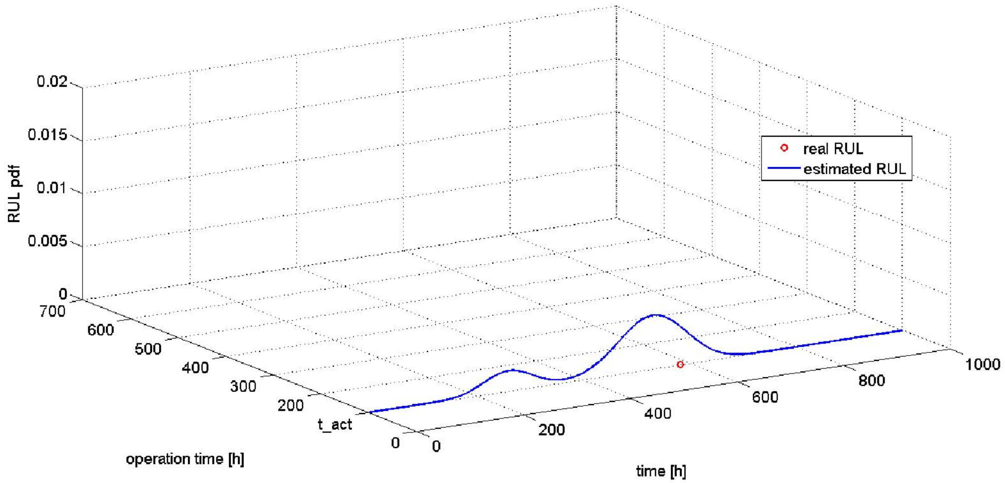
  - Mode 1: $\gamma_1 = 0$ (slow)
  - Mode 2: $\gamma_2 = 0.75$ (quick)



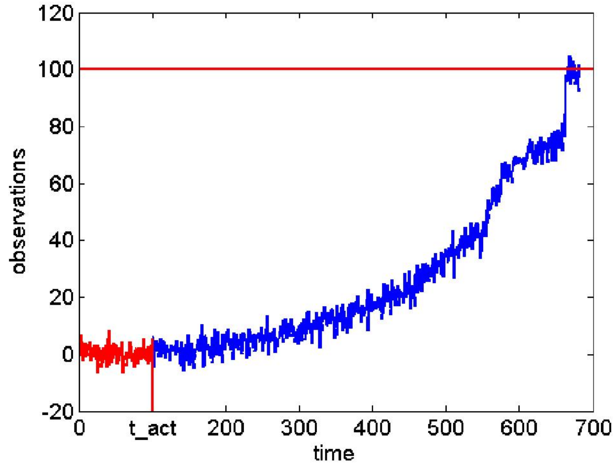
Two-mode deterioration data

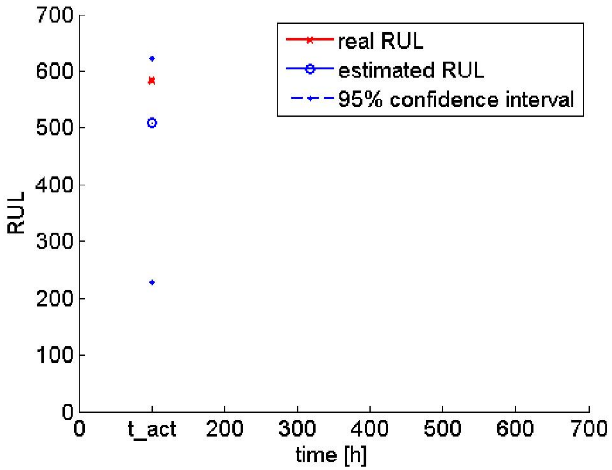
Numerical examples

Online RUL estimation (MB-HsMM model)



RUL pdf



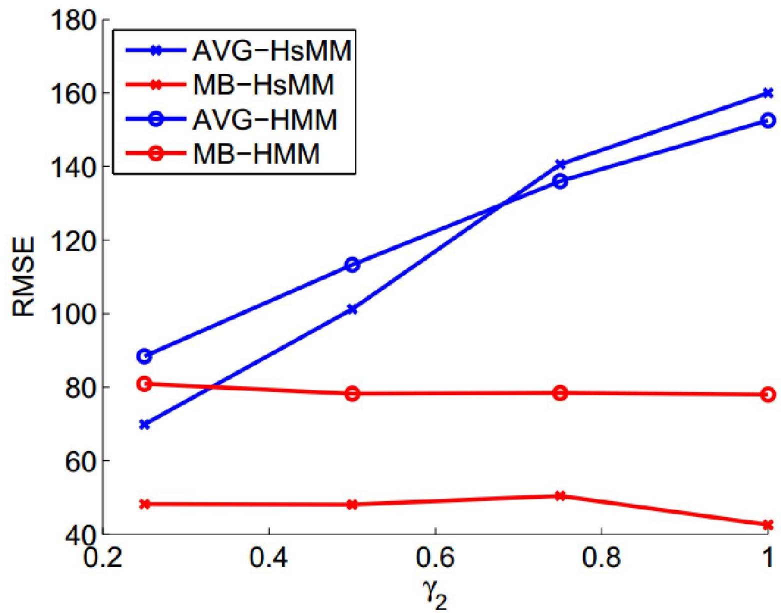


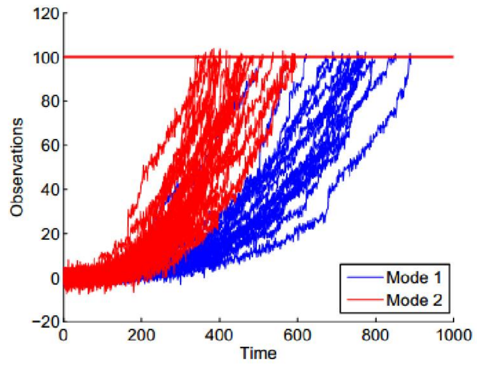
Mean value

Numerical examples

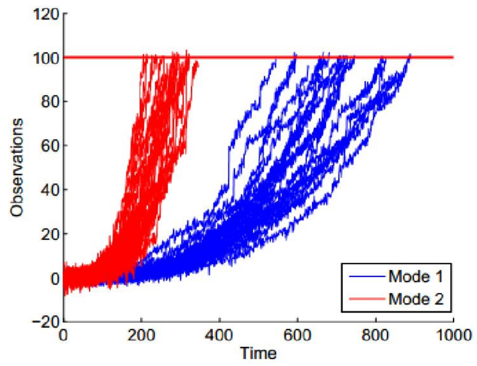
Multi-branch vs. Average model

- Mode "distance": difference between deterioration rates
- FCG case: mode distance ~ γ_2 (fix $\gamma_1 = 0$)
- Result





Small distance $\gamma_2 = 0.4$



Large distance $\gamma_2 = 0.8$

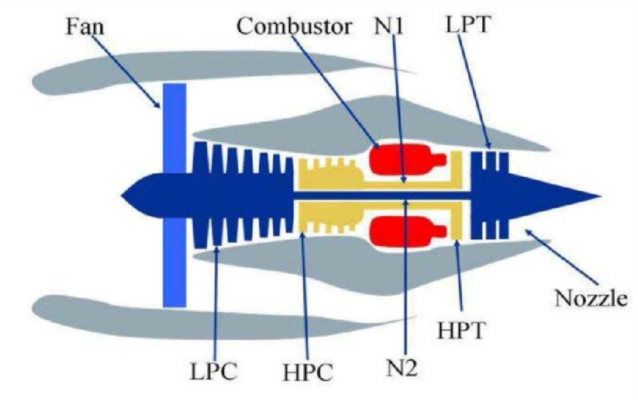
Case study (MB-HsMM model)

PHM08 competition

- C-MAPSS: large realistic commercial turbofan engine
- 2 data set: training & test
- One set: 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: $S = \sum_{i=1}^{218} S_i$

$$S_i = \begin{cases} e^{-d_i/13} - 1, & d_i \le 0 \\ e^{d_i/10} - 1, & d_i > 0 \end{cases}$$: penalty score

$$d_i = RUL_{est}^i - RUL_{real}^i$$



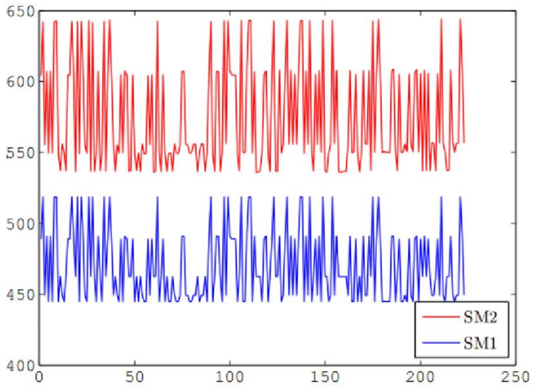
Simplified diagram of engine simulated in C-MAPSS

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

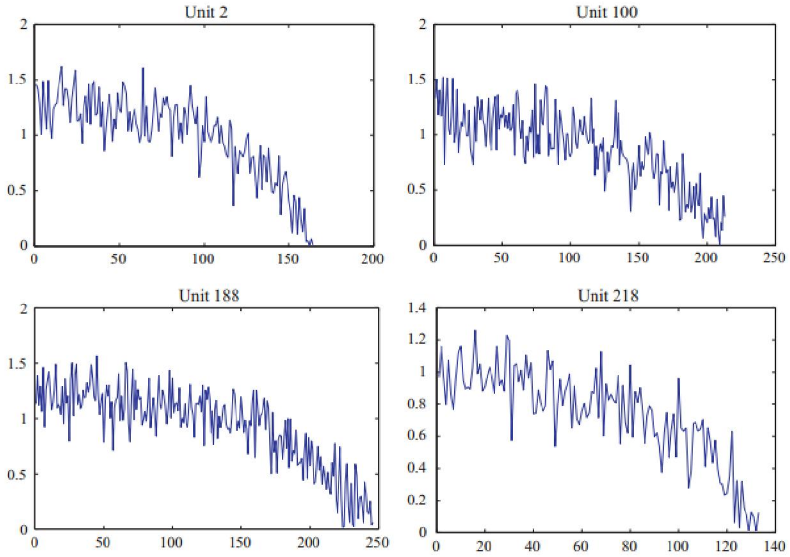
PHM08 data

Health indicator construction

- From [Le Son *et al.*]*



PCA-based



Health indicator evolution

- Clear tendency
- Better score than competition winners

* [Le Son *et al.*] Remaining useful life estimation based on stochastic deterioration models: A comparative study. *Reliability Engineering & System Safety 2012*

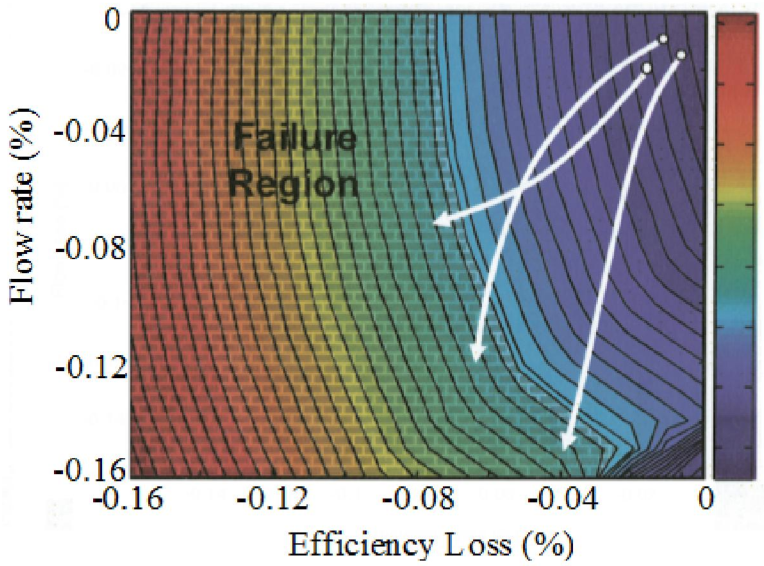
Application of the MB-HsMM model

Number of deterioration modes

- Different fault propagation trajectories depending on the decrease rates of the flow rate (f) and efficiency (e) parameters

- 3 scenarios

	2 modes	3 modes	4 modes
Mode 1	f < e	f < e	f << e
Mode 2	f > e	f ≈ e	f < e
Mode 3		f > e	f > e
Mode 4			f >> e
No branches	2	3	4



Fault propagation trajectories

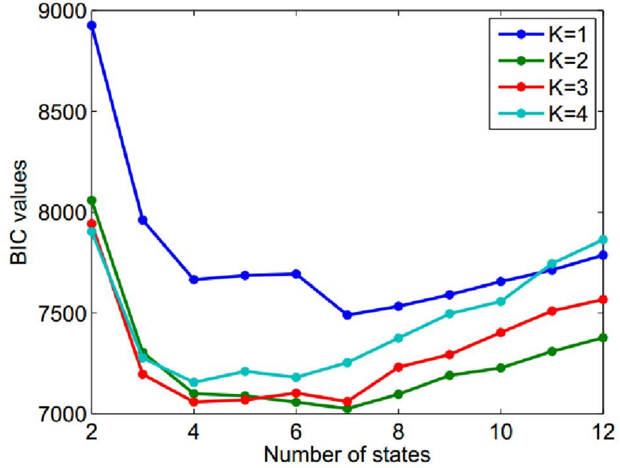
Application of the MB-HsMM model

Observations: mixture Gaussian model

$$b_j(\mathbf{x}) = \sum_{k=1}^{K} c_{jk} \mathcal{N}\left(\mathbf{x}; \mu_{jk}, \Sigma_{jk}\right)$$

Topology selection

- BIC criterion: N = 7; K = 2



BIC values

RUL estimation result

Method	Score	RSE	MSE
1-branch HsMM	12246	502	1157
2-branch HsMM	6456	451	936
3-branch HsMM	**5458**	**410**	**773**
4-branch HsMM	**3791**	**389**	**694**
Wiener-based method	5575	423	823
Gamma-based method	4107	434	864

Multi-branch discrete-state modeling

Summary

- Discrete health states => easy to interpret
- Multi-branch: take into account the co-existence of several deterioration modes
- Better RUL estimation performance
- No mode switching once initiated !

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Switching state-space model

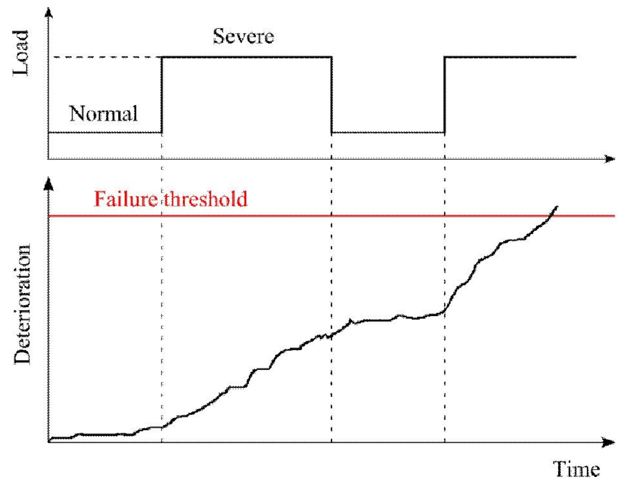
- State-space representation
- Load-dependent deterioration

=> Deterioration modes co-exist in competition

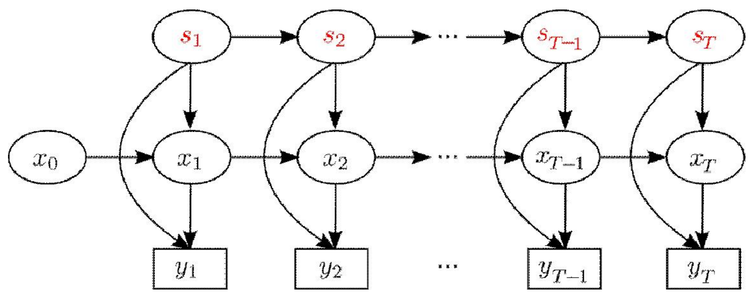
- Mode switching ~ Markov jumps

$$\begin{cases} x_t = f(x_{t-1}, \omega_t, s_t) \\ y_t = g(x_t, v_t, s_t) \end{cases}$$

s_t: realization at time t of discrete variable S



Load-dependent deterioration



Switching state-space model

Jump Markov Linear System

- Assumption: deterioration dynamic can be approximated by linear model

$$\begin{cases} x_t = A_{s_t} x_{t-1} + \omega_t \\ y_t = C_{s_t} x_t + v_t \end{cases} \qquad \begin{cases} \omega_t \sim \mathcal{N}\left(0, Q_{s_t}\right) \\ v_t \sim \mathcal{N}\left(0, R_{s_t}\right) \end{cases}$$

- M deterioration modes $s_t \in \{1, 2, \ldots, M\}$
- Mode transition ~ discrete-time Markov chain
  - Transition matrix: $$\Pi = \begin{pmatrix} \pi_{11} & \pi_{12} & \cdots & \pi_{1M} \\ \pi_{21} & \pi_{22} & \cdots & \pi_{2M} \\ \vdots & \vdots & \ddots & \vdots \\ \pi_{M1} & \pi_{M2} & \cdots & \pi_{MM} \end{pmatrix}$$
  - Initial state: $\pi_1(i) = P(s_1 = i)$
- Identifiability guarantee: C are fixed

Parameters learning problem

Model parameters

$$\Theta = \left\{ \left(A_i, Q_i, R_i \right)_{i=1,\ldots,M}, \mu_0, \Sigma_0, \Pi, \pi_1 \right\}$$

- X, S are hidden => Expectation-Maximization algorithm
  - E step: $\mathcal{Q}\left(\Theta \mid \Theta^{(k)}\right) = \mathbf{E}\left[\log \mathbb{P}\left(\mathcal{X}_T, \mathcal{S}_T, \mathcal{Y}_T \mid \Theta \right) \mid \mathcal{Y}_T, \Theta^{(k)} \right]$
  - M step: $\Theta^{(k+1)} = \arg\max_{\Theta} \mathcal{Q}\left(\Theta \mid \Theta^{(k)}\right)$

- Problem: Presence of switching dynamic

$$\mathcal{Q}\left(\Theta \mid \Theta^{(k)}\right) = \sum_{\mathcal{S}_T} \left(\mathbb{P}\left(\mathcal{S}_T \mid \mathcal{Y}_T, \Theta^{(k)} \right) \int p\left(\mathcal{X}_T \mid \mathcal{S}_T, \mathcal{Y}_T, \Theta^{(k)} \right) \log \mathbb{P}\left(\mathcal{X}_T, \mathcal{S}_T, \mathcal{Y}_T \mid \Theta \right) d\mathcal{X}_T \right)$$

- Computed over all possible sequences of discrete states $\mathcal{S}_T$ => Intractable

=> Approximated EM algorithm

Approximated EM algorithm

Pruning technique

- Idea: Calculate Q over the most "likely" state sequence

=> Adaption of the Viterbi algorithm

- Do not guarantee the convergence, but still sufficient in several practical cases

Approximated Q function

$$\mathcal{Q}\left(\Theta \mid \Theta^{(k)}\right) \approx \int p\left(\mathcal{X}_T \mid \mathcal{S}_T^*, \mathcal{Y}_T, \Theta^{(k)}\right) \log \mathbb{P}\left(\mathcal{X}_T, \mathcal{S}_T^*, \mathcal{Y}_T \mid \Theta\right) d\mathcal{X}_T$$

$\mathcal{S}_T^*$: the most likely state sequence

=> Calculated by Rauch-Tung-Streiber (RTS) smoother

JMLS based diagnostics

Mode probabilities

- Given test data until time t

$$\mu_t(i) = \mathbb{P}\left(s_t = i\right) = \frac{\mathbb{P}\left(\mathcal{S}^*_{t,i}\right)}{\sum_{i=1}^{M} \mathbb{P}\left(\mathcal{S}^*_{t,i}\right)} = \frac{1}{1 + \exp\left(\sum_{j \neq i} J_{t,j} - J_{t,i}\right)}$$

$\mathcal{S}^*_{t,i}$ the best state sequence at time t that ends in *i*

Health state assessment

- Mixture of mode-dependent states

$$\begin{cases} \hat{x}_t = \sum_{i=1}^{M} \mu_t(i) \hat{x}_{t,i} \\ \hat{\Sigma}_t = \sum_{i=1}^{M} \mu_i(t) \Sigma_{t,i} + \sum_{i=1}^{M} \mu_t(i) \left(\hat{x}_{t,i} - \hat{x}_t\right)\left(\hat{x}_{t,i} - \hat{x}_t\right)^T \end{cases}$$

RUL prediction

- Discrete time: $RUL = \left(\min k \geq 1 : x_{t+k} \geq L \mid x_t < L\right)$
- Mode switching: M fold increase in number of Gaussian distributions

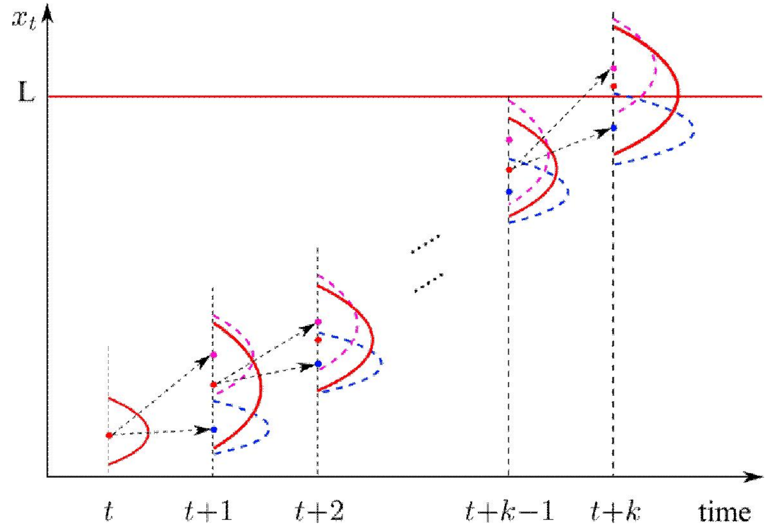
⇒ Intractable computation

⇒ Approximation: merge all one-step predicted Gaussian distributions into one

$$p\left(x_{t+1|t}\right) \approx \sum_{i=1}^{M} \mu_{t+1}(i) \mathcal{N}\left(x_{t+1|t,i}, \Sigma_{t+1|t,i}\right)$$

- Mode probability update

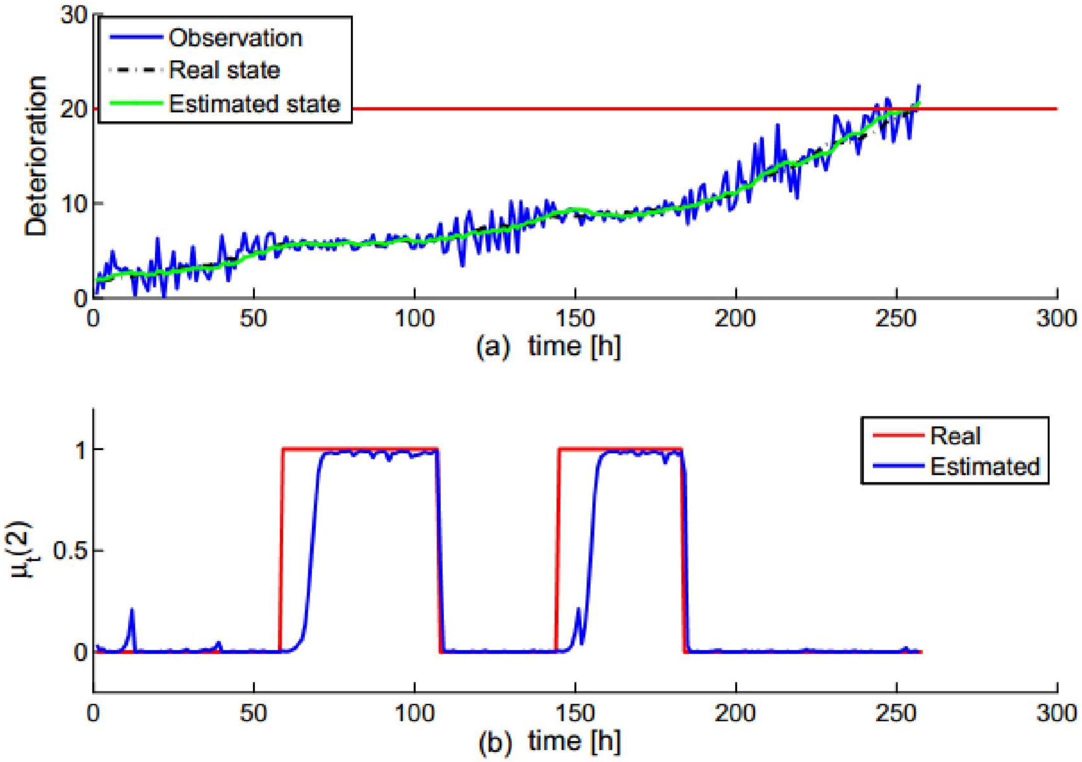
$$\mu_{t+1}(i) = \sum_{j=1}^{M} \pi_{j,i} \cdot \mu_t(j)$$



RUL prediction illustration for 2-mode case

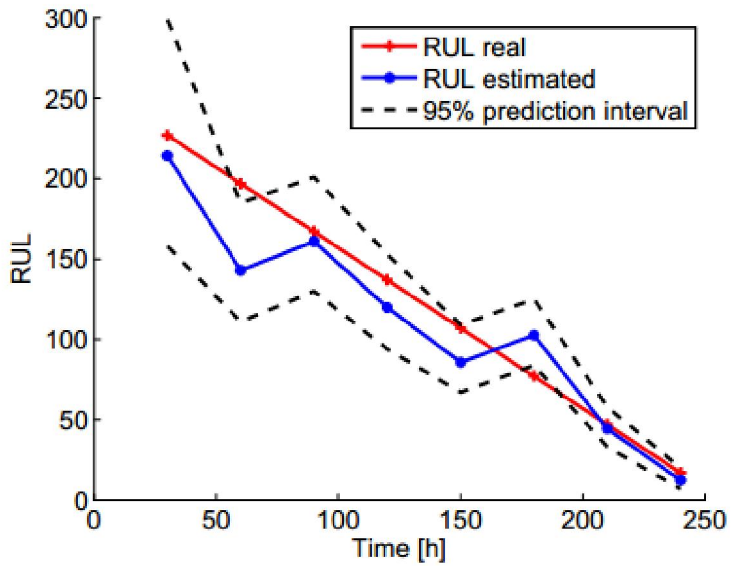
Diagnosis result

Mode detection and health assessment

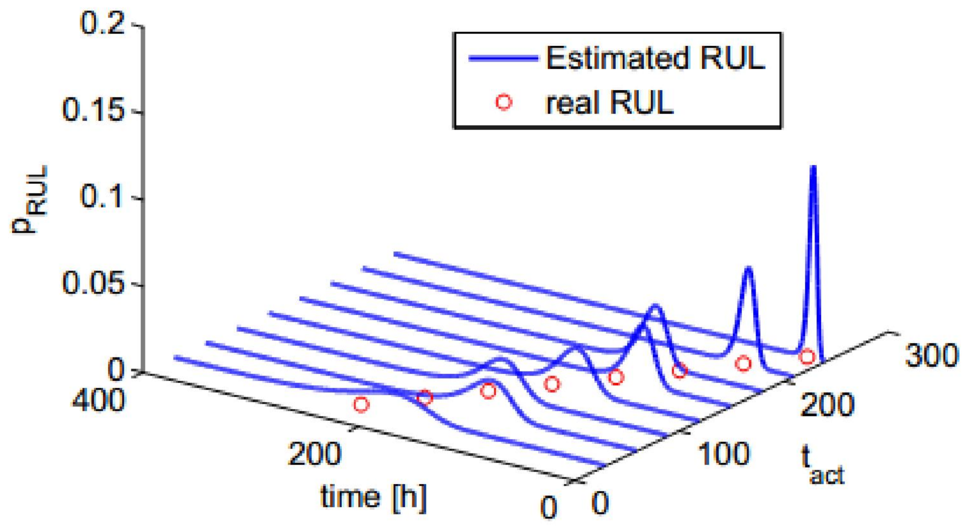


RUL estimation result

Online prediction



Mean estimated RUL at different times



Evolution of estimated RUL pdf

Outline

- Problem statement
- Multi-branch discrete-state models
- Jump Markov linear systems
- Conclusion & Perspectives

Conclusion & Perspectives

Conclusion

- Co-existence problem of multiple deterioration modes: multi-branch modeling
  - Discrete states: MB-HMM & MB-HsMM
  - Continuous states: JMLS
- Development of associated diagnostics & prognostics framework
  - Actual deterioration mode detection
  - Current health status assessment
  - RUL estimation

Conclusion & Perspectives

Perspectives

- MB-HMM & MB-HsMM models
  - Relax the left-right assumption
  - Allow mode switching
- JMLS model
  - Extension to non-linear models
  - Improvement of model learning methods
  - Semi-Markov mode transitions
- Dynamic adaptation of maintenance strategies based on RUL estimation results
- Models application with real-life data

Thank you for your attention!