Bayesian Identification of Hidden Markov Models with Application to Condition-Based Monitoring

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INTRODUCTION

Project Overview

Program Area: Condition Diagnostic and Prognostic

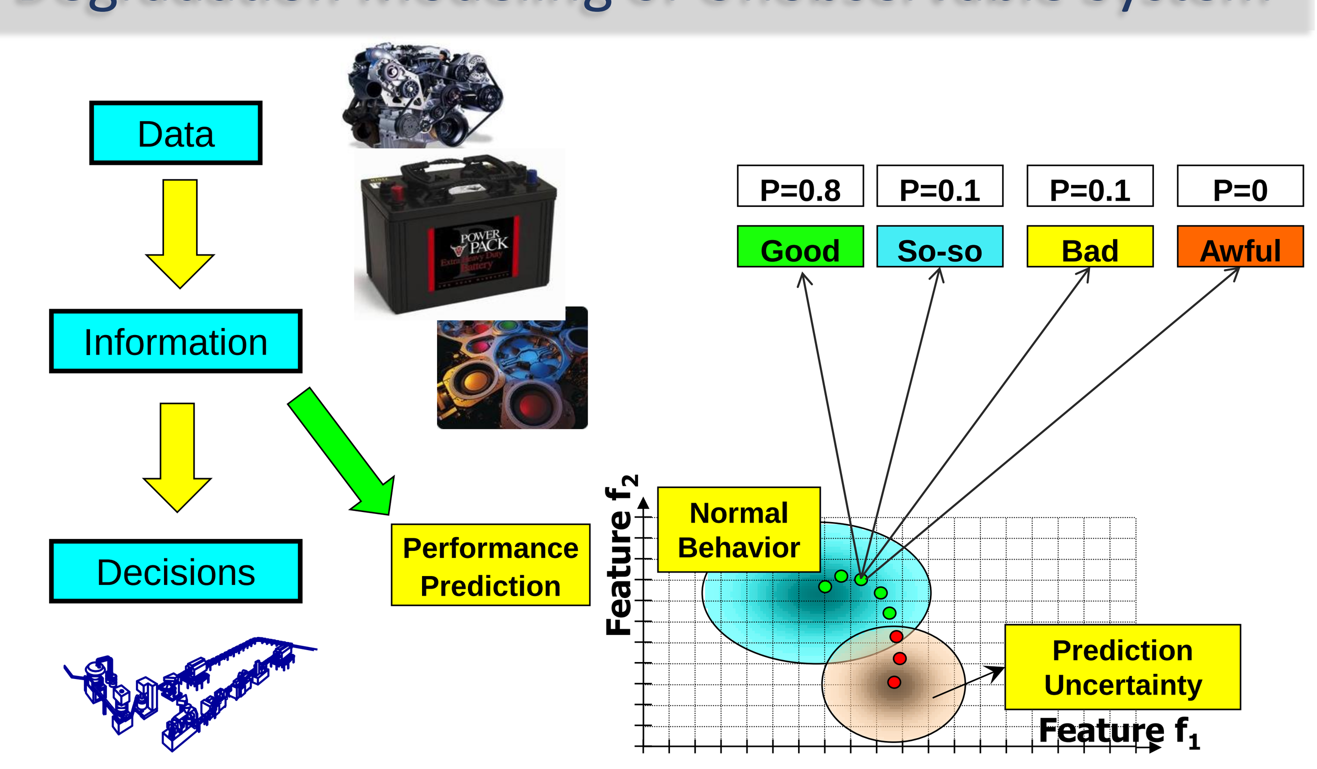
Objectives: Develop HMM-based generic condition monitoring methods that are aware of model uncertainty and applicable to partially observable processes.

Deliverables: HMM identification and monitoring code that works with features extracted from sensor signals collected from real manufacturing systems.

Expected Benefits of Project Deliverables

- **Powerful monitoring ability**: based on modeling of unobservable degradation process affected by imperfect maintenance operations. Model uncertainty addressed.
- **Wide and easy adaptability**: compatible with sensor signal of various types and frequencies requiring minor/moderate configuration for the user.
- **Cost-effective data usage:** use ONLY online process data. No dependency on external information resource.
- **Superior diagnostic performance**: 10% ~ 20% better than PCA to detect known machine abnormality , validated on semiconductor manufacturing process.

Degradation Modeling of Unobservable System



METHODOLOGY

Hidden Markov Model

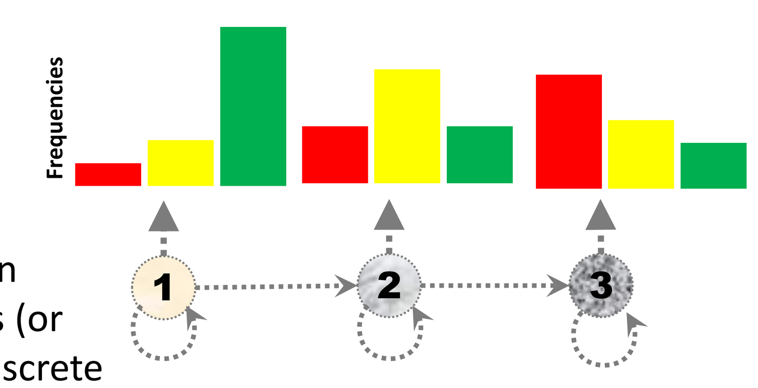
Definition: A **hidden Markov model** is a doubly embedded stochastic process $\{(X_t, Y_t)\}_{t=0}^{\infty}$ that satisfies the Markov property in X_t and parameterized by

$$\boldsymbol{\theta} = (\boldsymbol{\nu}, \boldsymbol{P}, \boldsymbol{\phi})$$

Initial distribution

Transition probability matrix

Observation parameters (or matrix in discrete case)



Bayesian Estimation for HMM Parameters

Prior + Data = Post-erior

$$\frac{\Pr(Model)\Pr(Data|Model)}{\Pr(Data)} = \Pr(Model|Data)$$

Risk Minimization Formulation

$$\widehat{\boldsymbol{\theta}} := \underset{\boldsymbol{\theta}=(\boldsymbol{\nu},\boldsymbol{P},\boldsymbol{\phi})}{\operatorname{argmin}} \int_{\Theta} L(\boldsymbol{\theta}, \boldsymbol{\theta}_0) \Pr(\boldsymbol{\theta}_0|\boldsymbol{y}_T)\, d\boldsymbol{\theta}_0$$

$$\text{s.t. } \textstyle\sum_{i=1}^{m} \nu_i = 1, \nu_i \geq 0, \forall i$$

$$\textstyle\sum_{j=1}^{m} p_{ij} = 1, \forall i, p_{ij} \geq 0, \forall i, j,$$

$$\boldsymbol{\phi} \in \Phi.$$

Theoretical solution: *posterior mean*

$$\widehat{\boldsymbol{\theta}} = E(\boldsymbol{\theta}_0|\boldsymbol{y}_T) = \int_{\Omega} \boldsymbol{\theta}_0 \Pr(\boldsymbol{\theta}_0|\boldsymbol{y}_T)\, d\boldsymbol{\theta}_0$$

It can be proved the $\widehat{\boldsymbol{\theta}}$ is the solution to the above problem under Dirichlet prior of $p_{i\cdot}, \forall i$, when no constraints applied on $\boldsymbol{\phi}$.

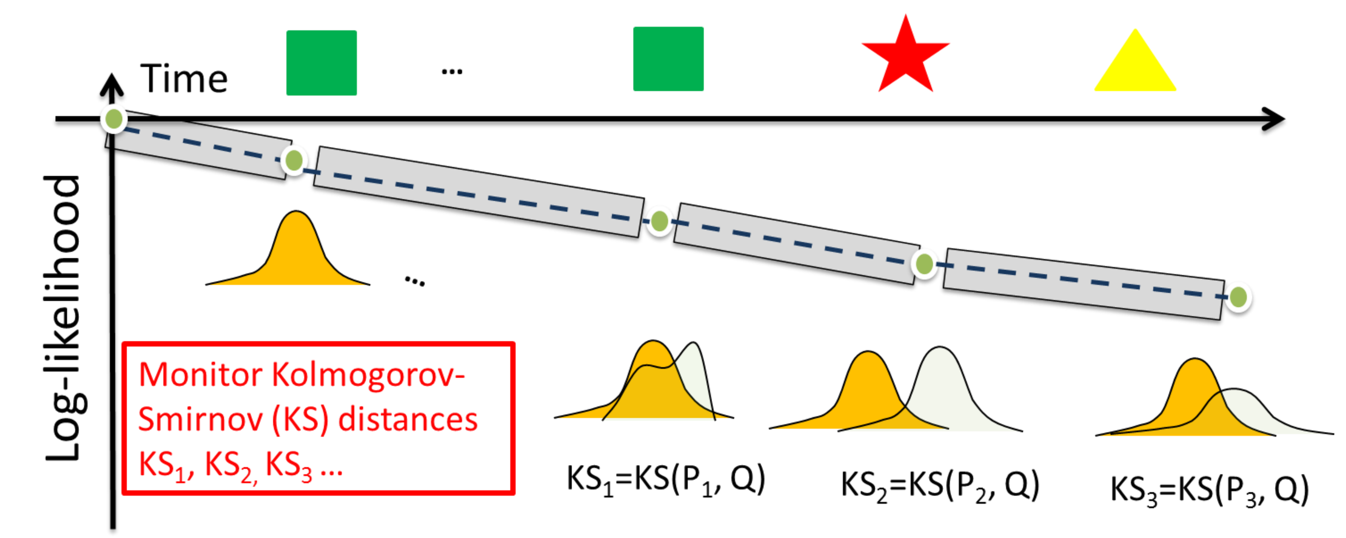
Computational solution: *Monte Carlo approach*:

generate samples $\{\boldsymbol{\theta}^{(n)}\}_{n=1}^{N}$ from joint posterior distribution $\Pr(\boldsymbol{\theta}_0|\boldsymbol{y}_T)$ so that

$$E(\boldsymbol{\theta}_0|\boldsymbol{y}_T) \approx \frac{1}{N}\sum_{n=1}^{N} \boldsymbol{\theta}^{(n)}$$

METHODOLOGY

Process Monitoring Using HMM



Using HMM parameters and their uncertainty, system dynamics can be characterized by distribution of log-likelihood slope (DLLS)

$$\Lambda = \frac{\log \Pr(\boldsymbol{y}_{t_2}|\boldsymbol{\theta}) - \log \Pr(\boldsymbol{y}_{t_1}|\boldsymbol{\theta})}{t_2 - t_1}$$

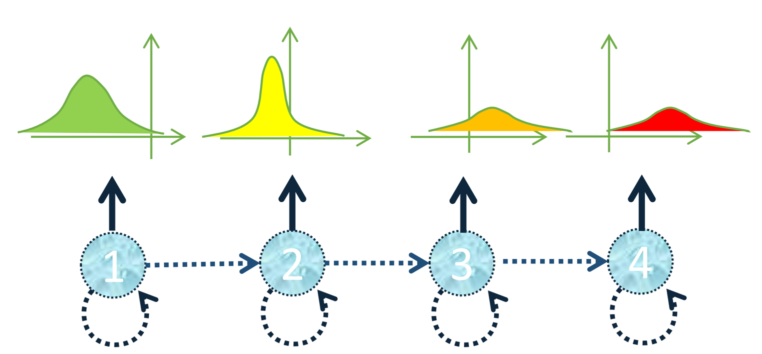
The Kolmogorov-Smirnov (KS) distance between nominal DLLS Λ_0 and current DLLS Λ_1 is

$$KS(\Lambda_0, \Lambda_1) = \sup_{x} |F_{\Lambda_0}(x) - F_{\Lambda_0}(x)|\,,$$

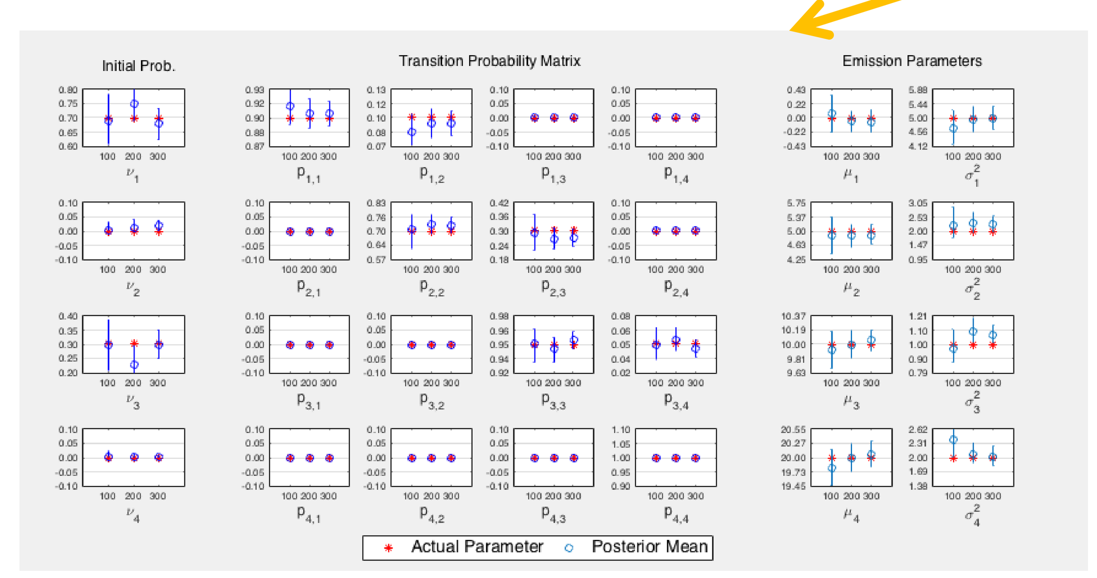
which indicates dynamical shift.

SIMULATION RESULTS

Estimation of Gaussian Non-ergodic HMM



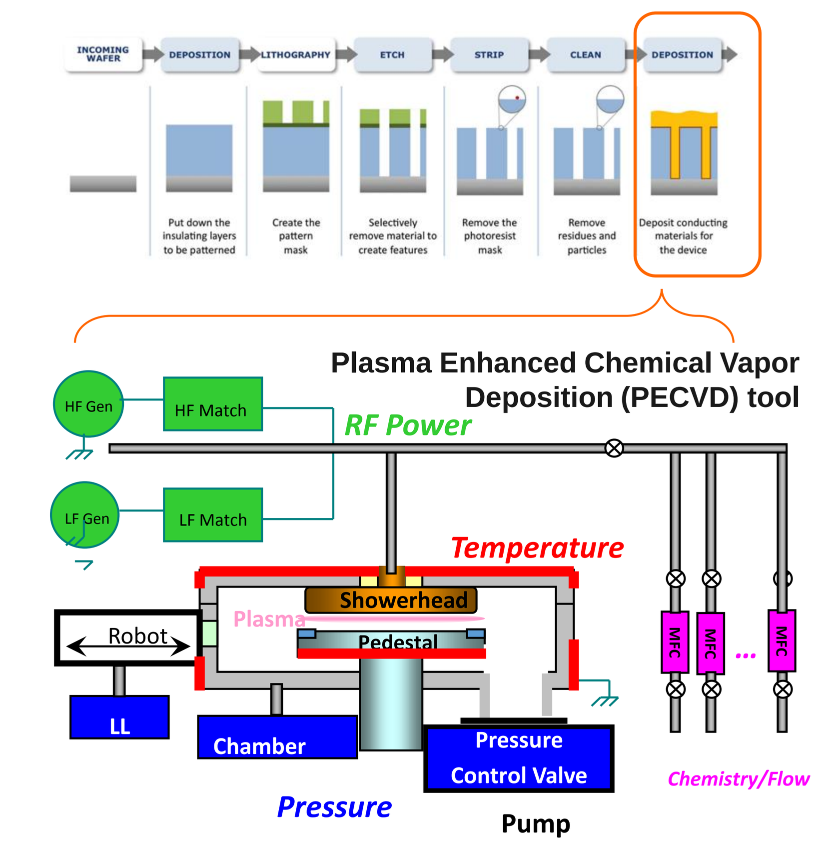
Using more and more simulated data (100/200/300 sequences of observations), all Bayesian estimates of HMM parameters converge to the true model parameters. In addition, model uncertainty , i.e. width of %95 credible intervals of the parameters , convergence to zero. This phenomenon occurs on estimation for all types of HMM we have studied, including discrete / Gaussian, ergodic / non-ergodic, and homogeneous / nonhomogeneous HMMs.



Simulation Configuration: Number of observations in each sequence: 10 to 25; Number of sequences in three experiments: 100/200/300s; Model information: $nstate = 4$; Gibbs sampling iterations $N0 = 100, N = 500$. Actual parameters : $\boldsymbol{\nu} = [0.7\ 0\ 0.3\ 1], \boldsymbol{\mu} = [0\ 5\ 10\ 20], \boldsymbol{\sigma}^2 = [\ 5\ 2\ 1\ 2], \boldsymbol{P} = [0.9\ 0.1\ 0.0\ 0.0\ ; 0\ 0.7\ 0.3\ 0\ 0\ ; 0\ 0\ 0.95\ 0.05; 0\ 0\ 0\ 1]$; Prior distribution: $p_{i\cdot} \sim \mathrm{Dir}(1,1,1,1), \mu_i \sim \mathrm{N}(0,10), \sigma_i^2 \sim \mathrm{IG}(1,1)$ for $i = 1,2,3,4$.

RESULTS ON REAL DATA

Monitoring Benchmark on a PECVD process



Multiple Months of Production Tool Data:

RF : HF power, Load Cap, Tune Cap, LF power

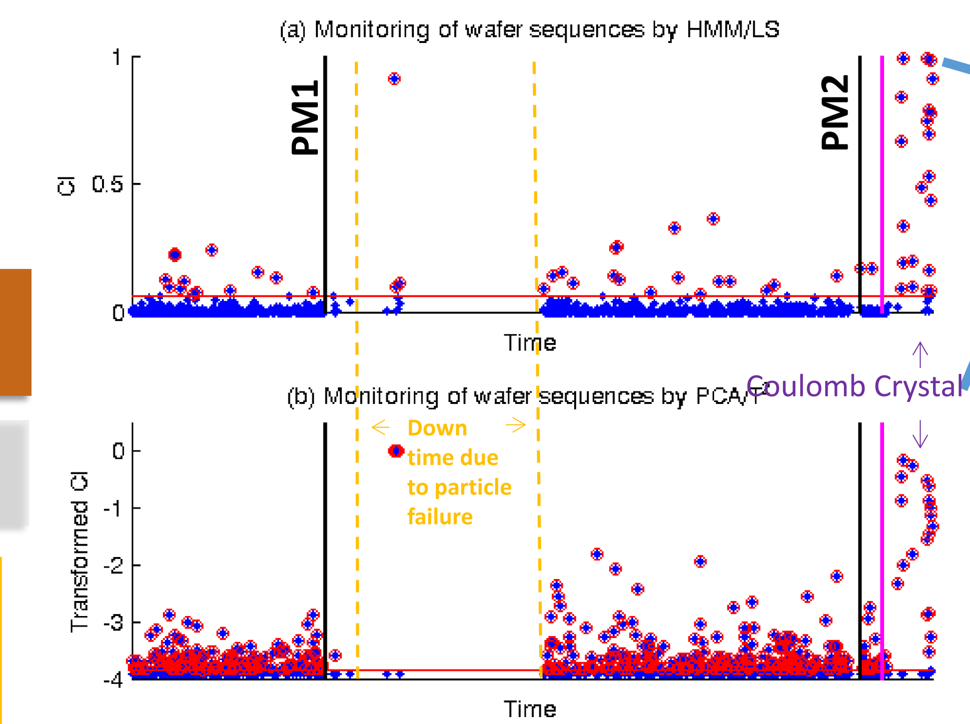
Pressure: Chamber, PCV angle, Loadlock

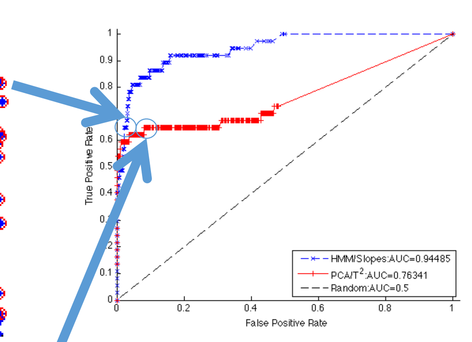
Chemistry: Gas Flows

Temperature: Chamber, Pedestal

Production schedules/maintenance events

On-Board metrology – thickness, uniformity





HMM based monitoring method reduces 20% of false alarm rate on average than traditional Principle Component Analysis (PCA) / T[2] stats based monitoring method

ONGOING WORK

1. Extension of methodology to handle imperfect maintenance

   Imperfect maintenance events can cause dynamical changes that are not easily detectable by sensors. To capture those changes, we are experimenting new modeling and monitoring approaches. Preliminary results are available from application of the new methods to both PECVD and plasma etch processes in semiconductor manufacturing.

2. Analysis of statistical properties of Bayesian estimator

   Asymptotic normality of the posterior distribution of HMM parameters is under investigation.