Introduction to Prognostics

Annual Conference of the PHM Society 2019

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XUSH KELIBSIZ
FOGADTATÁS
DOBRODOŠLI
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ТАВТАЙ МОРИЛНО УУ
ДОБРО ПОЖАЛОВАТЬ
ЛАСКАВО ПРОСИМО
ДОБРЕ ДОШЪЛ
MALIGAYANG PAGDATING

Introduction

Acknowledgments:

- Dr. Kai Goebel and the PHM Society
- Previous tutorial presenters
- SGT Inc., Diagnostics & Prognostics Group, NASA Ames
- Prof. Yongming Liu and his team for the crack growth dataset

Topics of the tutorial

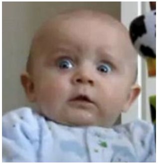
What is prognostics?

Why prognostics?

Prognostic process

Examples (with codes)

Your feelings during this tutorial if:

	you know (some) PHM	Uh? PHM? prediction?
What is prognostics?		
Why prognostics?		
Prognostic process		
Examples (with codes)		

Today's material

Download this presentation and tutorial code at:
phmsociety.org/events/conference/phm/19/tutorials

Scripts and dataset:
particleFilterPrediction.py *gpRegression.py* *CO2data.txt*

Libraries we'll use:
numpy *scipy* *matplotlib*

Instructions to install Python and libraries:
README.txt

What is prognostics?

- What is prognostics?
- Why prognostics?
- Prognostic process
- Examples (with codes)

Definition

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Definition

Prognostics is an engineering discipline focused on predicting the time at which a system or a component will no longer perform its intended function*

*Vachtsevanos GJ, Lewis F, Hess A, Wu B. Intelligent fault diagnosis and prognosis for engineering systems. Hoboken: Wiley; 2006 Sep.

Approaches to prognostics

Thanks to Prof. J. W. Hines, PHM Tutorial 2009

Type I: Reliability-based

$\lambda = \lambda(t)$, MTTF, MTBF, ...

Approaches to prognostics

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Type I: Reliability-based

$\lambda = \lambda(t)$, MTTF, MTBF, ...

Type II: Stress-based

E.g., proportional hazard models
$\lambda = \lambda(t, z)$, where z are "stressors"

Approaches to prognostics

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Type I: Reliability-based

$\lambda = \lambda(t)$, MTTF, MTBF, ...

Type II: Stress-based

E.g., proportional hazard models
$\lambda = \lambda(t, z)$, where z are "stressors"

Type III: Condition-based ← **what we'll see today**

Modeling individual failure mechanisms, cumulative damage models, state extrapolation, ...

Why prognostics?

What is prognostics?

Why prognostics?

Prognostic process

Examples (with codes)

Why prognostics?

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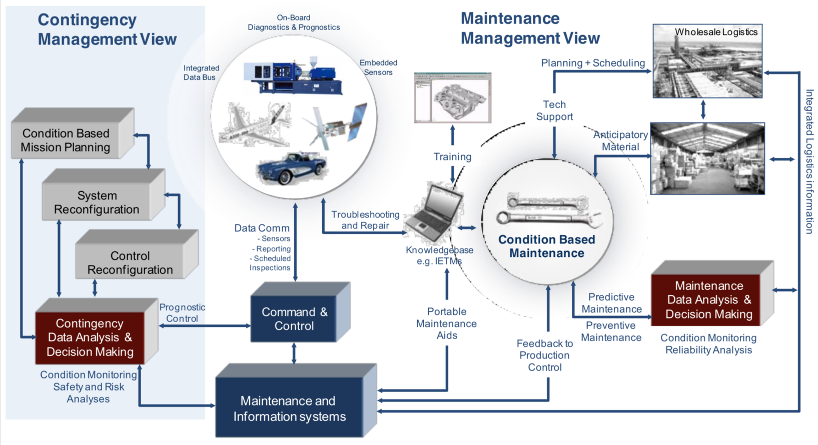

Thanks to: Dr. Abhinav Saxena

Schematic adapted from: A. Saxena, Knowledge-Based Architecture for Integrated Condition Based Maintenance of Engineering Systems, PhD Thesis, 2007.

Why prognostics?

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Safety

prevent unexpected failures
minimize impact on other systems
be prepared to initiate contingency plans

Why prognostics?

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Logistics

reduce spare parts stock

logistics footprint

Why prognostics?

Maintenance

reduce unnecessary interventions
"Just-in-time" approach
optimize fleet maintenance

Why prognostics?

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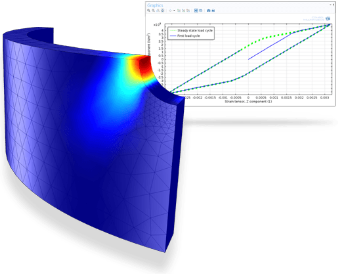


Reliability & Performance

product reputation
reduced safety factors

Why prognostics?

Safety

prevent unexpected failures
minimize impact onto other systems
implement contingency plans

Logistics

reduce spare parts stock
logistics footprint

Maintenance

reduce unnecessary interventions
"Just-in-time" approach
optimize fleet maintenance

Reliability & Performance

product reputation
reduced safety factors

Thanks to: Dr. N. Scott Clements. Please refer to his tutorial PHM Tutorial 2011 for more information on industrial applications

Prognostic process

What is prognostics?

Why prognostics?

Prognostic process

Examples (with codes)

What we are trying to predict

Future behavior

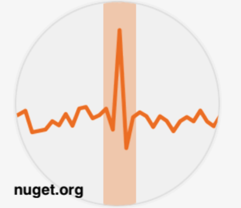
Calculate the future values of the quantities of interest to infer future behavior of the system

End-of-life

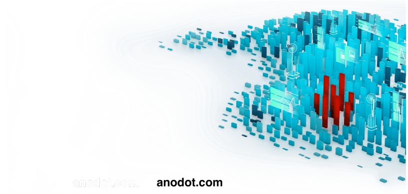
Calculate the time-to-failure or the remaining useful life (RUL) of a component/system, which current condition is known with certain confidence.

Steps of the prognostic process

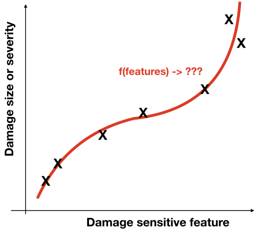
1. Anomaly / fault detection



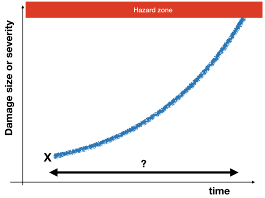
2. Identification and isolation



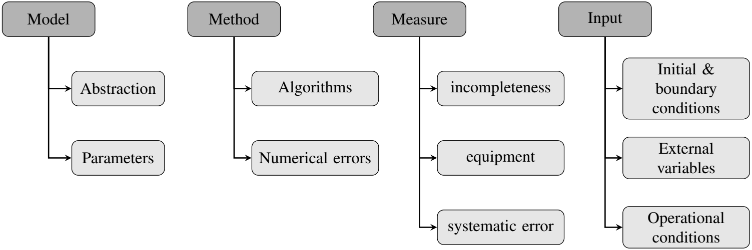
3. Quantification



4. Prognosis



Source of information (and uncertainty)



Measures

- Ground truth measures are hard to come by, and sometimes there's no term for comparison (e.g., Golden Gate bridge)
- Many times measures are noisy, corrupted by systematic errors or faulty measurement systems
- Health-related quantities are typically hard to measure (i.e., measures are intrusive or destructive)
- Some times it's simply not possible (physically or economically) to measure some variables

Models

- Models are mere representations of reality
- Models do not (typically) accommodate all physical phenomena affecting the system. If they do, they may not be suitable for real-time applications
- They always require calibration and validation.
- They may require correction terms to be updated in real-time (every time) or to be tuned on a case-basis

Environmental & operational conditions (input)

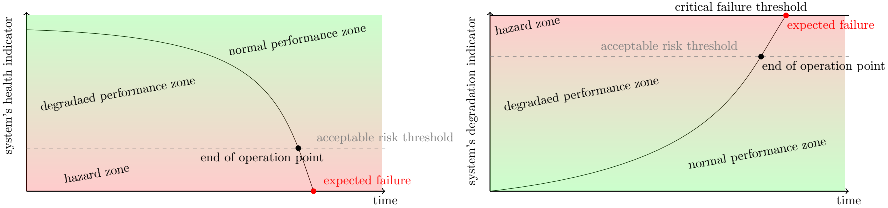
- Varying environmental conditions can drastically change algorithm performance (or even make algorithms useless)
- Many damage-sensitive features are also affected by operational profiles (e.g., vibrations in a wind turbine generator change with produced power)
- Environmental variables May be unknown, hard to measure or their future values hard to predict (i.e., wind speed and direction in urban environments)
- Finding causal relationships: dependencies from external factors are hard to quantify

Computing methods

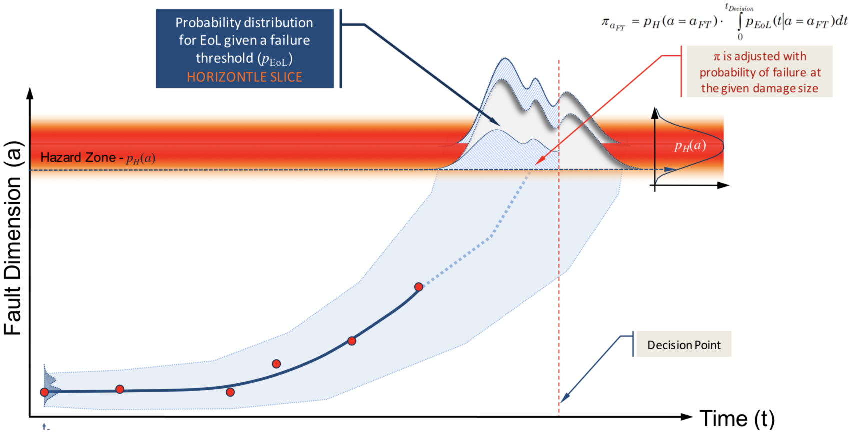
- Rounding errors or machine precision may not be negligible for the problem we're looking at
- If the algorithm goal is minimization or filtering, they may get stuck into a local minima (e.g., the results change at different runs)
- They often need tuning of parameters, or in case of data-driven methods, their performance depends on the amount of training data
- Convergence not always guaranteed

Prognosis in a cartoon

Tracking health vs. tracking degradation



Prognosis in a cartoon



Thanks to: Dr. Abhinav Saxena, GE
See his prognostics tutorial from Annual PHM Conference 2010 here.

Examples (with codes)

What is prognostics?

Why prognostics?

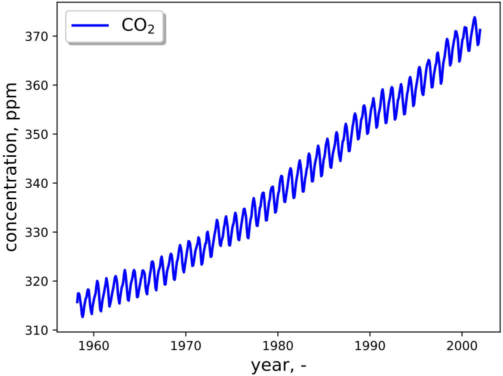
Prognostic process

Examples (with codes)

Example 1
Data-driven CO_2 concentration prediction

CO_2 concentration prediction

Monthly average atmospheric CO_2 concentrations (in parts per million by volume, ppmv) collected at the Mauna Loa Observatory in Hawaii between 1958-2001[1].



What will the CO_2 concentration be after 2001?

[1] credits for the idea to Rasmussen and Williams, Gaussian Processes for Machine Learning, and Sci-kit learn, and NOAA for the dataset.

Gaussian Process Regression

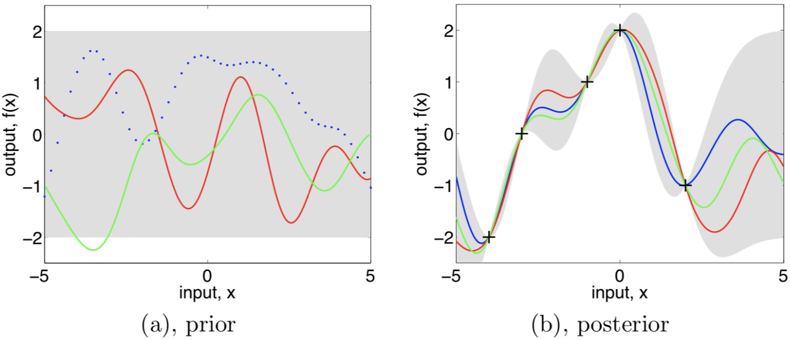
We use Gaussian Processes (GP) to predict the concentration over the years after 2001.
The process $f(\boldsymbol{x})$ is a GP if can be specified by a mean and covariance function:

$$f(\boldsymbol{x}) \sim \mathcal{GP}\left(m(\boldsymbol{x}), k(\boldsymbol{x}, \boldsymbol{x}')\right)$$

The covariance function $k(\boldsymbol{x}, \boldsymbol{x}')$ **is the key** containing info about time-correlations and dispersion.

Once we learn the covariance function, we can perform predictions far from training points.

GP - prior vs posterior



Example from Rasmussen and Williams, *Gaussian Processes for Machine Learning*, 2006.

Building the covariance function

The covariance function k is the key: To fit the CO_2 time series, we build k as a sum of elementary covariance functions:

$k_1(x,x') = \theta_1^2 \exp\left(-\frac{1}{2}\frac{(x-x')^2}{\theta_2^2}\right)$	long-term rising trend
$k_2(x,x') = \theta_3^2 \exp\left(-\frac{(x-x')^2}{2\theta_4^2} - \frac{2\sin^2(\pi(x-x'))}{\theta_5^2}\right)$	periodicity
$k_3(x,x') = \theta_6^2 \left(1 + \frac{(x-x')^2}{2\theta_8\theta_7^2}\right)^{-\theta_8}$	medium term irregularities
$k_4(x,x') = \theta_9^2 \exp\left(-\frac{(x_p-x_q)^2}{2\theta_{10}^2}\right) + \theta_{11}^2\delta_{p,q}$	noise

$$k(x,x') = k_1(x,x') + k_2(x,x') + k_3(x,x') + k_4(x,x')$$

$$\boldsymbol{\theta} = [\theta_1, \theta_2, \ldots, \theta_{11}]$$

Find hyper-parameter vector $\boldsymbol{\theta}$

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Find the hyper parameters $\boldsymbol{\theta}$ that best fit the training data. We do so by maximizing the marginal likelihood $p(\mathbf{y}|X)$ in log-form:

$$\log p(\mathbf{y}|X) = -\frac{1}{2}\mathbf{y}^T \left(k + \sigma_n^2 I\right)^{-1} \mathbf{y} - \frac{1}{2}\log|k + \sigma_n^2 I| - \frac{n}{2}\log 2\pi$$

covariance function
model error (noise)

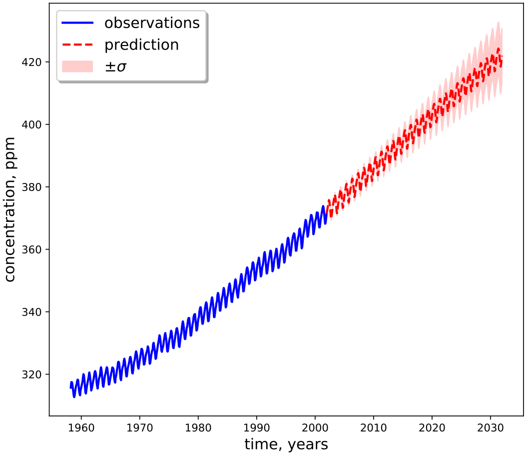
See *Rasmussen & Williams, GP for ML, 2006*.

Code

open *gpRegression.py*. make sure *CO2data.txt* is in the same folder.

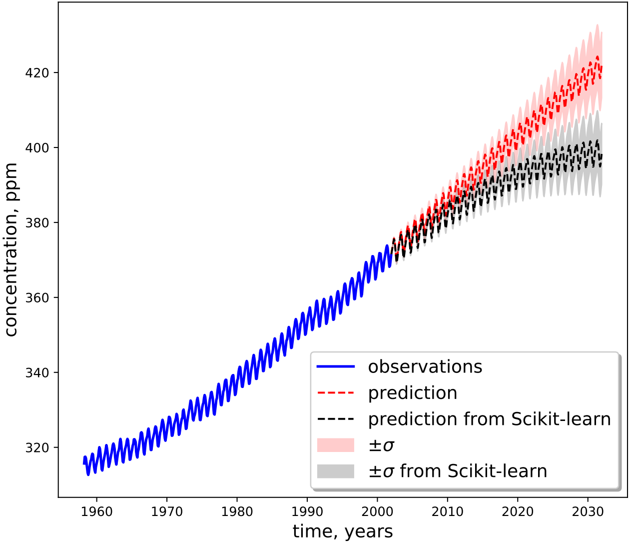
Prediction

Using (sub-)optimal parameters found via differential evolution algorithm[2].



[2] DE should converge towards *the* optimal parameters. For this problem, different runs produced different results, suggesting either that the population size or number of iterations was too small.

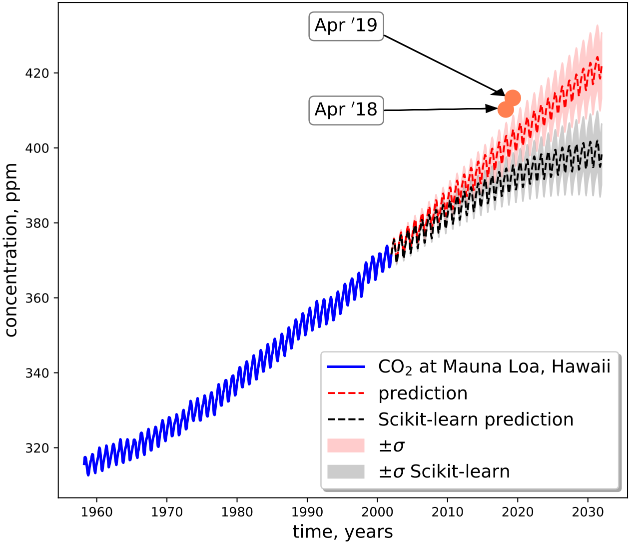
Prediction



420
400
380
360
340
320
concentration, ppm
1960
1970
1980
1990
2000
2010
2020
2030
time, years
observations
prediction
prediction from Scikit-learn
±σ
±σ from Scikit-learn

Prediction

What's the concentration today?



A few things to remember

What about model validation???

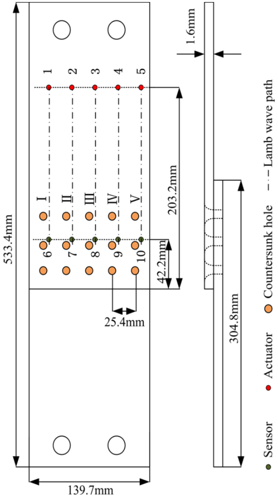
Here's some options you should try:

- Split dataset into training and validation
- Cross-validation with batches, leave-one-out, etc.
- Gather more data
- Try adding/removing different covariance functions

Example 2
Fatigue crack growth prognosis using particle filter

Fatigue crack growth prognosis

Data from 2019 PHM data challenge:

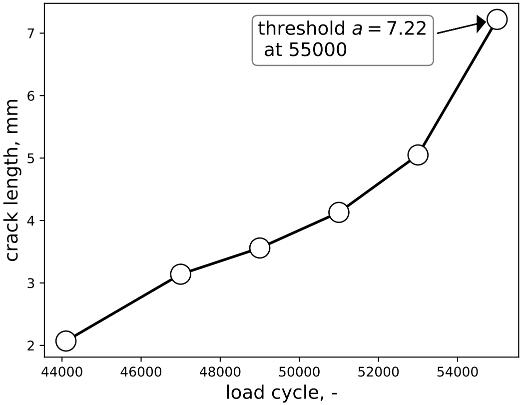


- fatigue crack growth at rivet holes
- tensile, constant amplitude fatigue loading

Thanks to: Prof. Yongming Liu and his team, ASU

Visit the 2019 PHM Data challenge website for more information.

Fatigue crack growth prognosis



Given the set of sequential measures of crack length, **can we predict the number of cycles to reach final length $a = 7.22$ mm (i.e., 55,000 load cycle)?**

Bayesian filtering equations

Chapman-Kolmogorov and Bayesian updating

$$p(\boldsymbol{X}_k|\boldsymbol{Y}_{k-1}) = \int_{-\infty}^{\infty} p(\boldsymbol{X}_k|\boldsymbol{X}_{k-1})\, p(\boldsymbol{X}_{k-1}|\boldsymbol{Y}_{k-1})\, \mathrm{d}\boldsymbol{X}_{k-1}$$

$$p(\boldsymbol{X}_k|\boldsymbol{Y}_k) = \frac{p(\boldsymbol{X}_k|\boldsymbol{Y}_{k-1})\, p(\boldsymbol{Y}_k|\boldsymbol{X}_k)}{p(\boldsymbol{Y}_k|\boldsymbol{Y}_{k-1})}$$

Far-ahead prediction stage:

$$p(\boldsymbol{X}_{k+l}|\boldsymbol{Y}_k) = \int_{\mathcal{X}} p(\boldsymbol{X}_k|\boldsymbol{Y}_k) \left[\prod_{j=k+1}^{k+l} p(\boldsymbol{X}_j|\boldsymbol{X}_{j-1})\right] \mathrm{d}\boldsymbol{X}_{k:k+l-1}$$

Particle filtering pseudo-code

Input: $\boldsymbol{x}_{k-1}^{(i)}, \forall \quad i = 1, \cdots, N_s$, and y_k
Output: $p\left(\boldsymbol{X}_k | Y_k\right)$, $p\left(\mathrm{RUL}_k | Y_k\right)$

1. Approximate posterior pdf

$\boldsymbol{x}_k^{(i)} \sim p(\boldsymbol{X}_k | \boldsymbol{x}_{k-1}^{(i)}) \leftarrow$ propagate samples with model function

$\ell\left(y_k | \boldsymbol{x}_k^{(i)}\right) \leftarrow$ compute likelihood for all samples

$w_k^{(i)} \propto w_{k-1}^{(i)} \ell\left(z_k | \boldsymbol{x}_k^{(i)}\right) \leftarrow$ assign weights

$p(\boldsymbol{X}_k | Y_k) \approx \sum_{i=1}^{N_s} w_k^{(i)} \delta_{\boldsymbol{X}_k, \boldsymbol{x}_k^{(i)}} \leftarrow$ approx. posterior pdf

2. Systematic re-sampling

$\boldsymbol{x}_k^{(j)} \sim p\left(\boldsymbol{X}_k | Y_k\right) \quad : \quad \Pr\{\boldsymbol{x}_k^{(j)} = \boldsymbol{x}_k^{(i)}\} = w_k^{(i)}$

$w_k^{(j)} = 1/N_s \quad \forall \quad j = 1, \cdots, N_s$

3. Prognosis

```
for i = 1, 2, ··· , N_s do
    l = 0
    while x_k^(i) ∈ safe domain do
        x_k^(i) ~ p(X_{k+l} | x_{k+l-1}^(i))
        l += 1
    end
    t_f = t_{k+l} ← extract time at which sample i reached threshold x_th
    RUL_k^(i) = t_f − t_k ← extract remaining useful life for sample i
end
```

Assign variables

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$\boldsymbol{x} = [a, \log C, m]^T$	augmented state vector
$\boldsymbol{z} \to z = a + \epsilon_g$	unbiased, noisy measures
$\boldsymbol{u} \to u = \Delta S = 95$ MPa	applied stress range ($R \approx 0.05$)
$\boldsymbol{\theta} = [\log C, m]^T$	state model parameter vector
$\boldsymbol{\epsilon}_f = [e^{\omega}, \epsilon_{\log C}, \epsilon_m]^T$	state model error

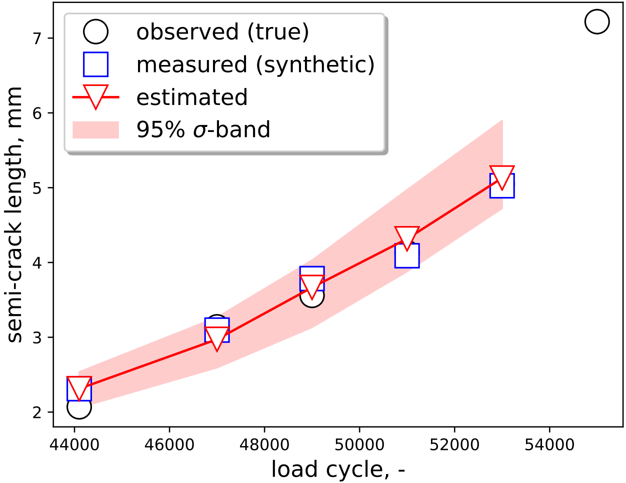
where:

$$\omega \sim \mathcal{N}(-\tfrac{\sigma_\omega^2}{2}, \sigma_\omega^2), \quad [\epsilon_{\log C}, \epsilon_m] \sim \mathcal{MVN}(\mathbf{0}, \Sigma_{\boldsymbol{\theta}}), \quad \epsilon_g \sim \mathcal{N}(0, \sigma_g^2)$$

Code

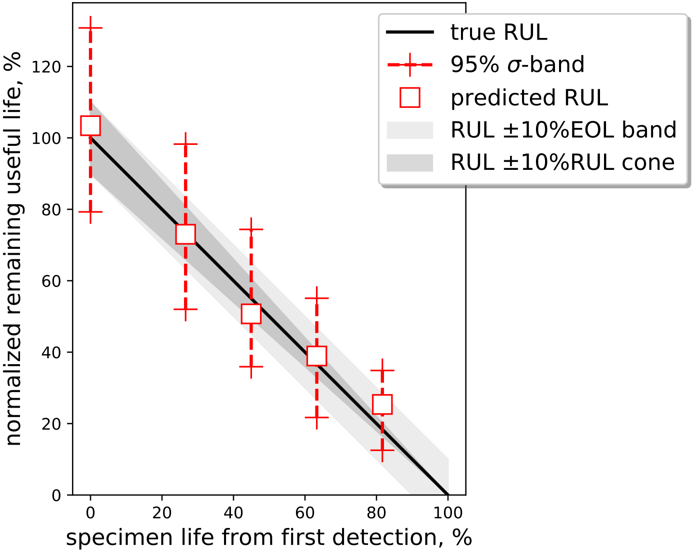
open *particleFilterPrediction.py*

Prediction



observed (true)
measured (synthetic)
estimated
95% σ-band
semi-crack length, mm
load cycle, -
7
6
5
4
3
2
44000
46000
48000
50000
52000
54000

Prediction



true RUL
95% σ-band
predicted RUL
RUL ±10%EOL band
RUL ±10%RUL cone
normalized remaining useful life, %
specimen life from first detection, %
0
20
40
60
80
100
120
0
20
40
60
80
100

A few things to remember

- The model error (or process noise) e^{ω} has that form for a reason. Please see *Corbetta et al. MSSP 2018, 104; 305:322*
- Try to implement Kernel smoothing instead of artificial dynamics for better performance (see *Liu J, West M. In Sequential Monte Carlo methods in practice 2001; 197:223 Springer, NY.*)
- Using unbounded processes to estimate bounded parameters usually results in poor performance

Useful links

Prognostics Center of Excellence (PCoE)

Web page:
http://prognostics.nasa.gov

Data repository:
https://ti.arc.nasa.gov/tech/dash/pcoe/prognostic-data-repository/

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QUJAN
THANK YOU
QUJANARSUAQ
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THANKS
MITELA
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