Experiments for PHM:
needs, developments and challenge

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About Myself

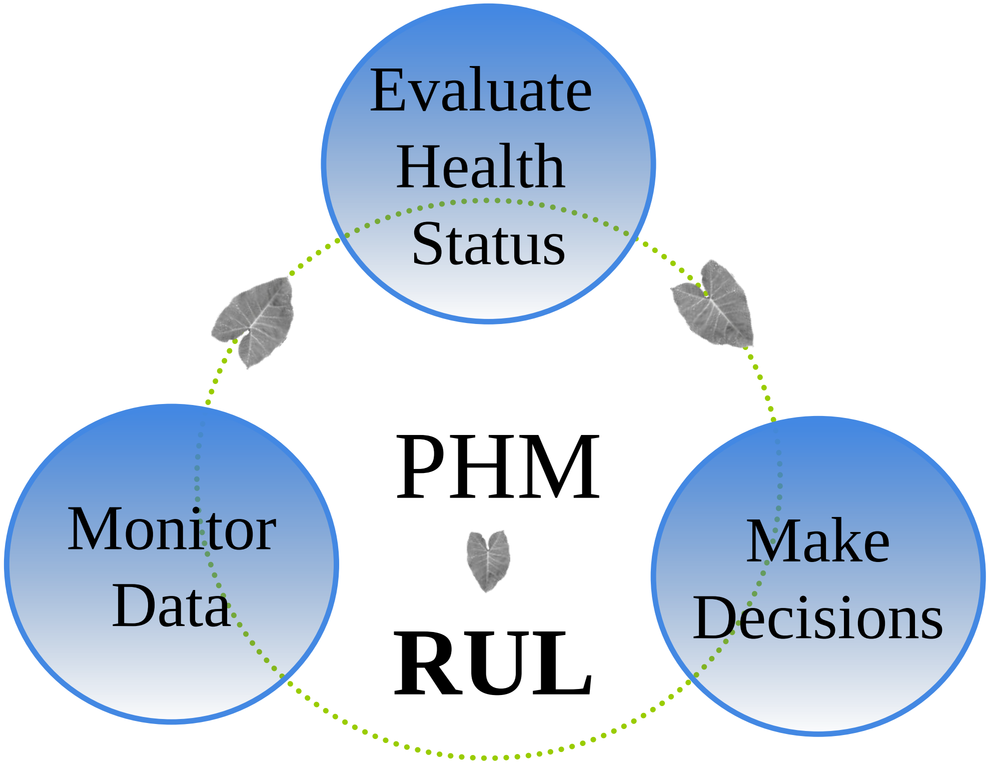
Le Liu

I’m a PhD student from Beihang University and my research interests are Accelerated Testing, Uncertainty Analysis, Prognostics and Health Management (PHM). This paper will share our ideas on traditional PHM from the perspective of remaining useful life prediction with you.

Contents

Background： PHM

- **Prognostics and Health Management (PHM)**



Focus of RE:
From
Quality-centered
To
Service-centered
(Zio 2012)

Mainly care about the phrase when products have been released to customers!

Background: limitations

- **The availability of data, in particular for new products/systems**
  - ➢How can we get time to failure data since running systems to failure can be a lengthy and rather costly process
  - ➢How can we get degradation data to compare and benchmark the performance of algorithms
- **Model validation and verification:**
  - ➢How can the proper operation of life prediction algorithms be validated, especially on new systems?

Traditional life prediction method: needs

- **Data**
  - Integrating expert knowledge or historical information with monitoring usage data. (Zio 2010, Wang 2011, Vaidya 2011)
  - Considering in-field experiments, accelerated testing which can short the test time and gather sufficient failure/degradation data. (Liao 2013, Li 2013)
- **Model**
  - Model comparison or combination of physical-based, data-driven or hybrid models. (Saha 2009, Zio 2011, Liu 2012, Zhao 2013, Liao 2014)

Traditional life prediction method: needs

- **The importance of experiments for PHM**
  - Quantitative and Qualitative experiments are conducted in pre-design, final design and manufacturing phases, i.e. HALT, ALT/ADT, etc.
  - To collect more degradation and life information within a limited time
  - To assist model selection and provide usage-oriented life prediction model set

The needing of experiment-based PHM

Experiment-based framework: developments

Methodology

Pre-Design → Final-Design → Trial → Manufacture → Field use

Step1

• Degradation behavior simulation

•Failure mechanism

•Theoretical model (M1)

Step2

• Accelerated testing

• Failure/ degradation data

• Test model (M2)

Step3

• Small sample trial

• Evaluate algorithm performance

• Trial model (M3)

Step4

• Process monitoring

• Product variation

Step5

• Real-time life prediction

•On-line data

• Actual model (M4)

Experiment-based framework: developments

- **Step 1: Product degradation behavior simulation based on PoF models**

1. Boundary

Environment
Geometry
Material property
Load levels
etc.

2. Components

Degradation mechanism
Wear, corrosion, etc.
Platform: ANASYS, FLUENT, etc.

3. System

Performance response model: transfer function
Platform: AMESim, HyPneu, etc.

4. Performance

Static/Dynamic response
System Performance

$$M_1 : \begin{cases} P = f(t, M, S_{sim}) \\ T = g(P, S_{sim}, D) \end{cases}$$

Experiment-based framework: developments

- **Step 2: Life prediction modelling based on accelerated testing**

M1, Stresses — On the basis of accelerated model from simulation, M1 and sensitive stresses can be acquired for accelerated testing.

↓

Life prediction — Model M1 can be verified by testing data and new models may be introduced, otherwise eliminated.

↓

New model M2 — Understand life pattern for new products and update life prediction model set.

$$M_2 : \begin{bmatrix} M_{1\to 2} \\ M_{0\to 2} \end{bmatrix}$$

Experiment-based framework: developments

- **Step 5: On-line predictive maintenance through PHM**

Model

The above steps has provided alternative prediction model set M1, M2 and (or) M3.

Data

When on-line data is available, life prediction can be accom-plished by model selection or combination.

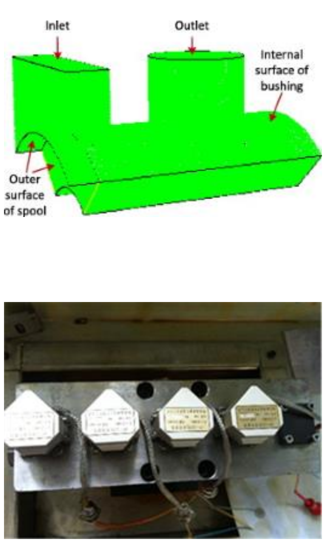
Policy

With the selected life prediction models, RUL can be given based on specific failure threshold, then compute the applicable mainten-ance policy.

Case studies

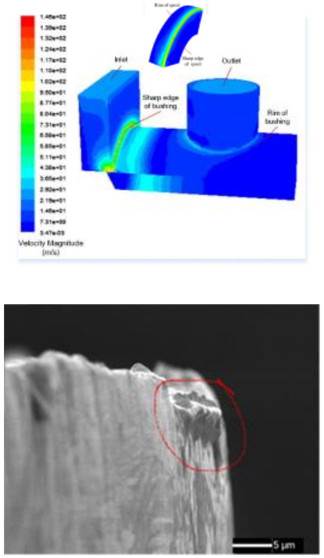
- **Life prediction modelling for Double nozzle flapper electro-hydraulic servo valve**

Component Level



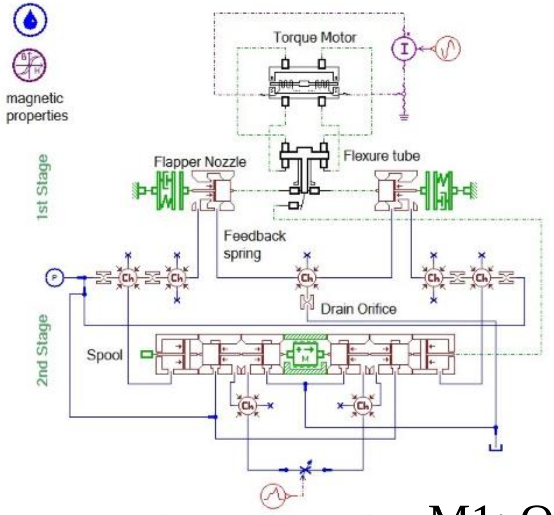
(a)

Wear Damage



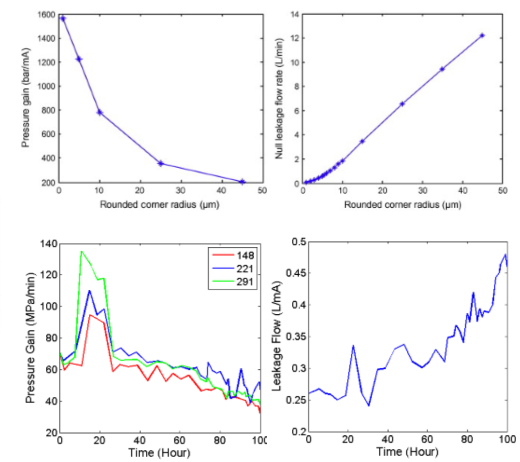
(b)

System Level



(c)

Pressure Gain **Leakage Flow**

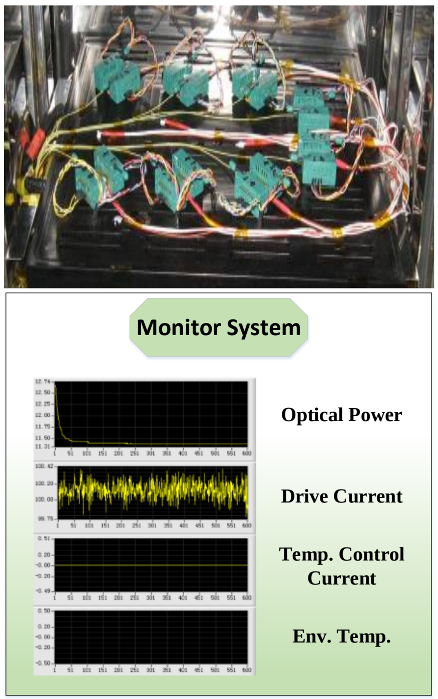


M1: Quadratic or linear function

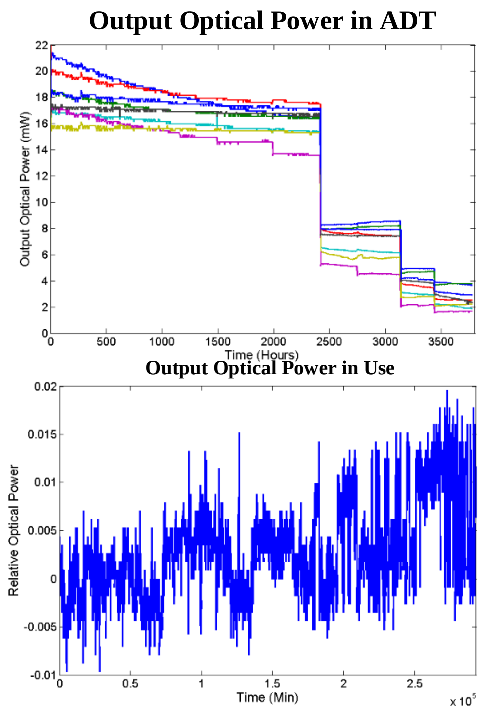
M2: Drift Brownian Motion

(d)

- **Life prediction modelling and on-line updating for super luminescent diode**



(a)



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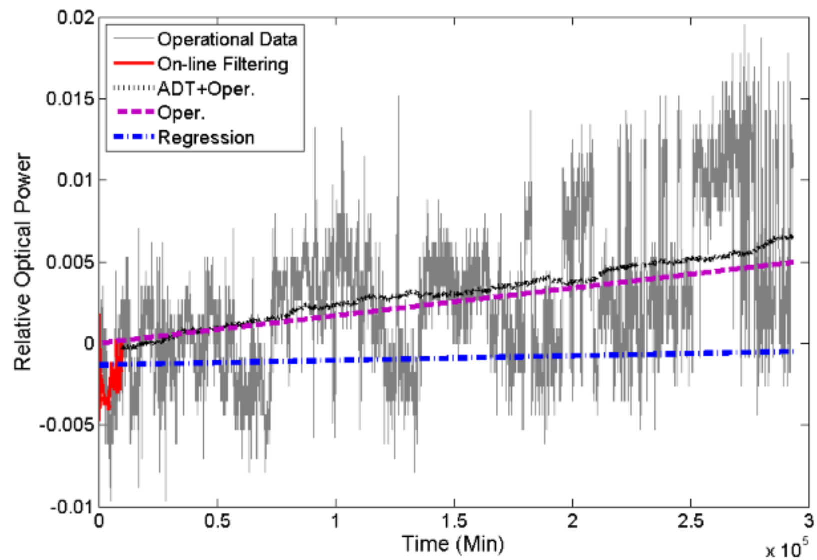
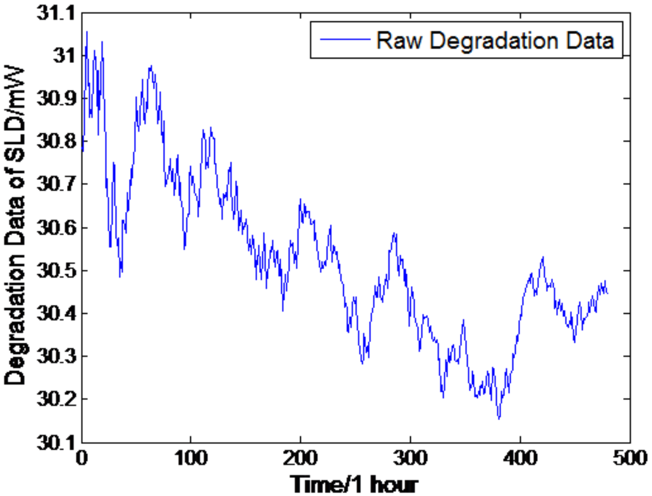


(c)

Case studies

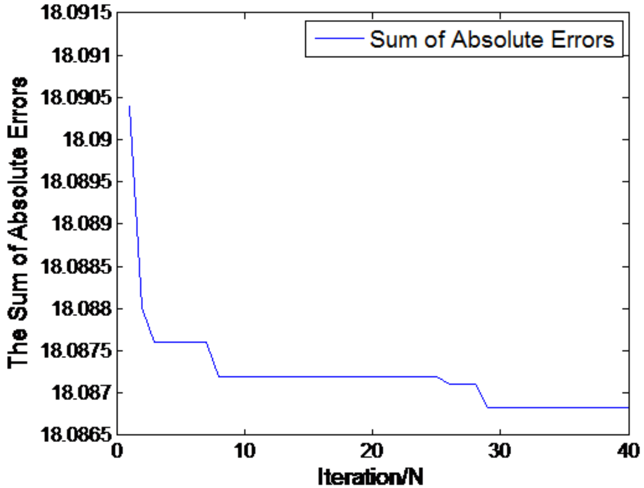
- **Life prediction based on combined algorithms**

Degradation Data



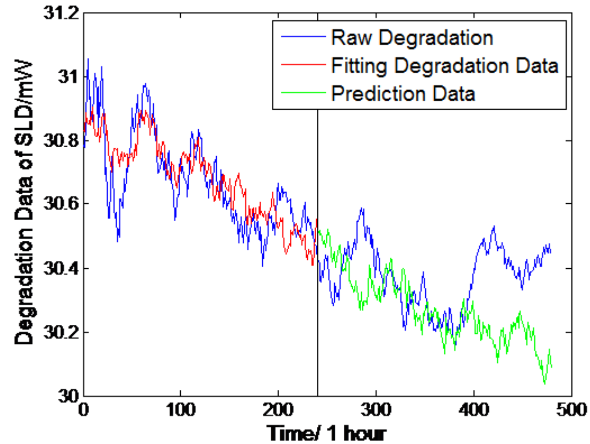
(a)

Coverage of Weight Assignation Algorithm



(b)

Prediction Results based on Combined Models



(c)

M1: BP neural network (f1)
M2: drift Brownian Motion (f2), & time series (f3)
M3: Particle filtering (f4)

Ranking:
f3>f2>f1>f4
while the encompassment test rejects f1.

Prediction accuracy:
f(combined)>f3>f2

Conclusions (challenges)

- **The values of the framework**
  - ➢Integrating the idea of prognosis and acceleration to enrich the connotation of reliability engineering
  - ➢Supporting the total life cycle management
  - ➢Shortening the development time by improving product reliability and life expectancy, realizing intelligent maintenance to ensure the safety
- **Challenges:**
  - ➢How to ensure the consistency of failure mechanisms for product in the lab and field, especially for accelerated tests
  - ➢How to update the actual model using all the models and data from different stage

Thank You !