Stochastic Modeling for System Remaining Life Prognosis

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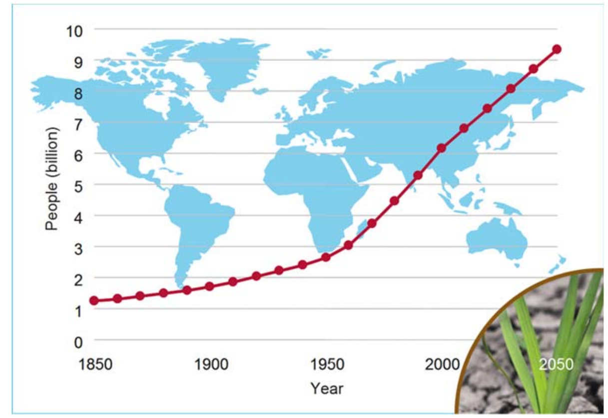
Prognosis: Predictive Science



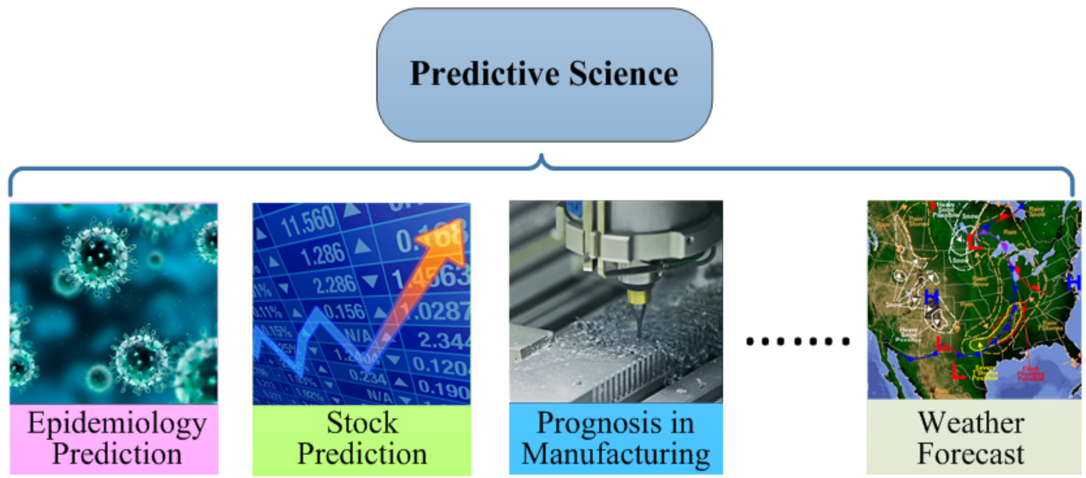
- **Definition**

  to forecast the likely outcome of an situation …

  - ✓ Disease/Epidemiology
  - ✓ Weather forecasting
  - ✓ Economic development

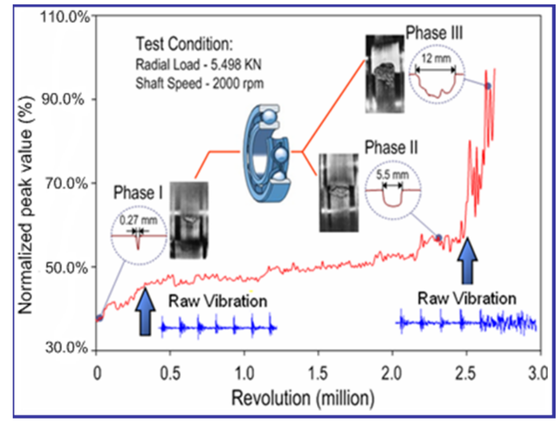
  — *Oxford Dictionaries Online*

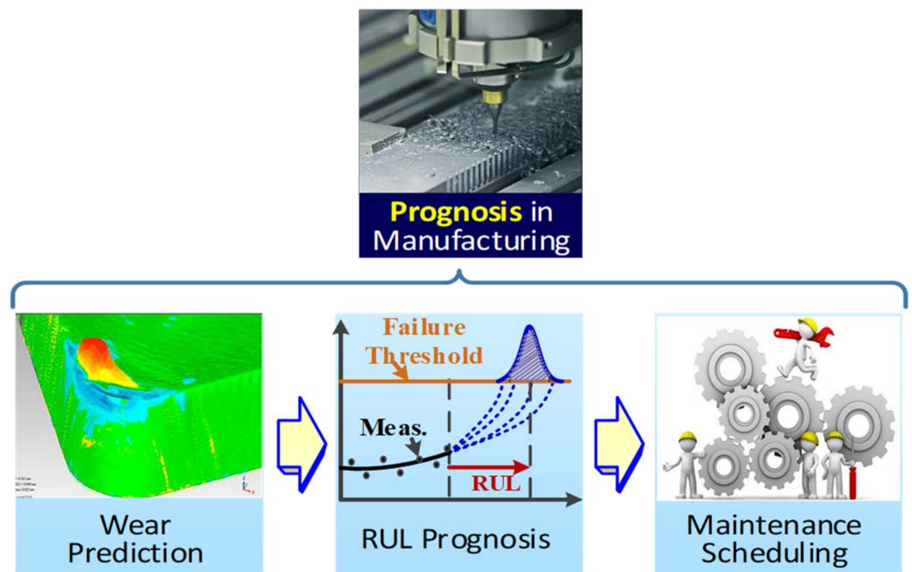
- Originally a *medical* term back in the 19th century:
  - ✓ Main aim was not to *cure* disease, but to give a medical *diagnosis* and *predict* the patient's chance of survival in terms of *remaining life*;
  - ✓ Focus shifted only decades later to *curing* disease.



In the Context of Manufacturing

- Predict expected ***progression*** of degradation in a machine or its components from its ***current*** state to ***future*** functional ***failure***, and the ***confidence*** associated with prediction;
- Identify short-term and long-term actions/decisions to improve ***remaining useful life*** *(RUL)* of a machine;
- Provide scientific and technical basis for ***maintenance*** scheduling, asset management, and effective ***decision*** making.



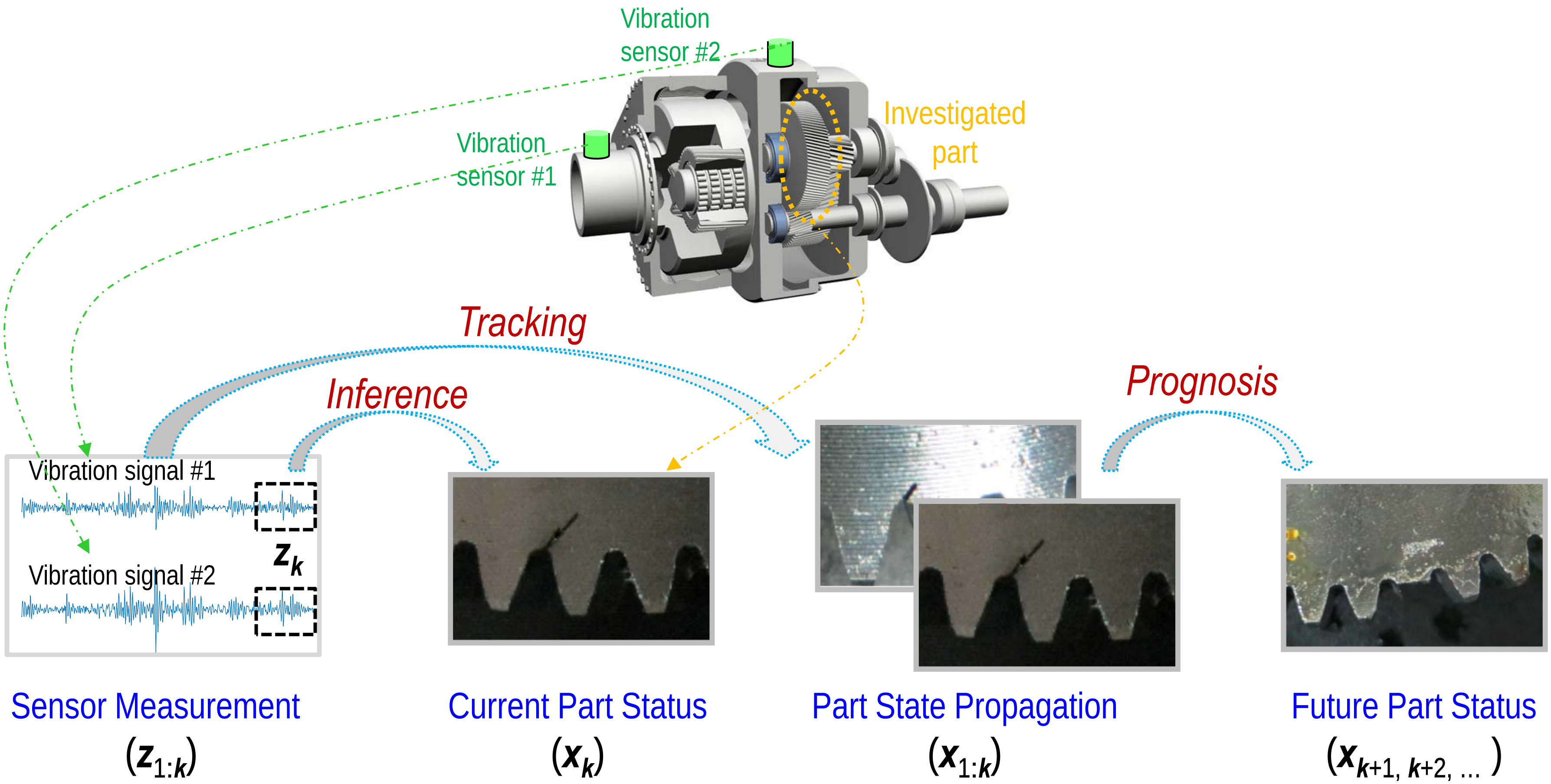


Malhi and Gao, Prognosis of defect propagation using recurrent neural networks, *IEEE Trans. Instr. Meas.*, 2010

Outline

- Background
  - ✓ Basic concepts
  - ✓ Major modeling techniques
- Particle Filter (PF)
  - ✓ Gradual degradation and time-varying rates
  - ✓ Multi-mode PF
- Case Study
  - ✓ Rolling bearing remaining life prognosis
- Conclusion and Future Work

Modeling: Inference, Tracking, and Prognosis

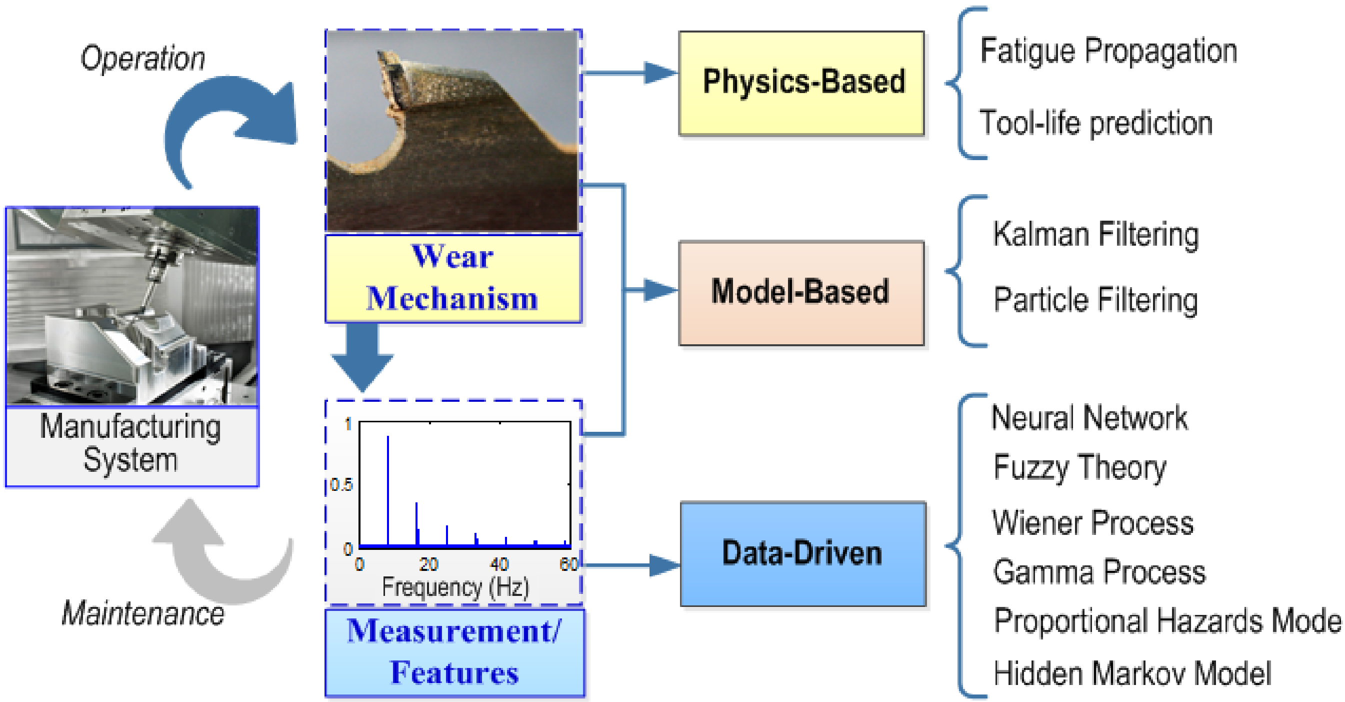


Inference: estimate system/part current state, based on current measurement

Tracking: identify propagation of state using historical measurements (*recursive* inference)

Prognosis: predict state propagation in the future, without available measurement

Prognostic Modeling Methods: Classification



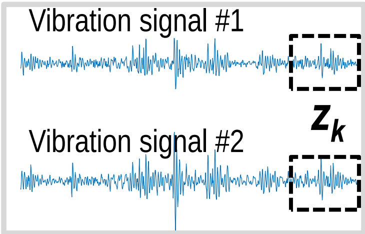
- **Physics-based**: describe system behavior analytically, parameters experimentally determined
- **Data-driven**: rely on measured data, numerically determine relation between current and future states
- **Model-based**: combine the two methods for improved robustness and prediction accuracy
- Alternative classification scheme: depending on how uncertainty is handled in the prediction process:
  - ✓ Deterministic: machine health as defined value
  - ✓ Stochastic (probabilistic): machine health as probability distribution, degradation as evolution of distributions

Gao *et.al.*, Cloud-enabled prognosis, *CIRP Annals*, 2015

Analytical Representation (1)

Sensor Measurement

($z_{1:k}$)



Current Part Status

(x_k)

Part State Propagation

($x_{1:k}$)

Future Part Status

($x_{k+1,\,k+2,\,\ldots}$)

Inference

✓ Estimate the current part status through a *posterior* PDF [1], realized Bayes' Rule [2]

$$\underbrace{P(x_k|\, z_k)}_{\text{Posterior PDF}} = \frac{\underbrace{P(x_k|x_{k-1})}_{\text{Prior PDF}}\underbrace{P(z_k|\, x_k)}_{\text{Likelihood}}}{\underbrace{P(z_k)}_{\text{Constant}}}$$

Tracking

✓ Identify the state propagation model (or recursively update the *prior* PDF) through *a series of posterior* PDF, following a Markov process [3]

$$P(x_1, x_2, \ldots, x_k|z_1, z_2, \ldots, z_k)$$
$$= P(x_1|z_1)P(x_2|x_1, z_2)\cdots P(x_k|x_{k-1}, z_k)$$

Prognosis

✓ Predict the future state using the identified state propagation model (*a series of prior* PDF)

$$P(x_{k+1}|x_k)P(x_{k+2}|x_{k+1})\cdots$$

(1) PDF: Probability Density Function
(2) Bayes' Rule: posterior PDF can be estimated through prior pdf and likelihood
(3) Markov process: current state x_k is only dependent on preceding state x_{k-1}

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Analytical Representation: (2)

- **Prior PDF** $P(x_k|x_{k-1})$

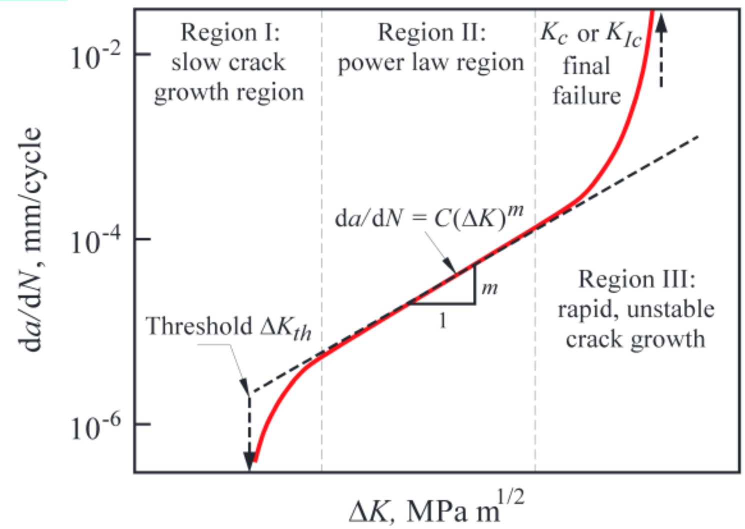
a: *crack length*
N: *cut number*
ΔK: *range of stress intensity*

$$x_k = f_{A_k, B_k}(x_{k-1}) + m_k$$

System state at time k | *Parameters to be estimated* | *Process-to-process variation*

✓ Also called ***State Evolution*** model
✓ Obtained from <u>physical</u> or <u>empirical</u> knowledge
✓ Sometimes conditional on parameters, $\{A_k, B_k\}$, which determines the <u>performance degradation rate</u> and may be *time-varying*

Paris law, describing crack propagation over time (i.e. from x_{k-1} to x_k)

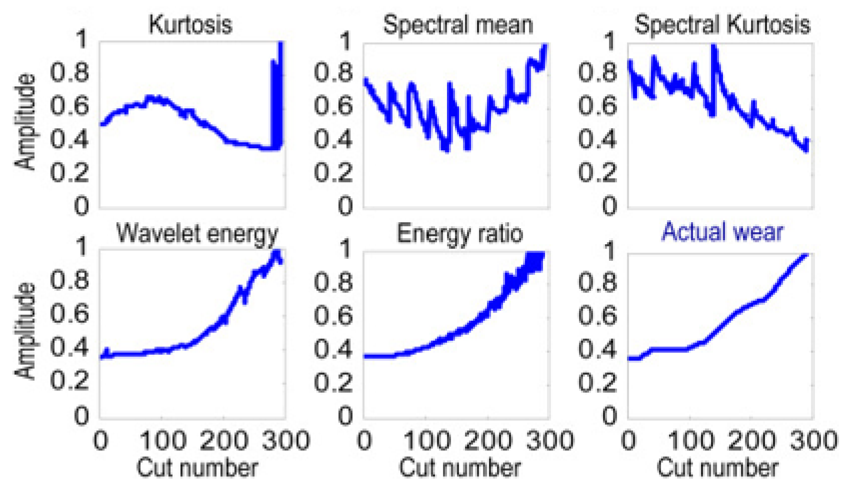


- **Likelihood Function** $P(z_k \mid x_k)$

$$z_k = g(x_k) + v_k$$

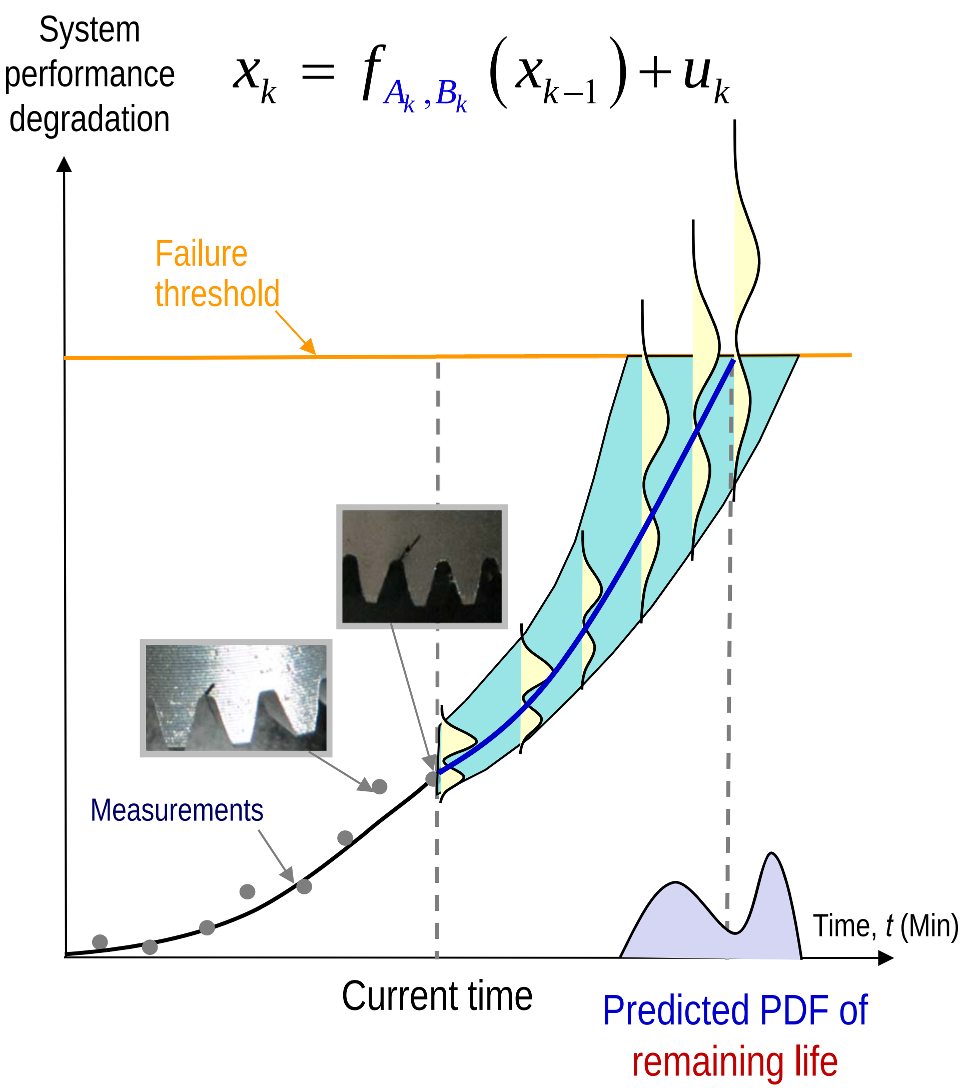
Sensor data or extracted features | *System state at time k* | *Measurement noise*

✓ Also called ***Measurement*** model
✓ *g*: *nonlinear* mapping, from data–driven model



Particle Filter

$$x_k = f_{A_k, B_k}\left(x_{k-1}\right) + u_k$$



- Each particle describes a specific state value and two coefficients $\left\{x_k^i, A_k^i, B_k^i\right\}$ (k: time; i: i^{th} particle);
- System state (e.g. tool wear) at a certain time is the *statistical sum* of values from a chosen number N of particles, expressed as a probability distribution;
- Particles' evolution directly determined by *state evolution model*, which can be linear or *nonlinear*
- State propagation is presented as progressive updates of prior PDF

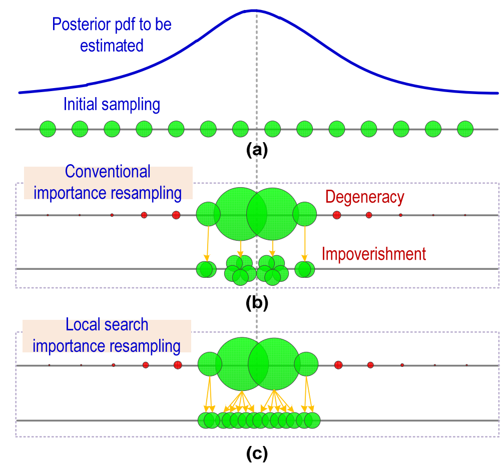
$$P\left(x_{k+1} \mid x_k\right) = \sum_{i=1}^{N} w_k^i P\left(x_{k+1}^i \mid x_k^i\right)$$

Recursively updated

Computed from state evolution model

Improvement on PF

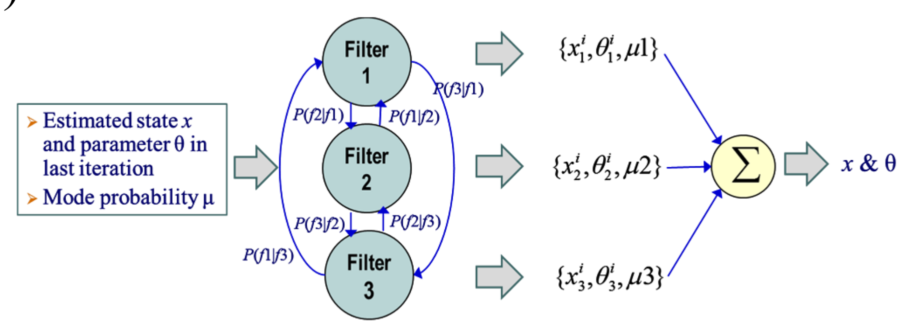
- **Limitation of PF**
  - ✓ *Particle degeneracy*: particles of weight 0 removed when estimating time-varying distribution
  - ✓ Not able to track and predict *time-varying* performance degradation



Wang & Gao, "Adaptive re-sampling-based PF", *JMS*, 2015

- **Improvement 1: Local Search PF** (LSPF)
  - ✓ For tracking and prognosis of *gradual* degradation with *time-varying* rates
  - ✓ Improve particles' diversity through *adaptive* change of positions of resampled particles, by adding a *perturbation*

- **Improvement 2: Multi-Mode PF** (MMPF)
  - ✓ For *transient* performance change
  - ✓ Each filter mode corresponds to one deterioration scenario
  - ✓ Mode transition *automatically* performed based on Bayesian inference



Wang & Gao, "Markov Nonlinear System", *ASME JGTP*, 2016

Bearing Failure and Life Prognosis

- Rolling bearing accounts for 30% rotating machine failure [1]
- Common causes for bearing failure [2]:
  - ✓ Fatigue
  - ✓ Excessive load
  - ✓ Overheating
  - ✓ Corrosion
  - ✓ Lubricant failure
  - ✓ Contamination
  - ✓ Misalignment
- ***Statistical*** bearing life, L_{10}:

$$L_{10} = \frac{\left(\frac{C}{P}\right)^{e} * 10^{6}}{60 * N}$$

C: dynamic load rating; ***P***: equivalent bearing load; ***N***: rotating speed; ***e***: constant

  - ✓ Not consider rffect of operating conditions
  - ✓ May deviate significantly from actual life, in some cases by nearly a *factor of 5* [3]

Fatigue

Corrosion

Contamination

Misalignment

[1] Tandon, A review of vibration, 1999
[2] SKF, Bearing damage chart
[3] Zaretsky, Bearing life prediction, 2000

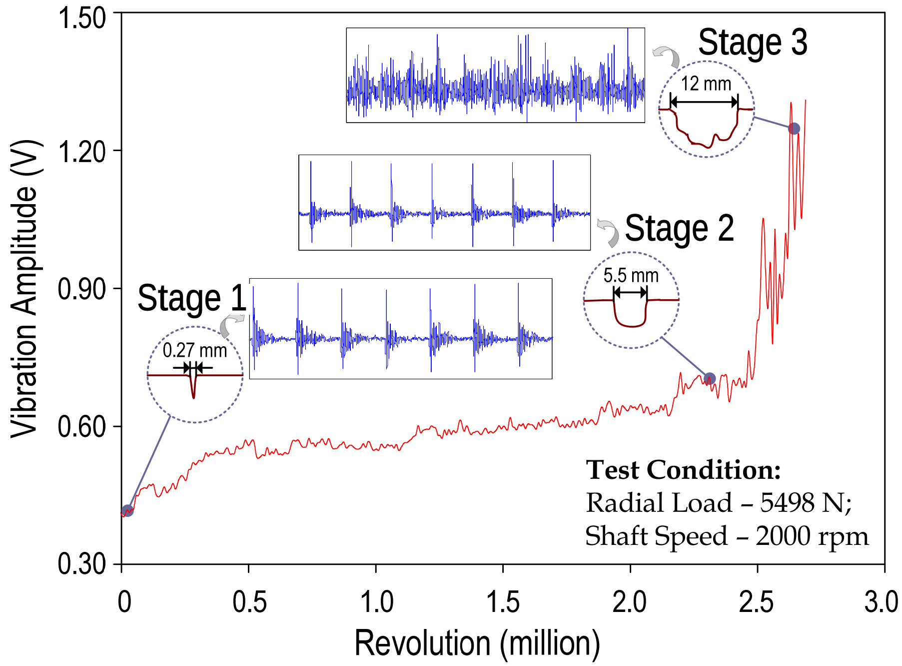
Multi-Stage Life Modeling

- **Bearing life stages**
  - ✓ Stage 1: *Normal operation*
  - ✓ Stage 2: *Defect initiation*
  - ✓ Stage 3: *Accelerated performance degradation*
- **Degradation modes**
  - ✓ Mode 1: *gradual degradation* (small vibration variation denoted by noise)

$$x_k = x_{k-1} + N(\mu_k, \sigma_k)$$

Vibration features | Time instance | Noise term

Life stages	Degradation modes
Stage 1	All Mode 1
Stage 2	Onset denoted by Mode 2
Stage 3	Most are Mode 2



- ✓ Mode 2: *exponential defect growth* (derived form spall propagation model)

$$\frac{dx}{dt} = \left(\frac{\Delta\tau}{C(1-x)}\right)^m = C' x^{m'}$$

C and *m*: material dependent parameters
$\Delta\tau$: shear stress range, constant

$$x_k = \left[x_{k-1}^{(1-m_k)} + C_k(1-m_k)\right]^{1/(1-m_k)}$$

Bearing Time to Failure Prognosis

- **Remaining Useful Life (RUL)**
  - ✓ Calculated as the *first passage time* T, at which the predicted vibration first passes the defined failure threshold

$$\begin{cases} RUL_p = \inf\left\{ T : x_k + \sum_{i=k+1}^{T} N(\mu_k, \sigma_k) \geq Threshold \right\} & \text{for Mode 1} \\ RUL_p = \inf\left\{ T : \left[x_{T-1}^{(1-m_T)} + C_T(1-m_T) \right]^{1/(1-m_T)} \geq Threshold \right\} & \text{for Mode 2} \end{cases}$$

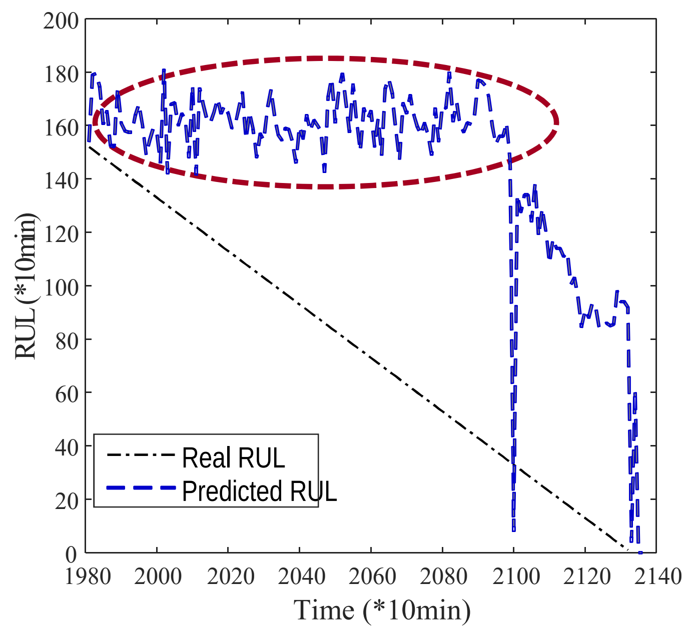
μ and σ: to be estimated by PF

C and m: to be estimated by PF

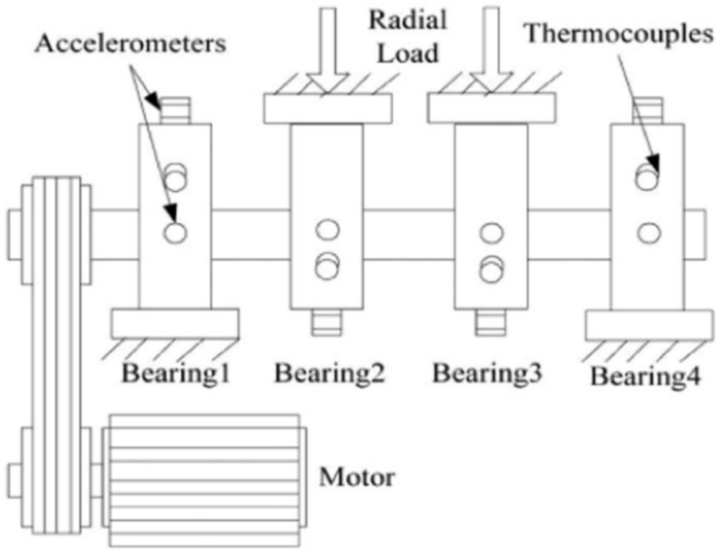
inf(•) denotes the first passage time

- **RUL Model Compensation**
  - ✓ Vibration maintain at a level before defect initiation → predicted RULs by Mode 1 almost *constant*
  - ✓ A *compensation* needed for Mode 1

$$RUL_{k,comp} = RUL_{k,predicted} - k\left(1 - \frac{x_k - x_1}{x_1}\right)$$



Experimental Setup



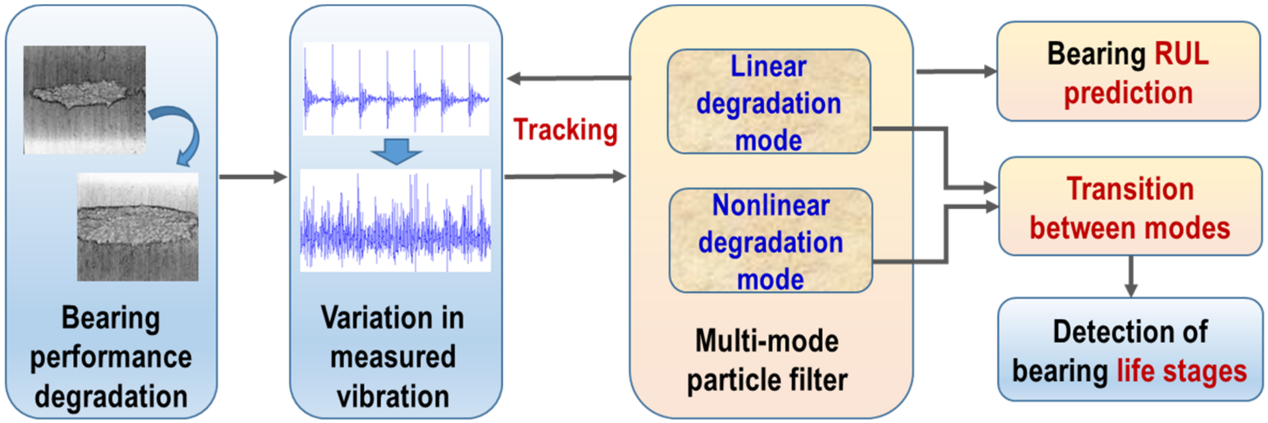
Inner-race defect

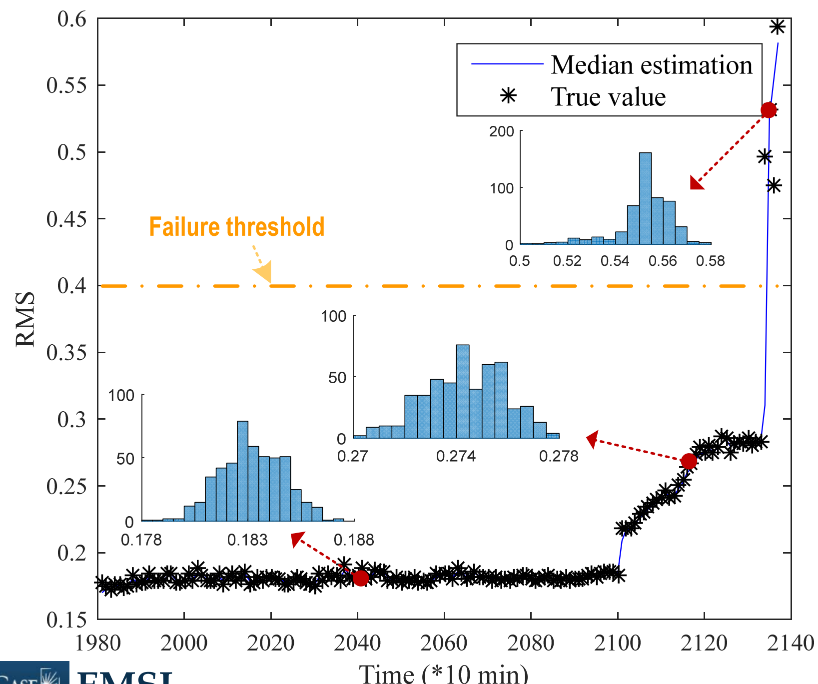
Outer-race defect

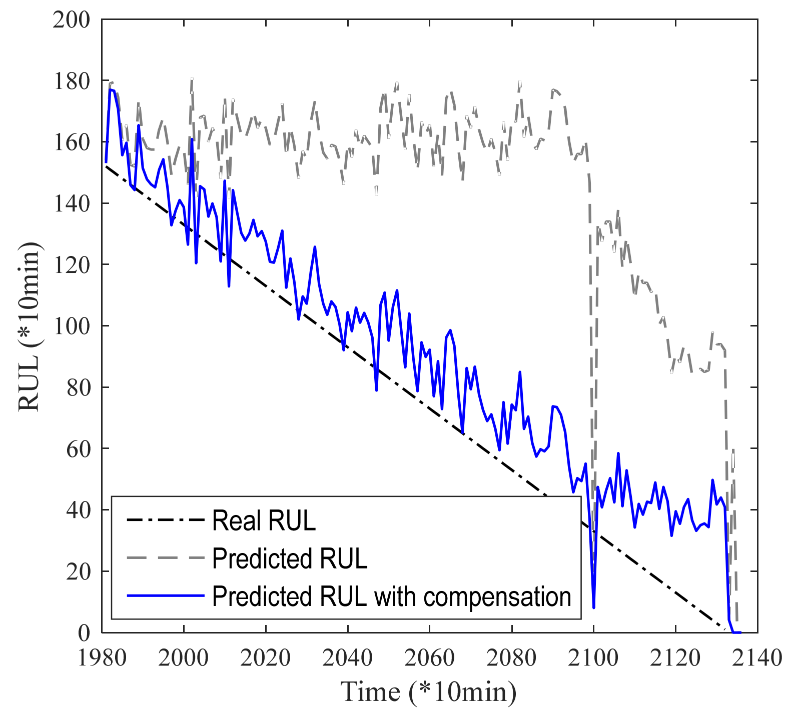
- ✓ *Constant rotational speed* at 2,000 rpm, a *radial load* of 6,000 lb
- ✓ Four ZA-2115 double row bearings, with force *lubricated*
- ✓ vibration data were collected every 10 minutes, with 20 kHz sampling rate
- ✓ A magnetic plug placed in the oil feedback pipe to collect debris; experiments stopped when the *accumulated debris* exceeded a certain level

Lee, J, IMS, University of Cincinnati. "Bearing Data Set", NASA Ames Prognostics Data Repository, 2007

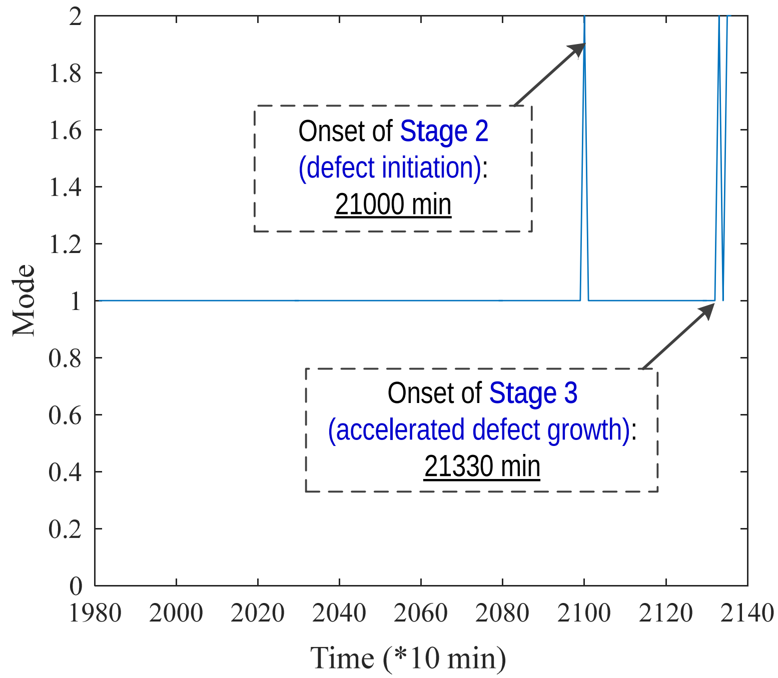
Multi-Mode Prognosis







Performance Evaluation

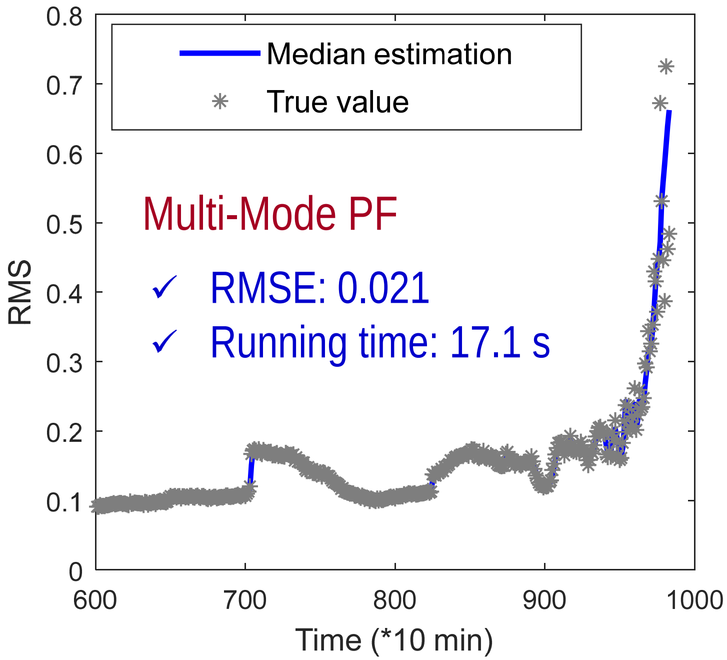


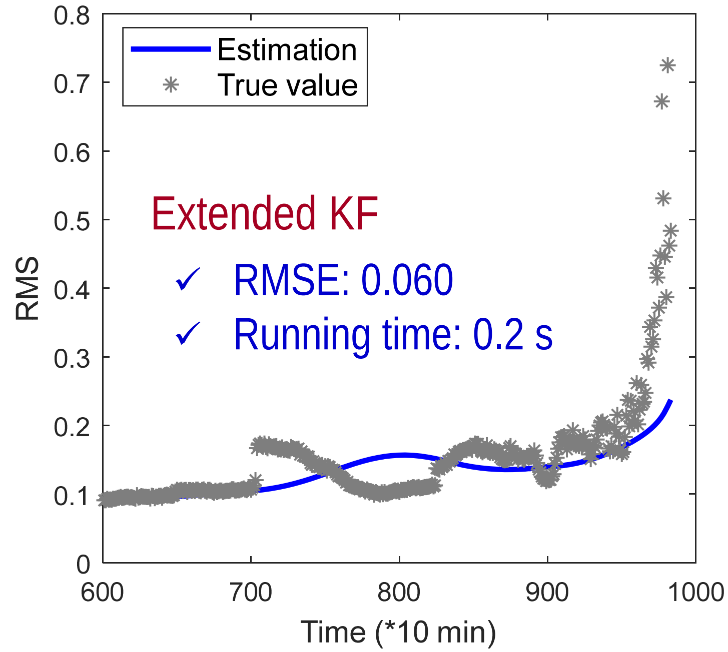
- **Automatic detection of transition among different bearing life stages**
  - ✓ Onset of stage 2: the *first transition* point in time from Mode 1 to Mode 2
    → a *jump* occurs in the measured vibration
  - ✓ Onset of stage 3: the point in time when Mode 2 is switched on
    → large vibration variation caused by *accelerated* spall propagation, accelerated material fracture

Comparison between standard PF and multi-mode PF

	Standard PF with nonlinear degradation function	Multi-mode LSPF
Prediction error RMSE [hour]	7.9	2.9

Comparison: PF vs. KF





Particle Filter		Extdended Kalman Filter	
Comp. Steps	Computational Complexity	Comp. Steps	Computational Complexity
Prediction	$N * (n^2 + n)$	Prediction	$n^3 + 2n^2 + n$
Update	$N * (2p^2 n + pn + p)$	Kalman gain	$2p^3 + 2p^2 n + 2pn + p$
Resampling	$N * (2anN + n^2 + 2n + qn)$	Update	$pn^2 + 2n^2 + 2pn + p + n$

Note: N: number of particles in PF; *n:* state dimension; *p:* measurement dimension
a: coefficient related to resampling strategy, between 0 and 1; *q:* constant

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Wang & Gao, "Adaptive re-sampling-based PF", *JMS*, 2015

Broad Applications of PF

(Wang and Gao, JMS, 2015)

Machine tool

Motor

Performance Tracking

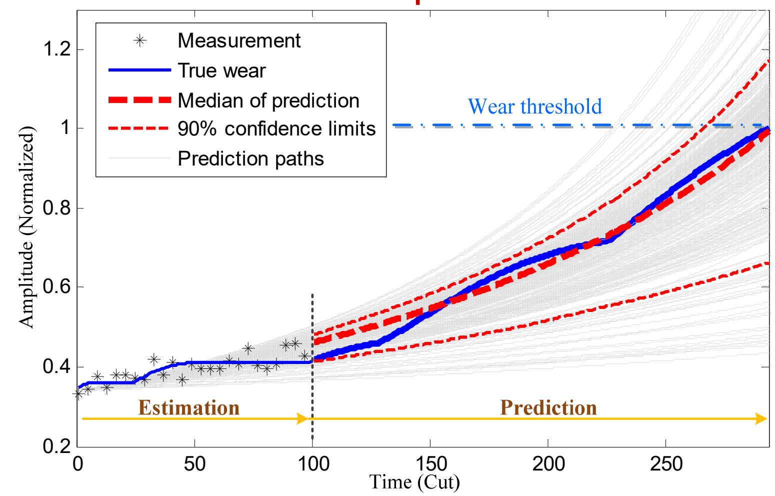
Gearbox

(Wang *et al*. JMS, 2017)

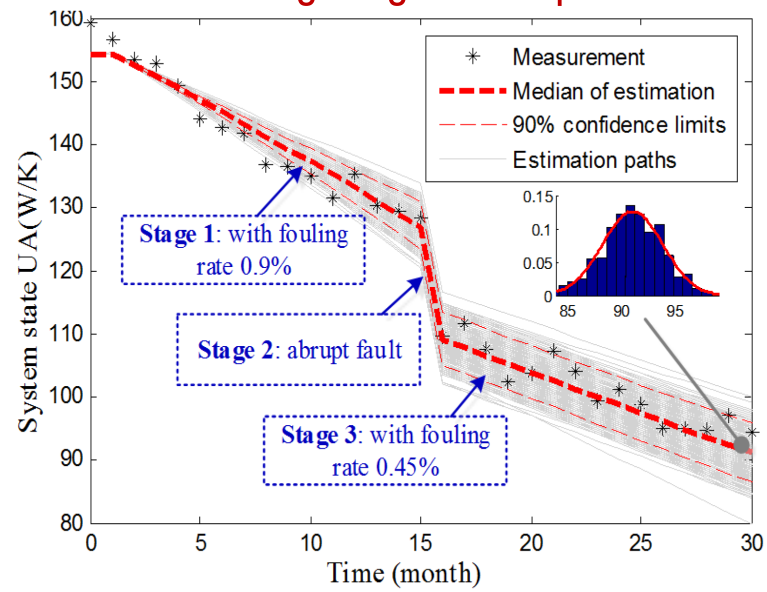
(Wang and Gao, IEEE TASE, 2017)

HVAC system

Tool wear prediction



Heat exchange degradation prediction



Moving Forward

Machines | **Sensor Measurement** | **Data Analytics**

Vibration

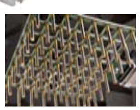
Temp

Speed

AE

Micro wireless sensing networks

Acoustic array



High-speed cameras

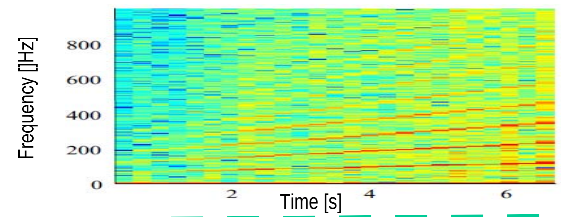
Current — React and Repair

Techniques

- Deterministic feature extraction
- Feature fusion through PCA
- Time-freq. analysis (e.g. STFT, wavelet)

Results

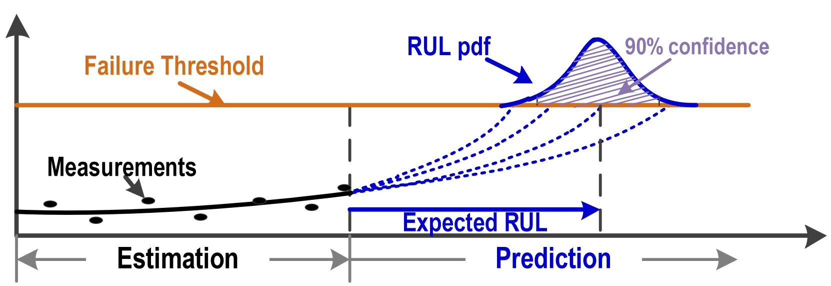
- Fault diagnosis: type and degree
- Condition-based maintenance



Future — Predict and Prevent

- Probabilistic inference (e.g. PF, Bayesian network)
- Deep Learning (e.g. DBN, DCNN)
- Multi-physics data fusion

- Fault Prognosis: degradation tracking and prediction
- Intelligent predictive maintenance



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Thank You!