Battery Prognostics

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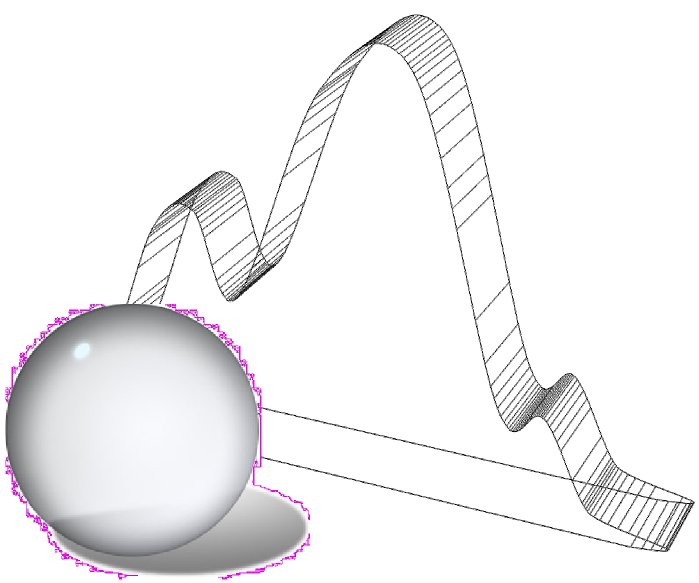

Prognostics Testbed

- Motivation
  - To facilitate research in prognostics, it is imperative to have a hardware testbed that mimics the complexities and issues encountered for a real system.
  - Such a system will support
  - Algorithm development
  - Testing and validation of prognostic tools
  - Benchmarking of different approaches
  - Development of metrics for prognostics
  - Collection and dissemination of run-to-failure data

- Goal

  Demonstrate ability to distinguish between components at different health states having similar external observables and then to predict the end of life

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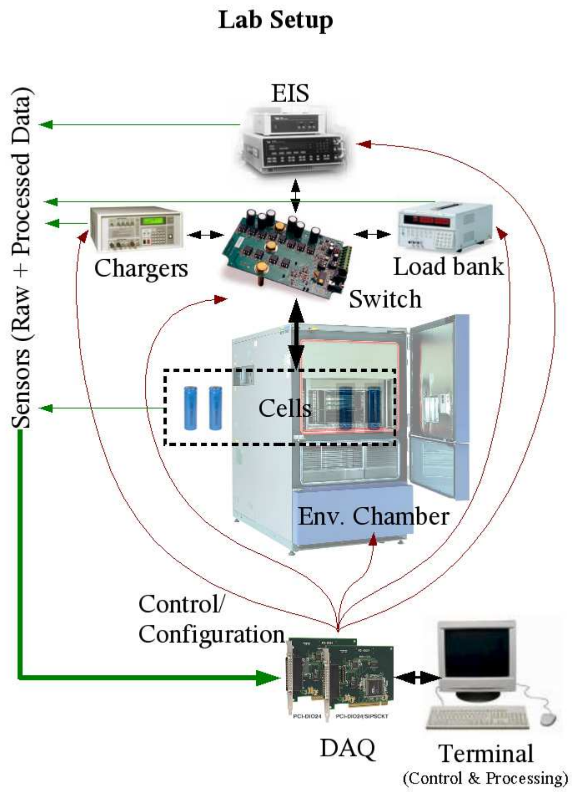
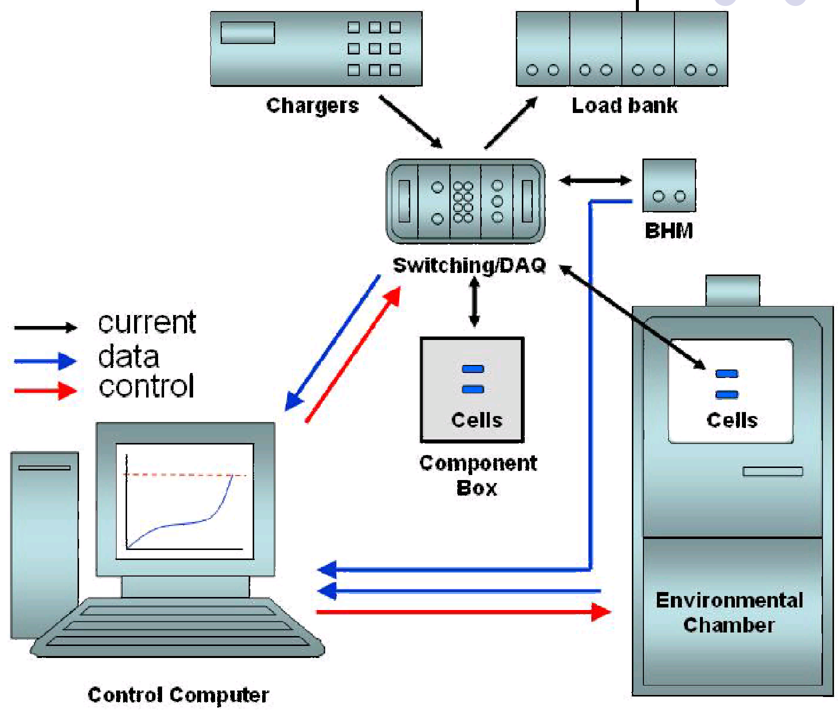
Why Batteries?

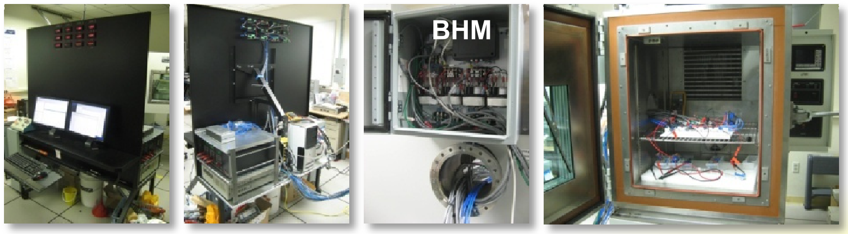
- Resemble a system that has real-world relevance
- Allow for repeated run-to-failure of components
- Perform run-to-failure in reasonable time
- Support monitoring of ground truth
- Collect data for state assessment
- Support demonstration of prognostic solutions
- Allow control of several operational and/or environmental variables
- Allow quantification of uncertainty sources
- Support repeated run-to-failure within a finite budget
- Support automated data collection during the aging



Battery Testbed

- Experimental Plan
- Cells are cycled through charge and discharge under different load and environmental conditions set by the electronic load and environmental chamber respectively
- Periodically EIS measurements are taken to monitor the internal condition of the battery
- DAQ system collects externally observable parameters from the sensors
- Switching circuitry enables cells to be in the charge, discharge or EIS health monitoring state as dictated by the aging regime





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Data Format

- Cycle
  - Charge/Discharge
    - Profile
    - Date
    - Time
    - Ambient temperature
    - Data
      - V, A, T (@ batteries)
      - V, A (@ charger/load)
      - time
  - Impedance
    - Parameters
    - Date
    - Time
    - Ambient temperature
    - Data
      - I_B
      - I_S
      - I_B/I_S
      - Z_B

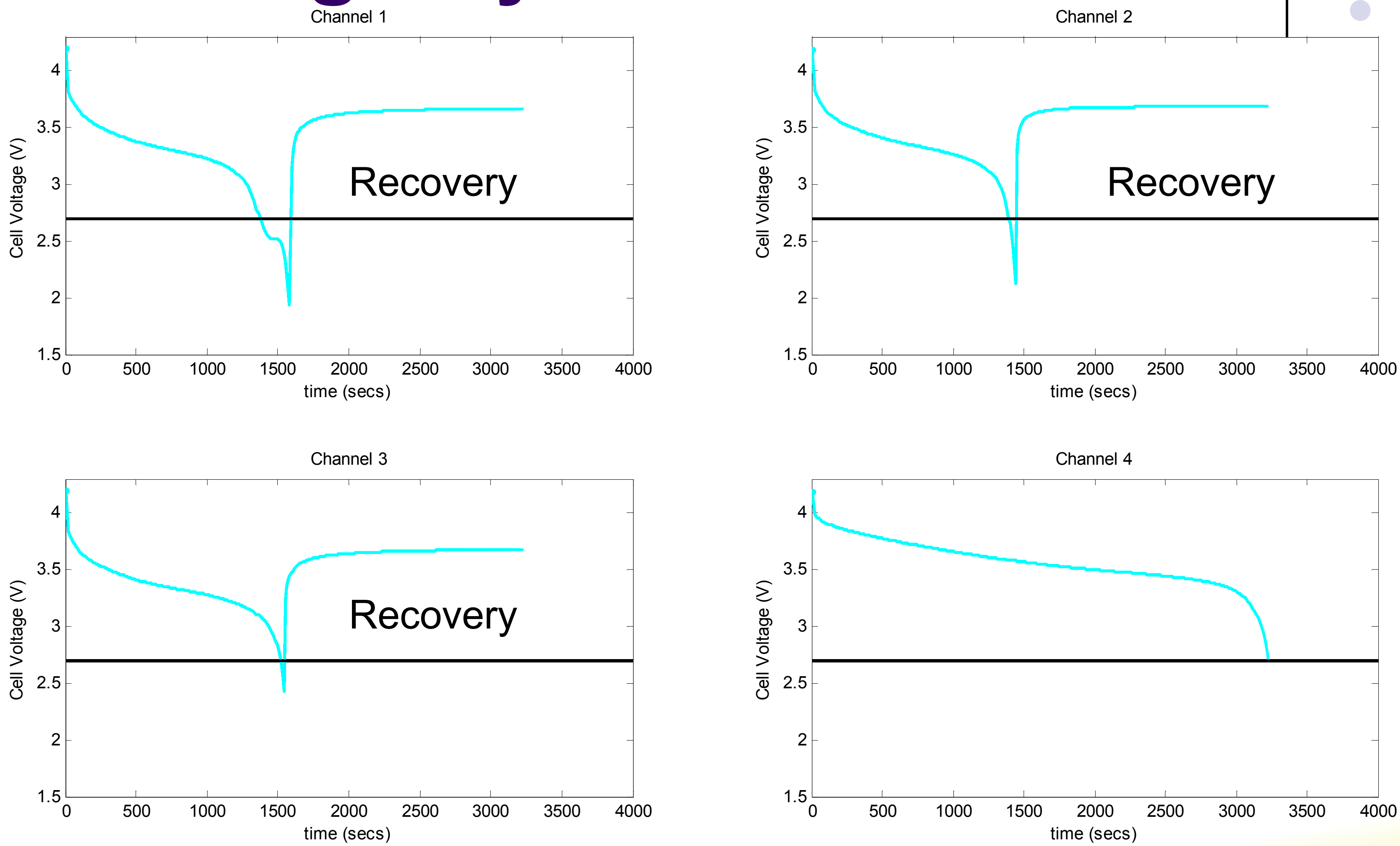
Predict

- End of charge
- End of life

Processes

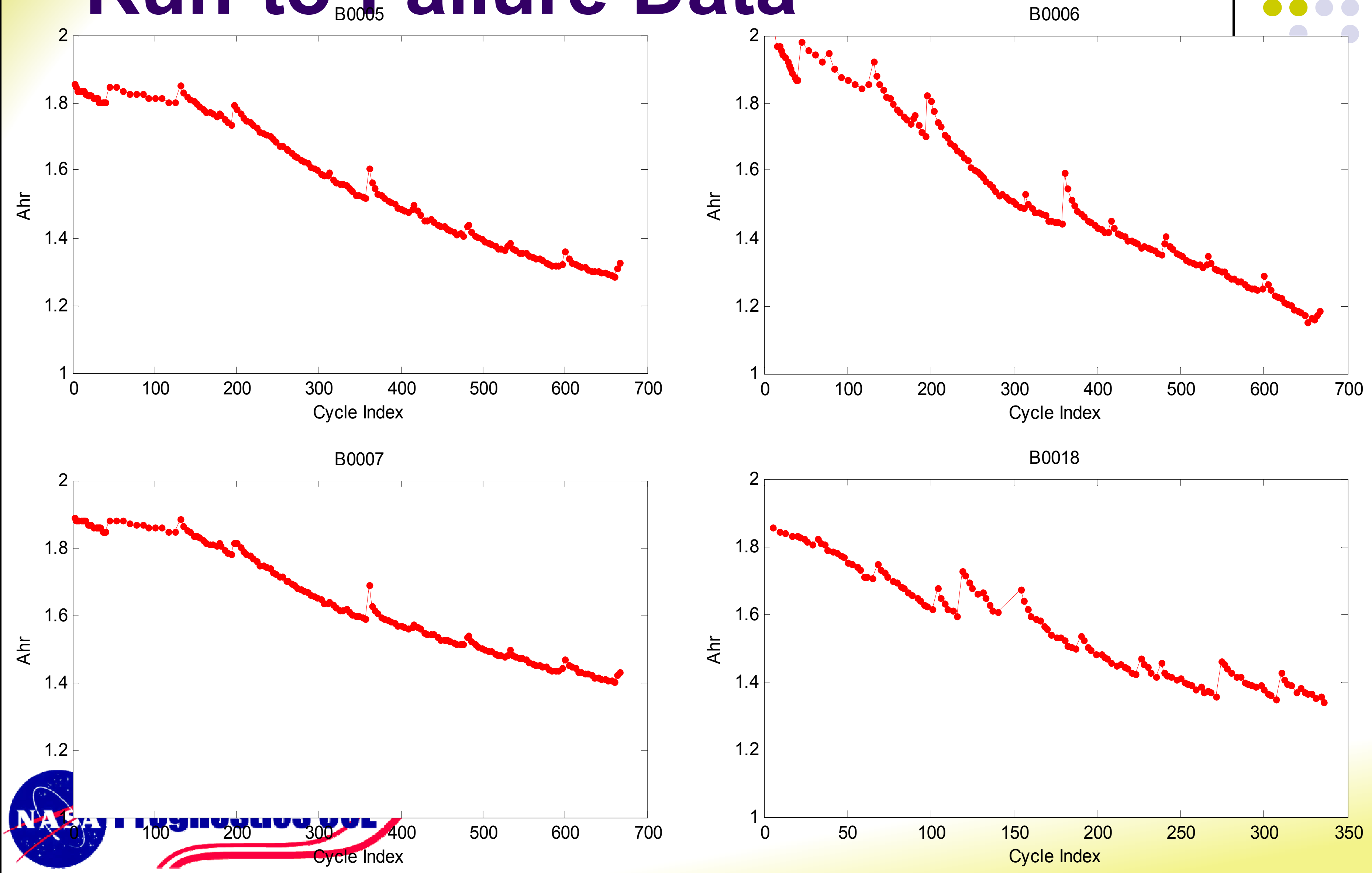
- Charge
- Discharge
- Recovery from rest

Discharge Cycle Data

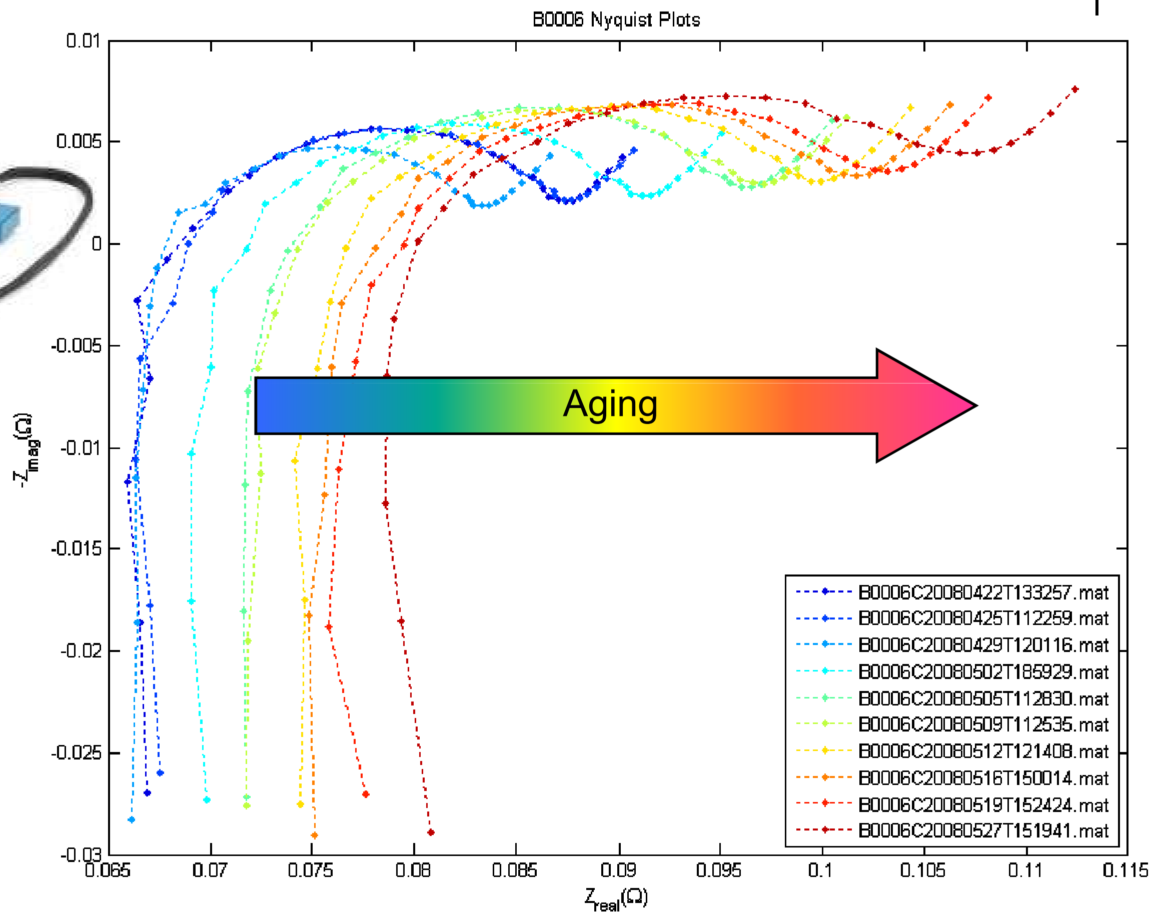


Prognostics CoE

Run-to-Failure Data



Aging Data

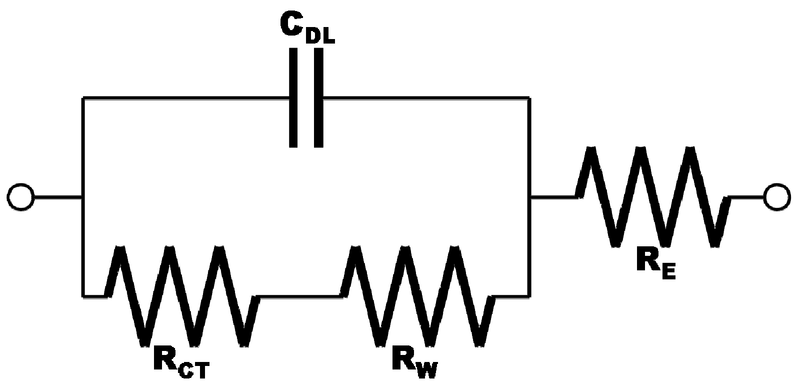


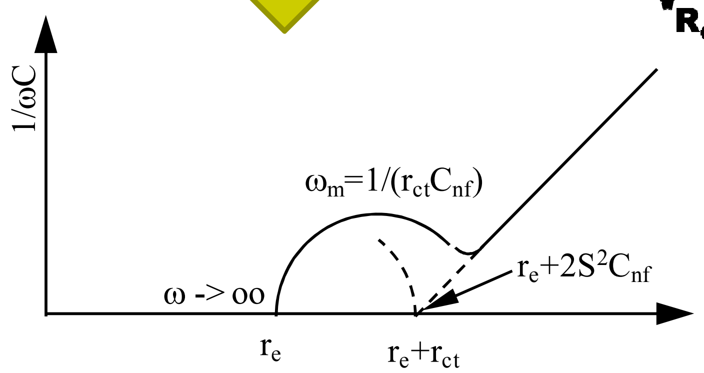
Prognostics CoE

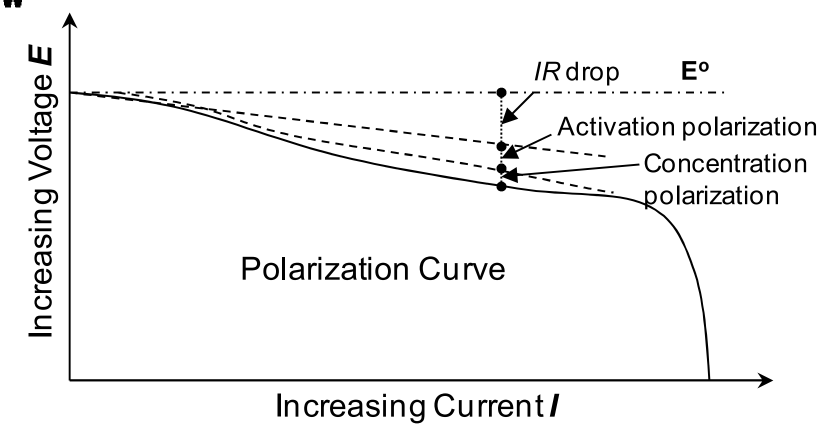
Modeling

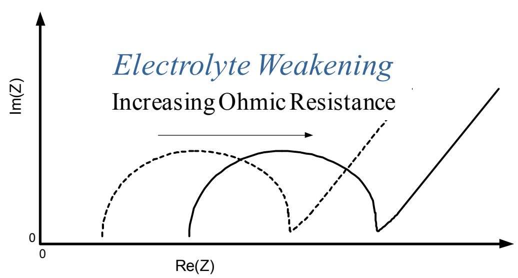
Freq. Domain

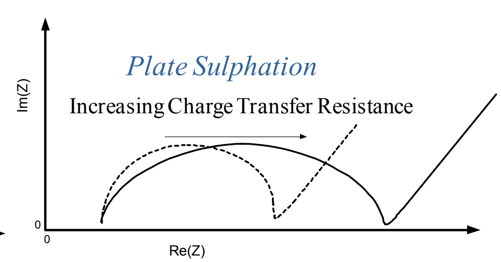
Time Domain

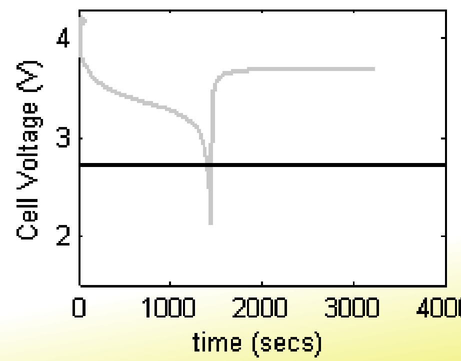












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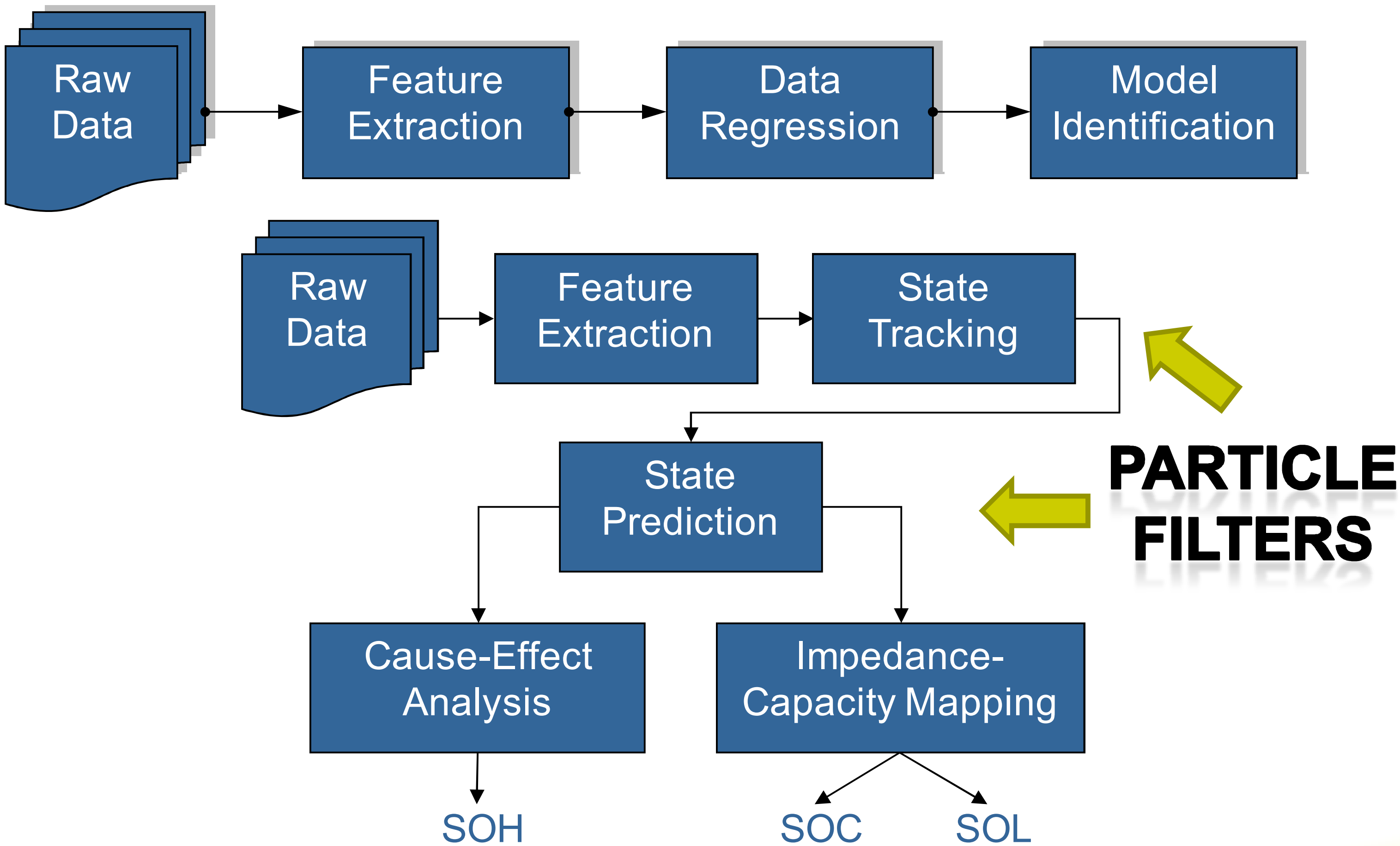
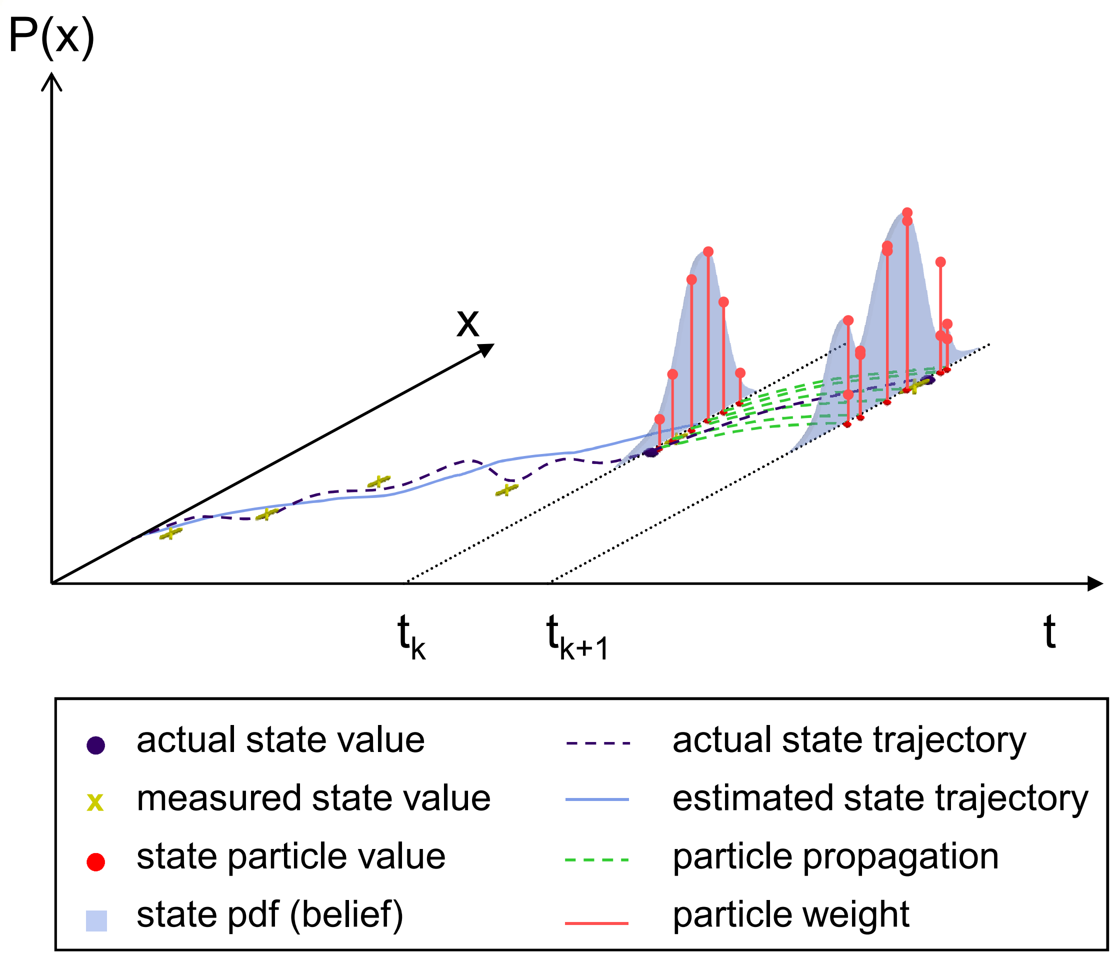
Logical Flowchart



Particle Filtering



- represent state as a pdf
- sample the state pdf as a set of particles and associated weights
- propagate particle values according to model
- update weights based on measurement

Particle Filtering

- A particle filter iteratively approximates the posterior *pdf* as a set:

$$S_k = \{\langle x_k^i, w_k^i \rangle \mid i = 1, \ldots, n\}$$

$$p(x_k \mid z_{1:k}) \approx \sum_{i=1}^{n} w_k^i \delta(x_k - x_k^i)$$

where:

x_k^i is a point in the state space

w_k^i is an importance weight associated with the point

Prognostics CoE

Particle Filtering

- Prediction step: use the state update model

$$p(\mathbf{x}_k \mid \mathbf{z}_{1:k-1}) = \int p(\mathbf{x}_k \mid \mathbf{x}_{k-1}) p(\mathbf{x}_{k-1} \mid \mathbf{z}_{1:k-1}) d\mathbf{x}_{k-1}$$

- Update step: with measurement, update the prior using Bayes' rule:

$$p(\mathbf{x}_k \mid \mathbf{z}_{1:k}) = \frac{p(\mathbf{z}_k \mid \mathbf{x}_k) p(\mathbf{x}_k \mid \mathbf{z}_{1:k-1})}{p(\mathbf{z}_k \mid \mathbf{z}_{1:k-1})}$$

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Resampling

- Particle weights degenerate over time
  - measure of degeneracy: effective sample size

$$\hat{n}_{eff} = 1/\sum_{i=1}^{n}(w_k^i)^2$$

use normalized weights

$$1 \leq \hat{n}_{eff} \leq n$$

  - resample whenever $\hat{n}_{eff} < n_{thr}$
  - new set of particles have same statistical properties

$$\{x_k^i, w_k^i\} \Leftrightarrow \{x_k^{i*}, 1/n\}$$

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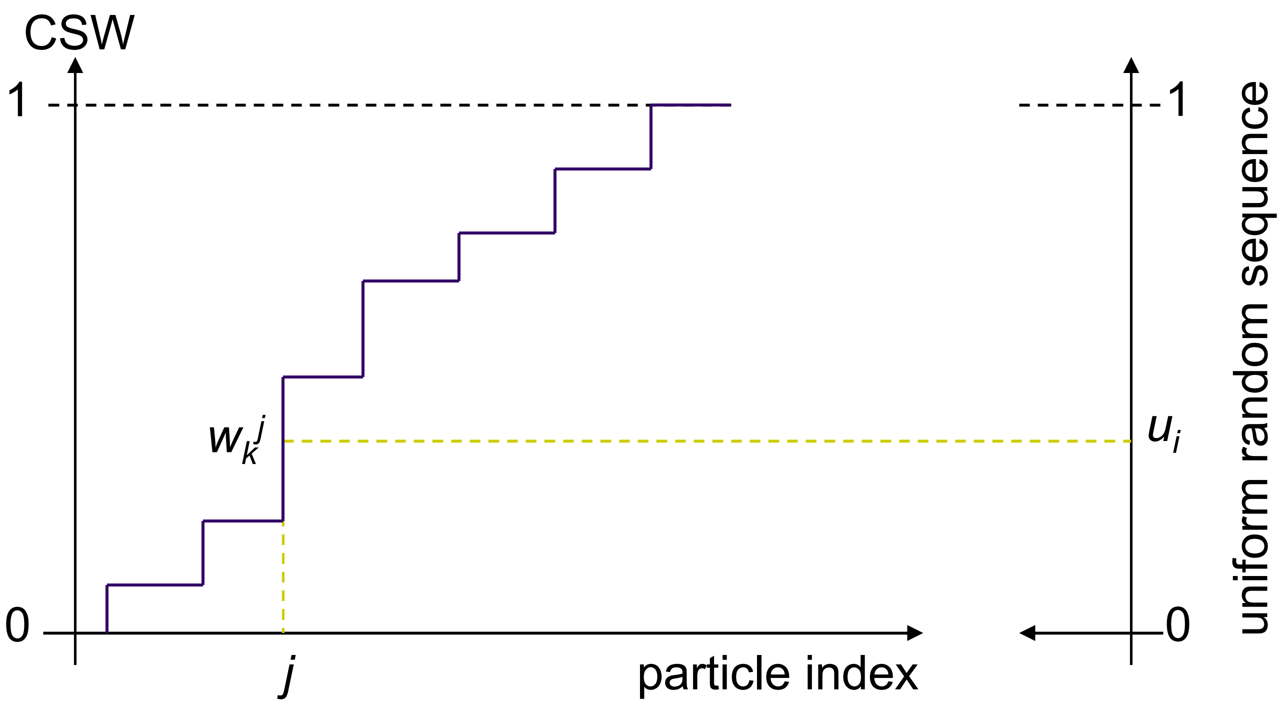
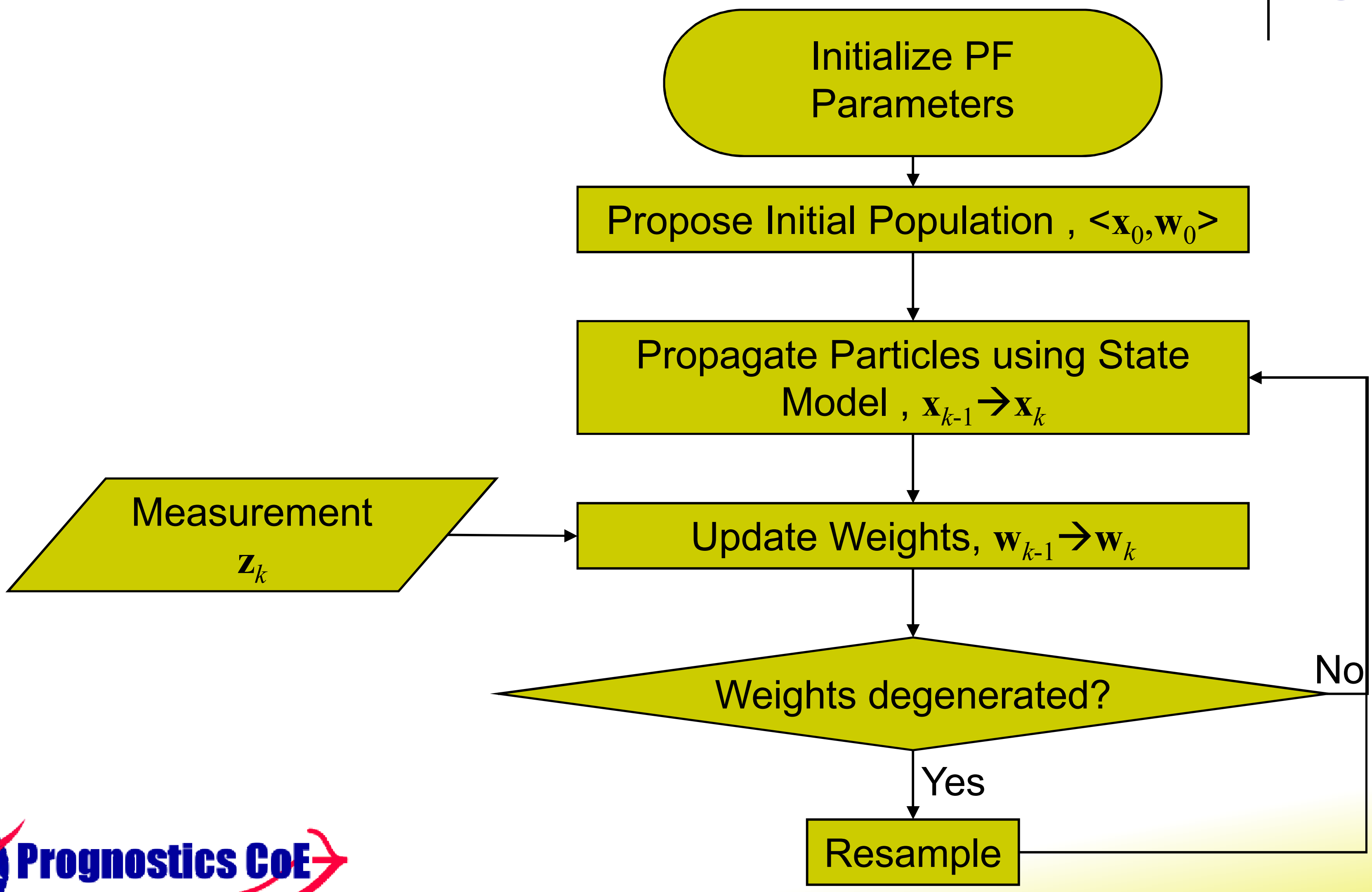
Resampling



PF Flowchart



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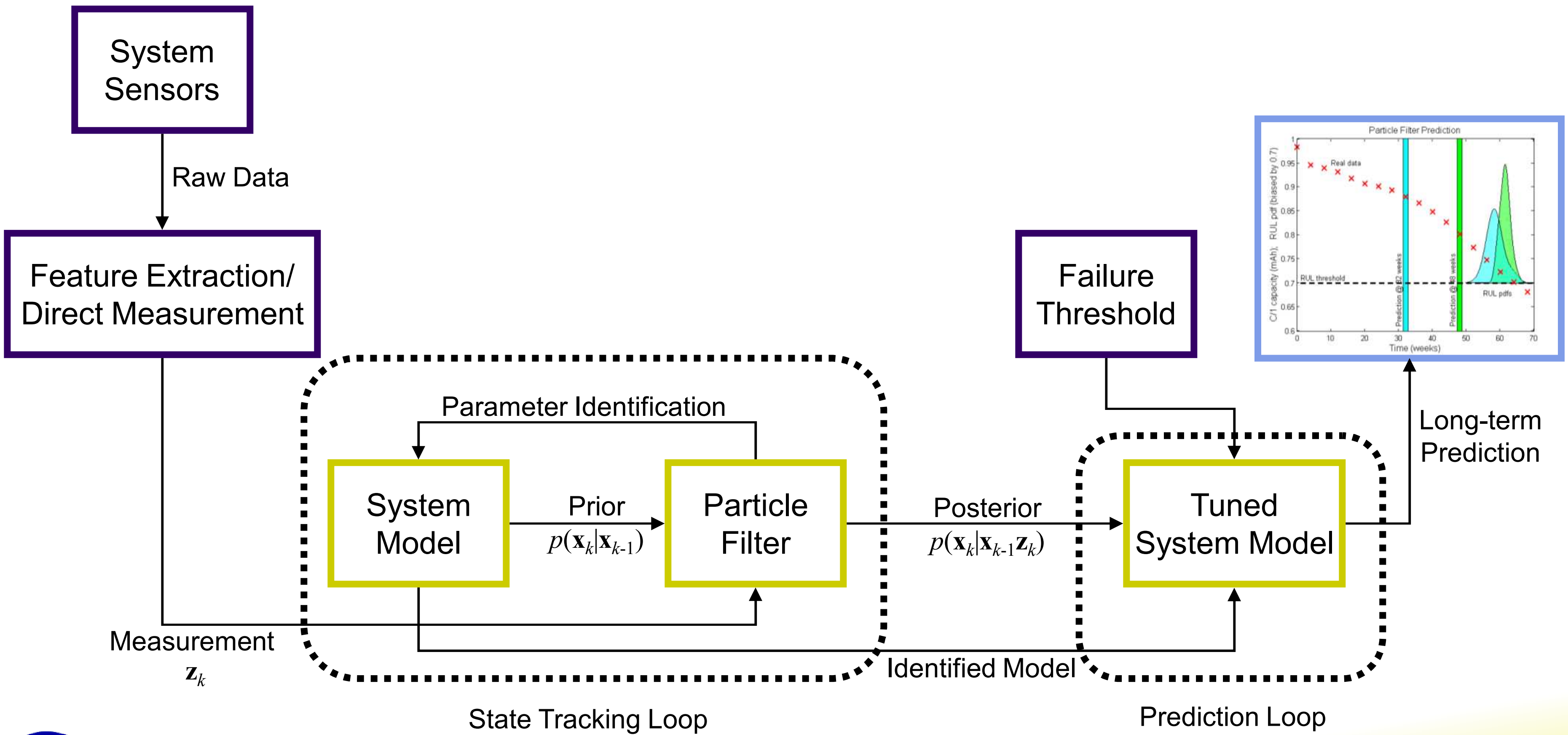
Prognostic Framework



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Particle Filtering as a Tool

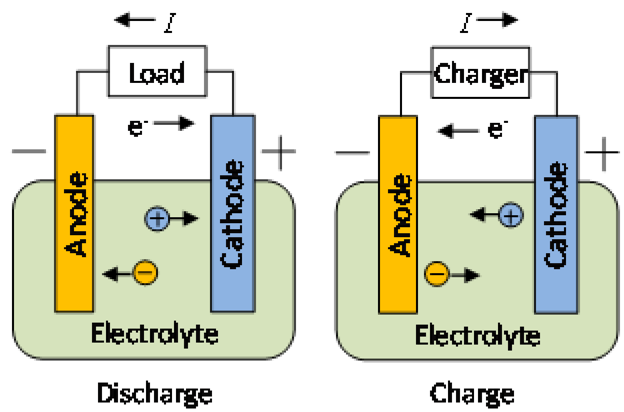
- Model adaptation
- State estimation, tracking and prediction
- Nice tradeoff between MC and KF
- Useful in both diagnostics and prognostics
- Represent uncertainty
- Manage uncertainty

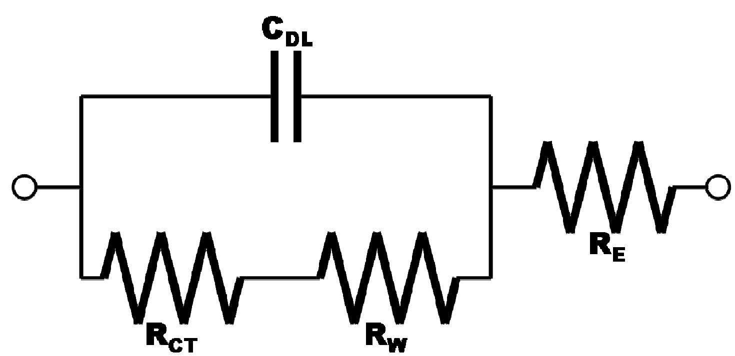
Prognostics CoE

Sources of Uncertainty

- Model
  - System complexity
  - Insufficient knowledge
  - Unknown environment
- Noise
  - Internal, external
  - Electrical, mechanical, thermal
- Sensor
  - Digitization
  - Bias
  - Deadbands, backlash, hysteresis
  - Nonlinear response

Modeling Uncertainty





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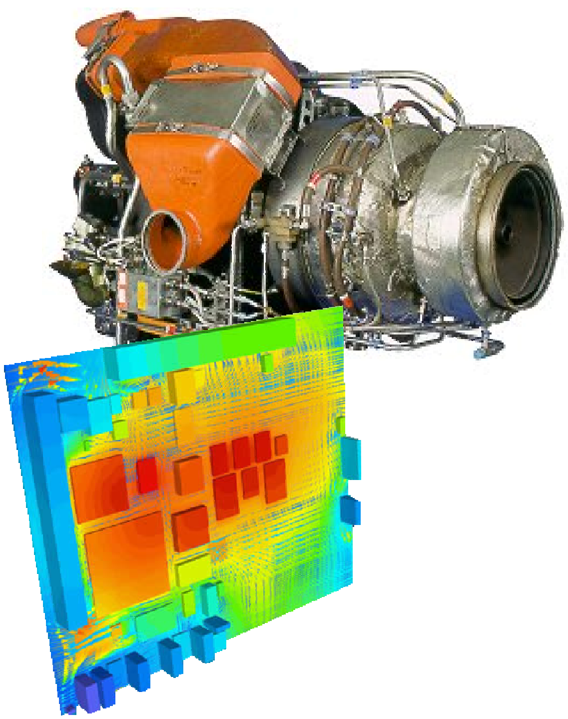
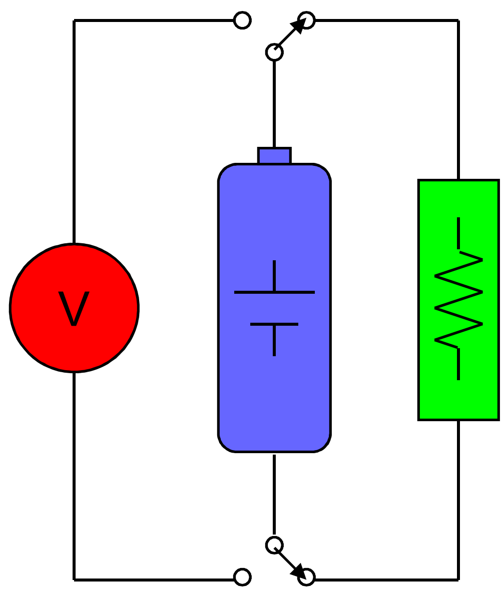
Noise Induced Uncertainty

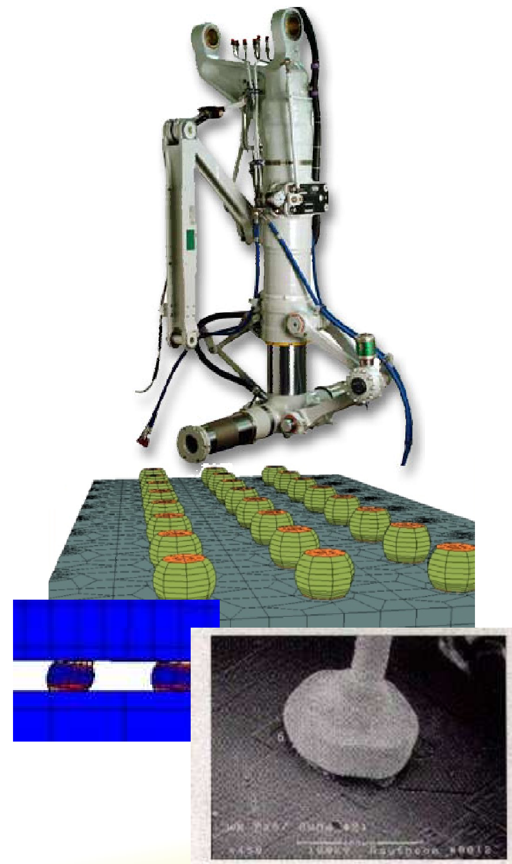


Switching



Charge

Discharge



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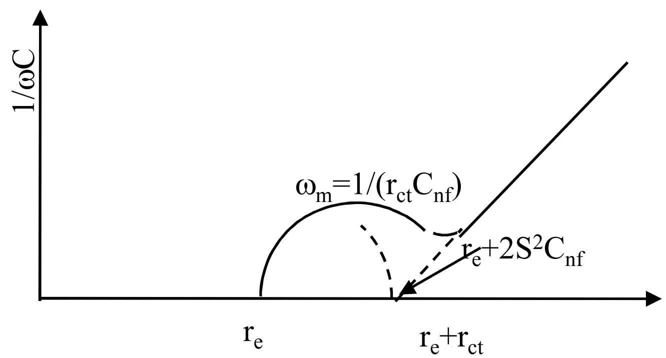
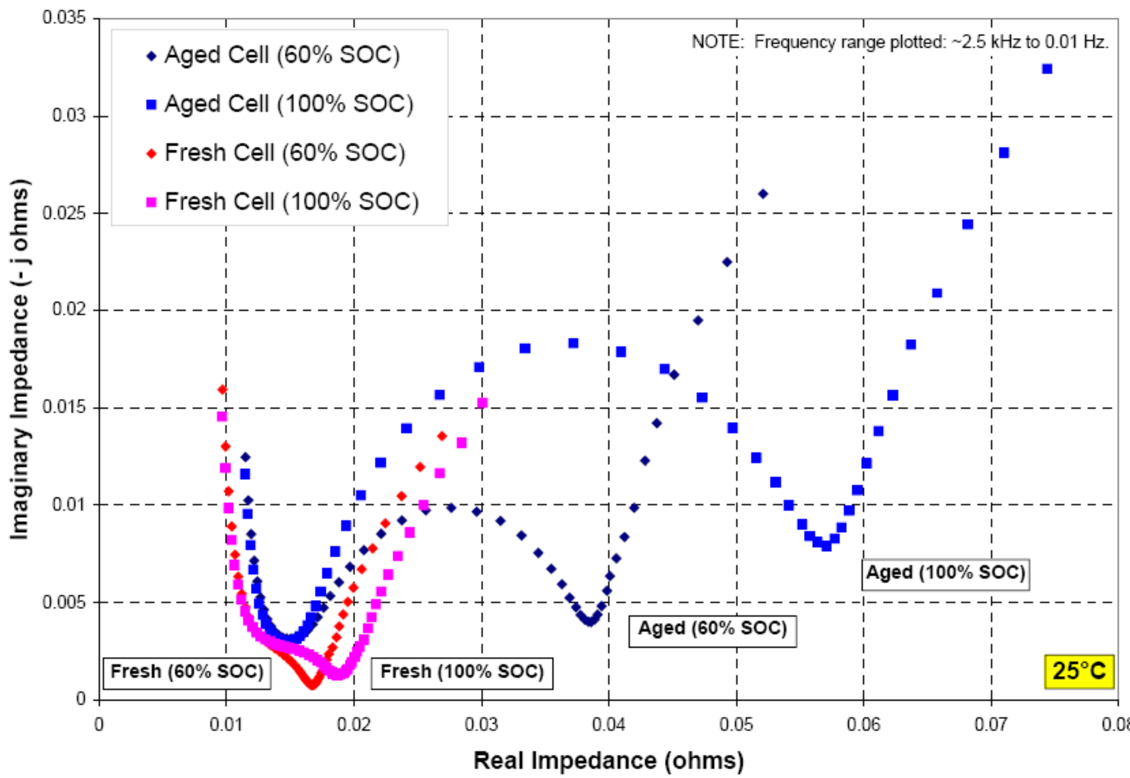
Sensor Uncertainty





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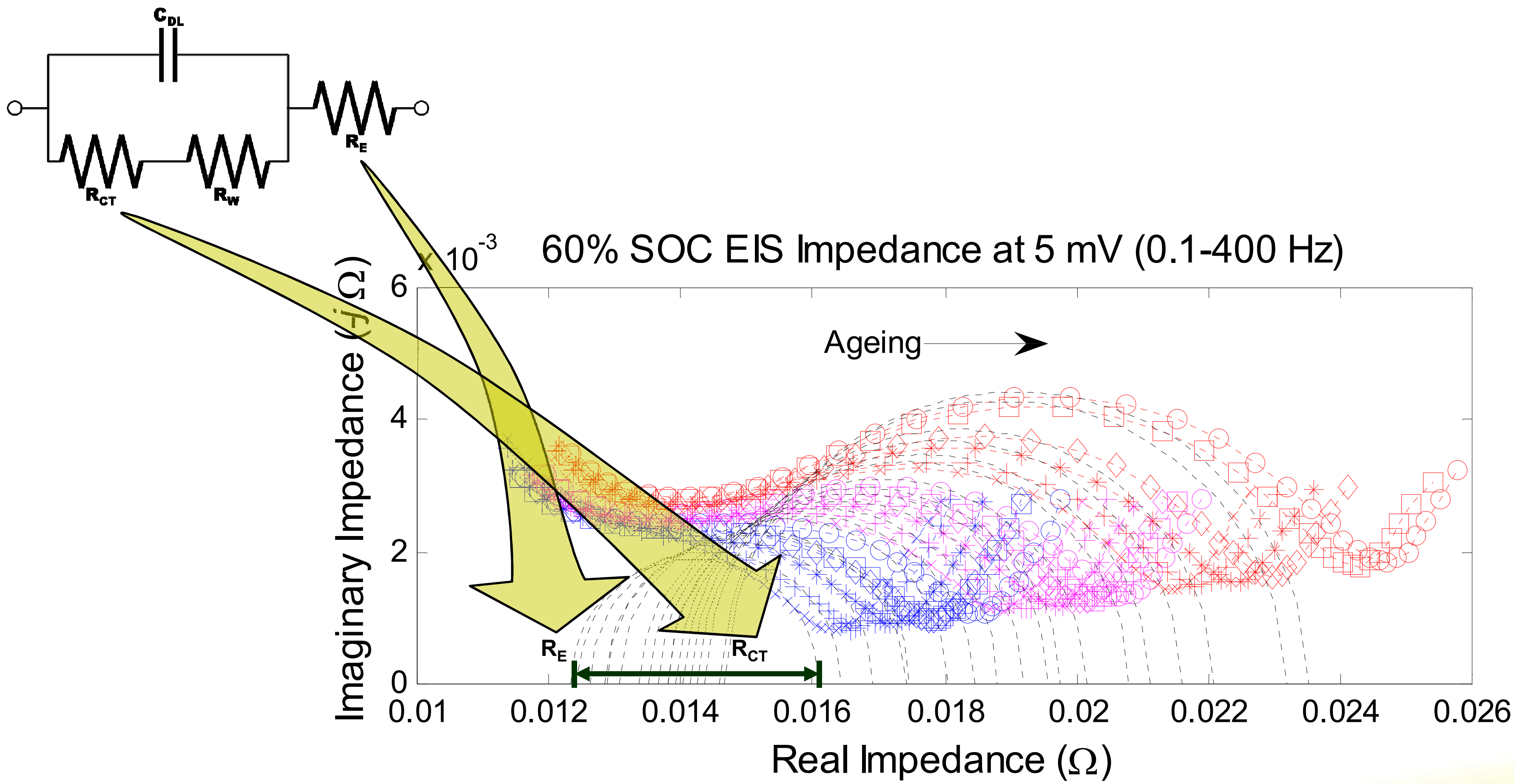
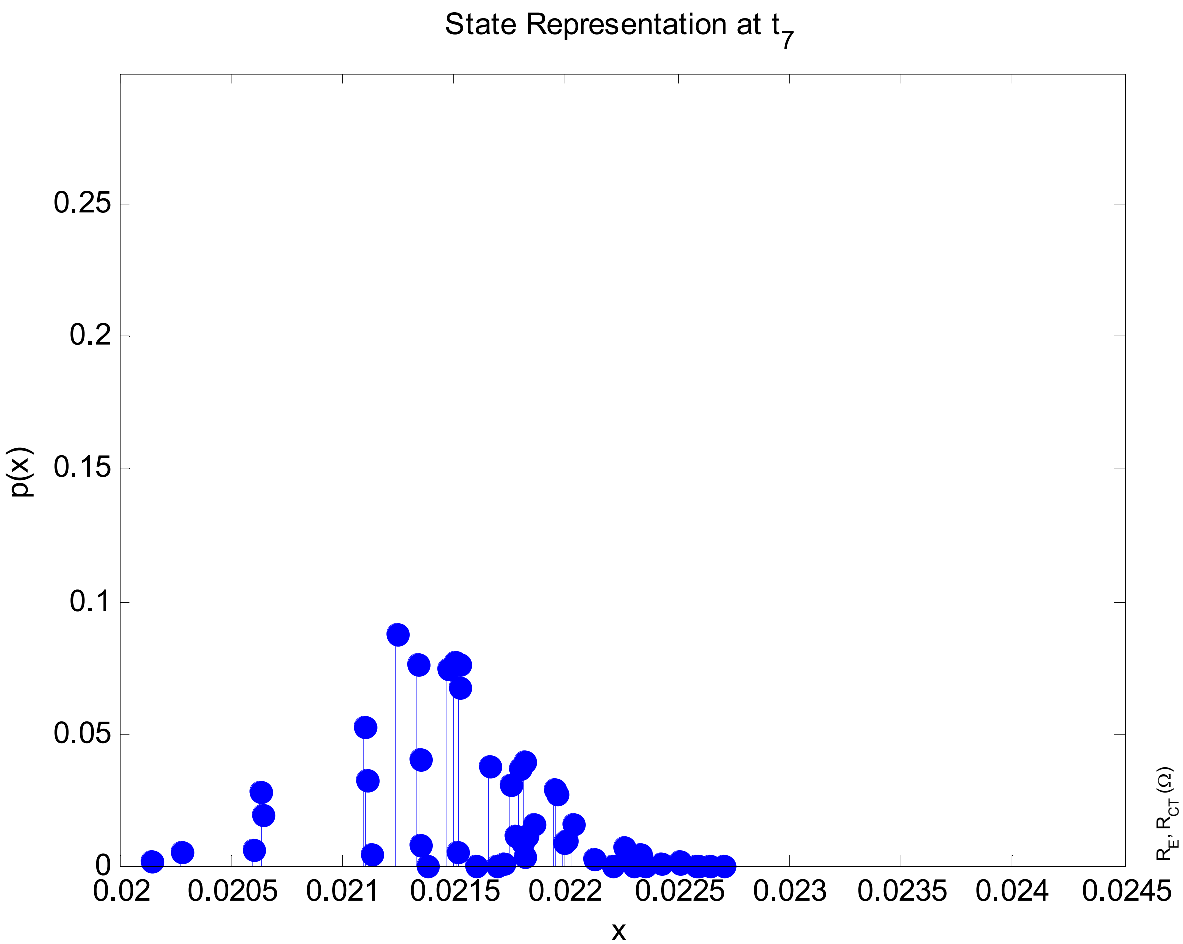
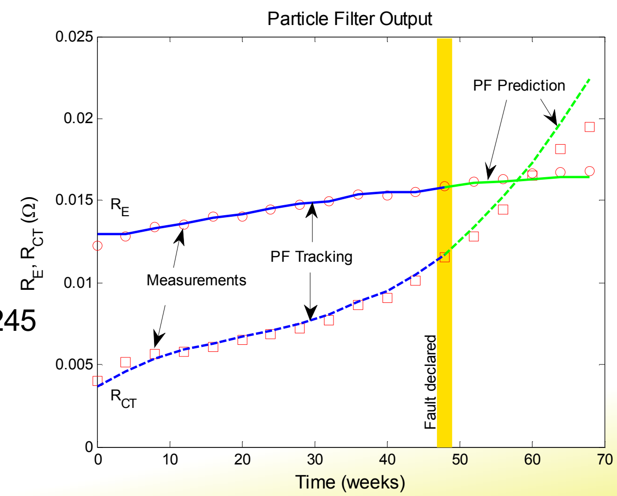
Results: Feature Extraction



Results: Intermediate Steps

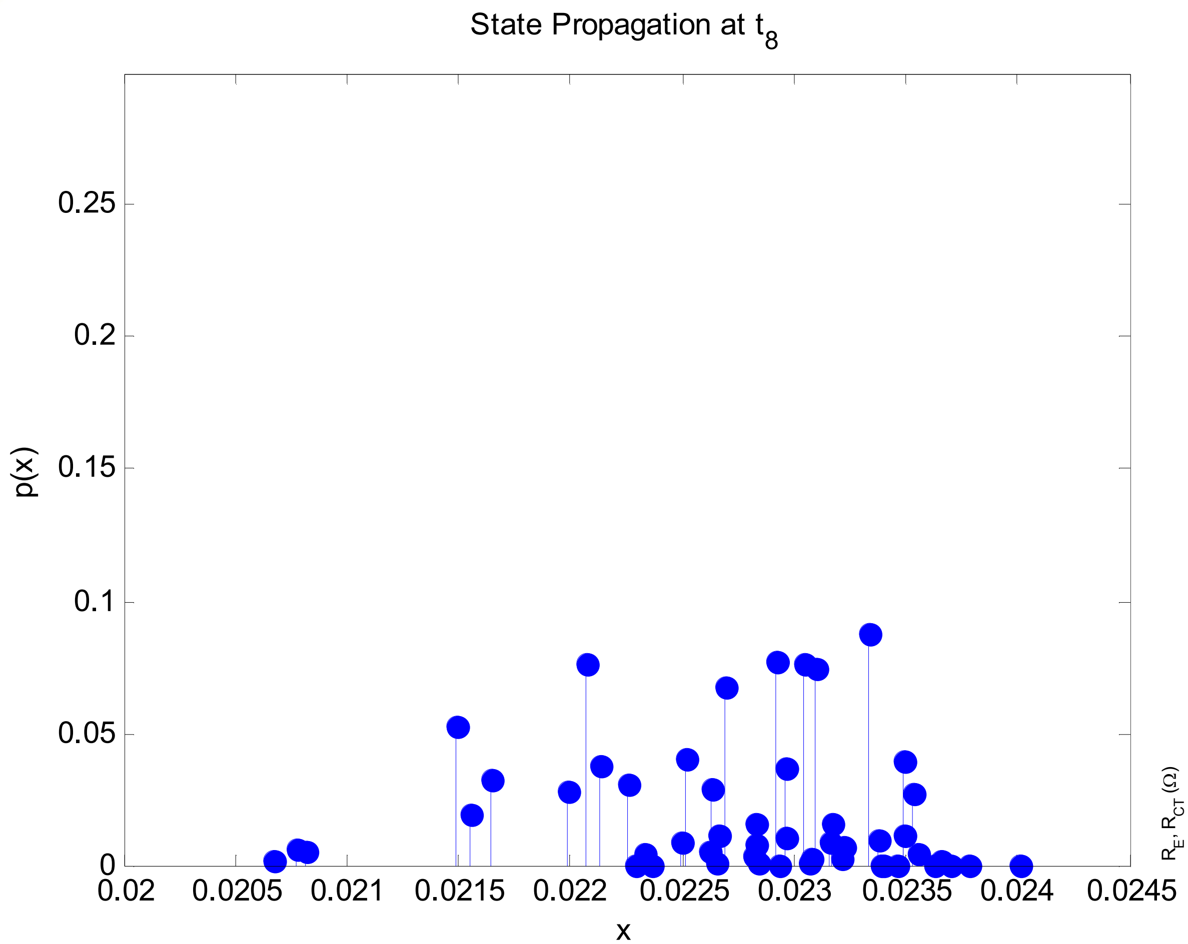


R_E (ohms)

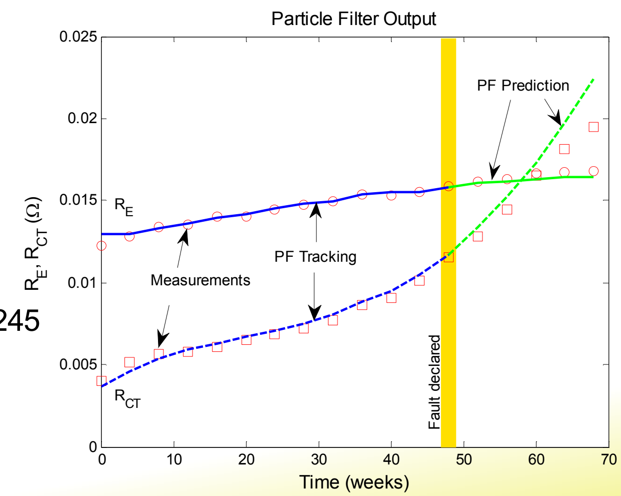


Prognostics CoE

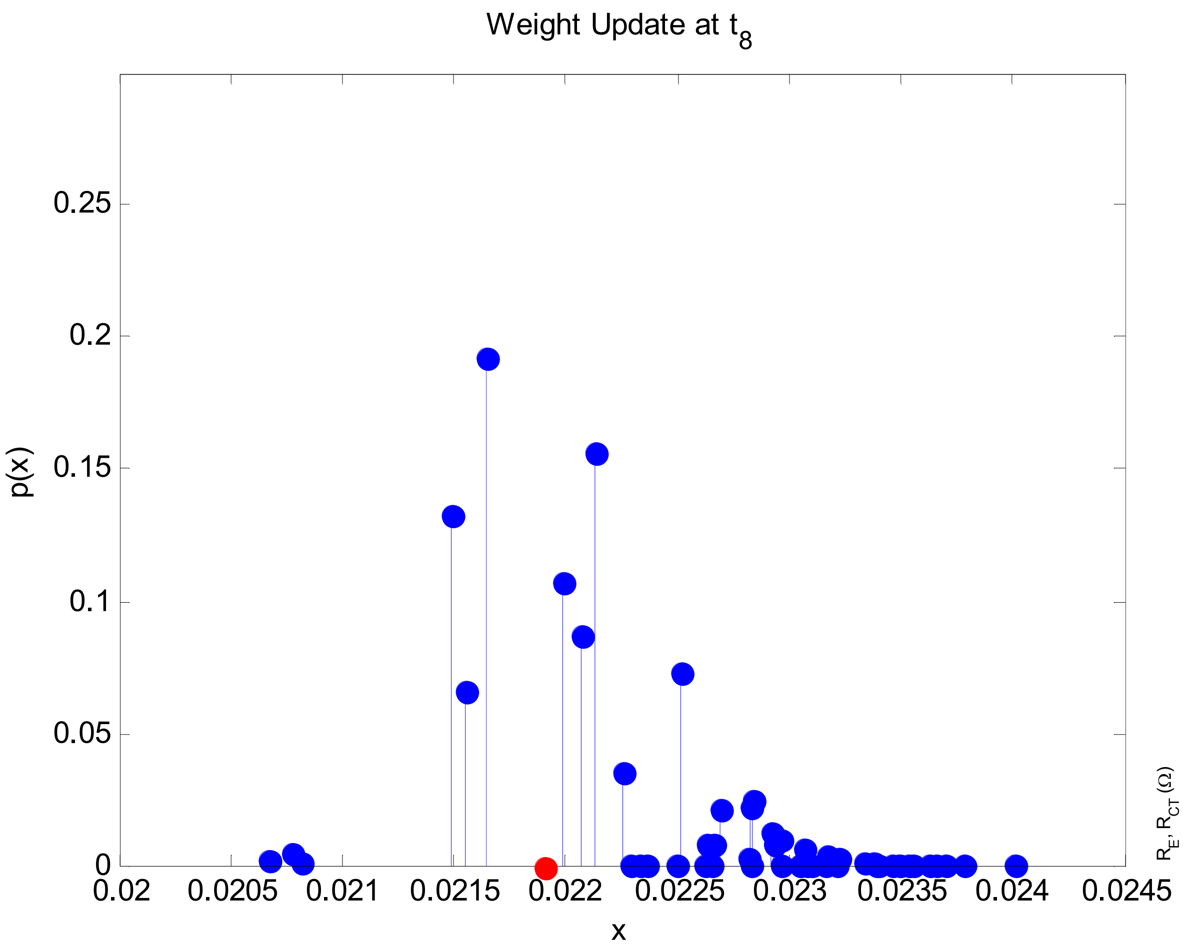
Results: Intermediate Steps



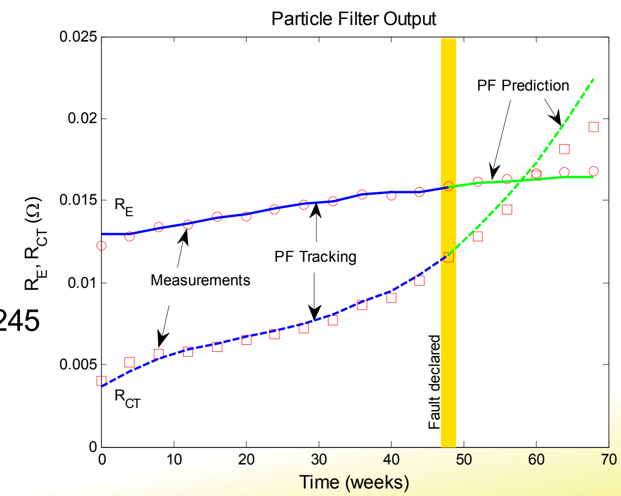
R_E (ohms)



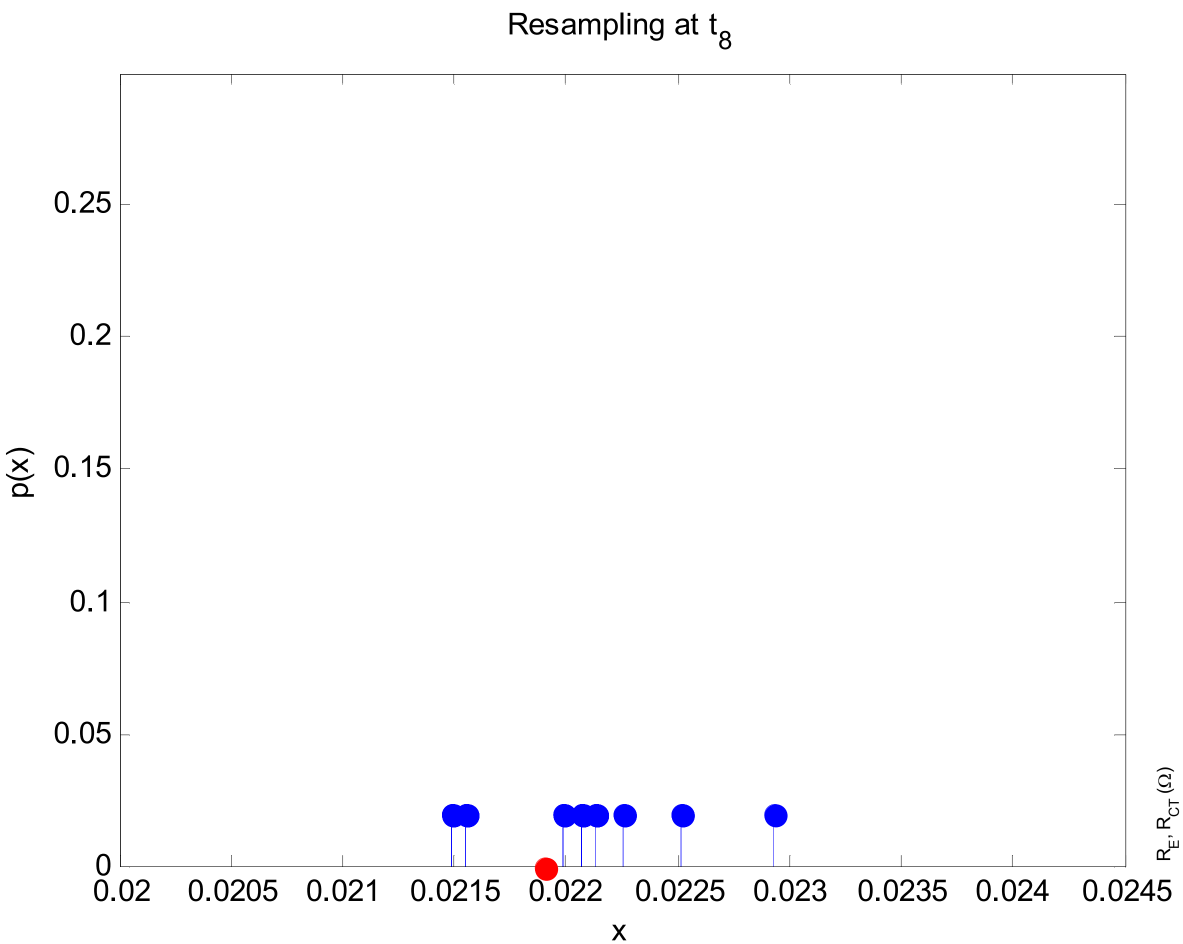
Results: Intermediate Steps



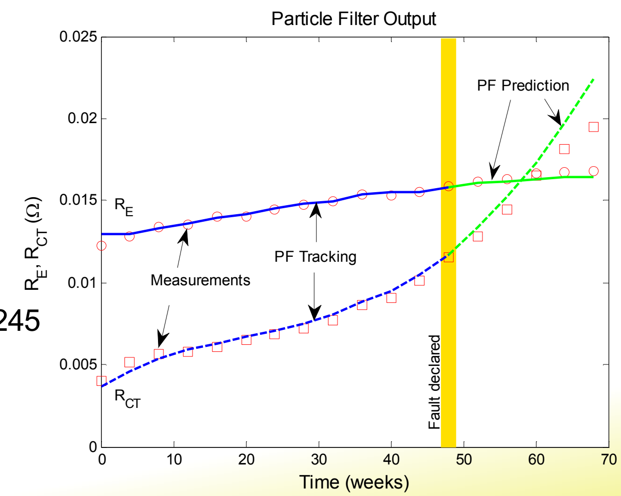
R_E (ohms)



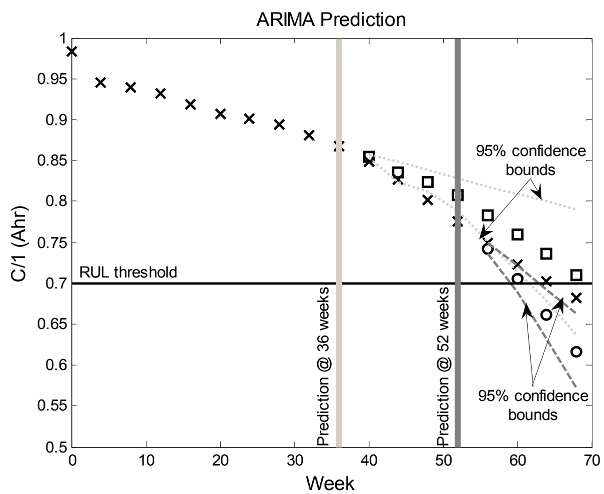
Results: Intermediate Steps

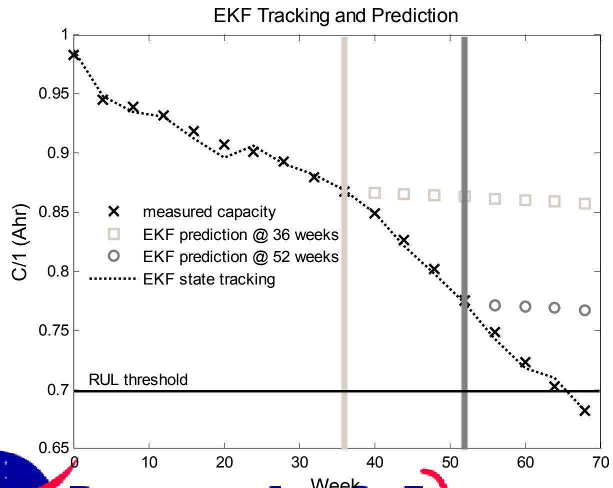


R_E (ohms)

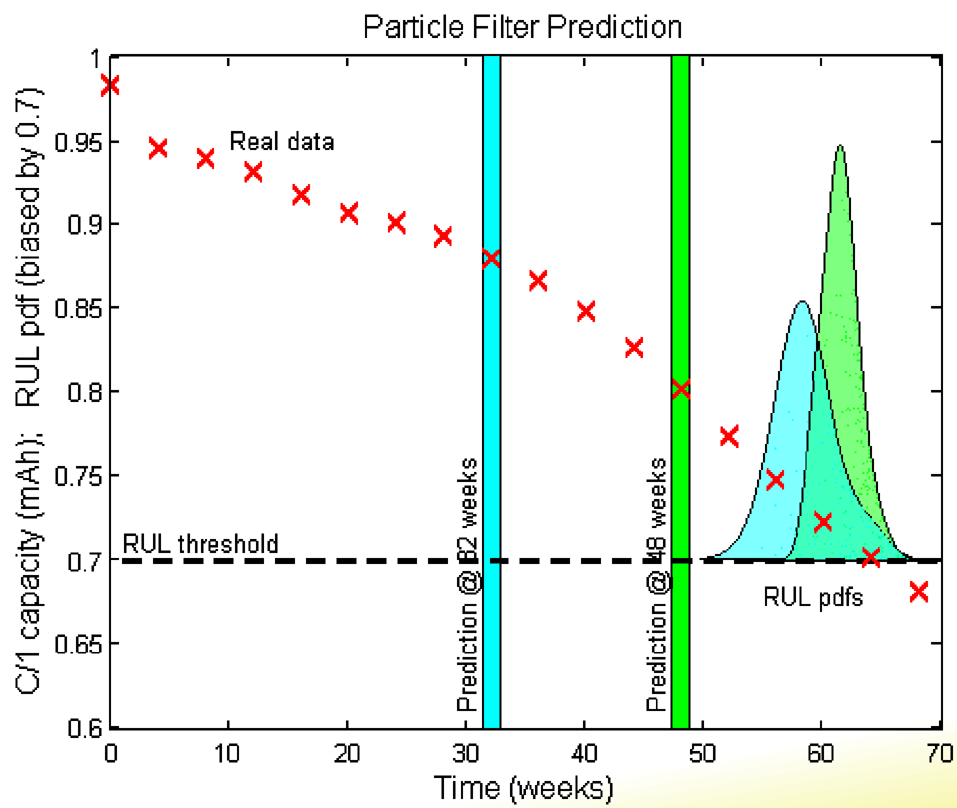


Results: PF Prognosis





Training@25°C,   Testing@45°C



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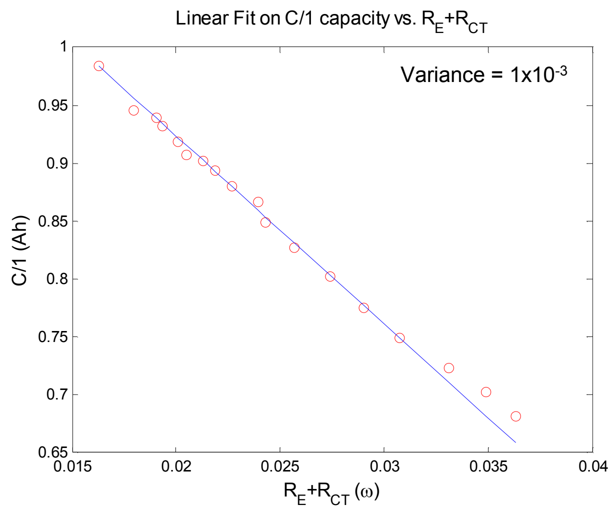
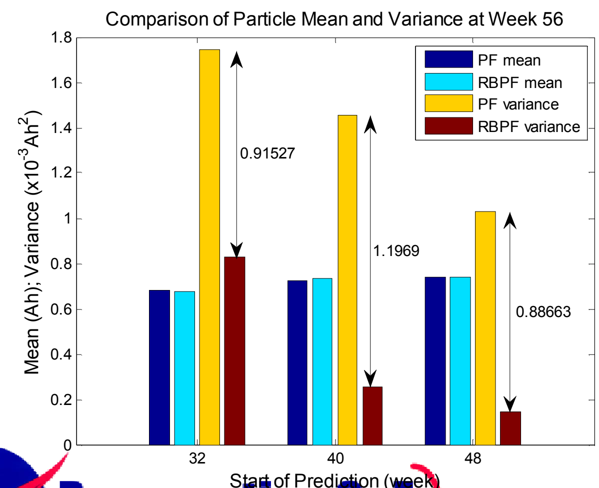
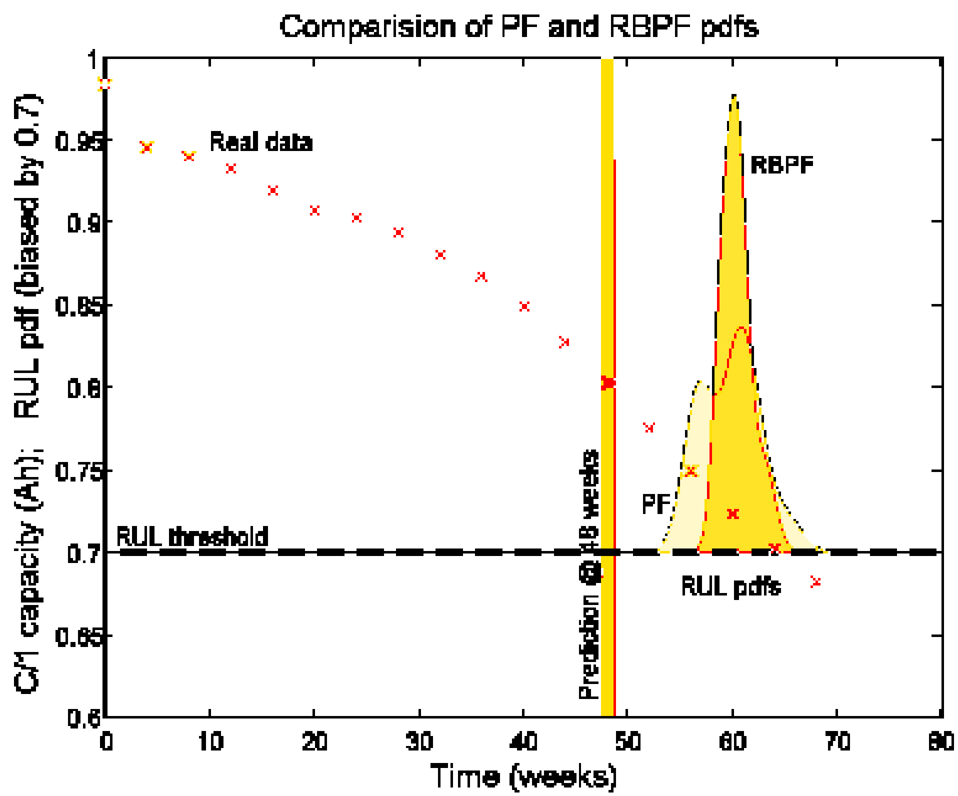
Results: RBPF Prognosis





Training@25°C, Testing@45°C



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Comments

- PF framework allows explicit representation and manipulation of uncertainty
- Mathematical guarantees of convergence
- A variety of models can be accommodated
- RUL pdfs are truer representations of reality than MTBFs