Damage Propagation Modeling in a Particle Filtering Framework

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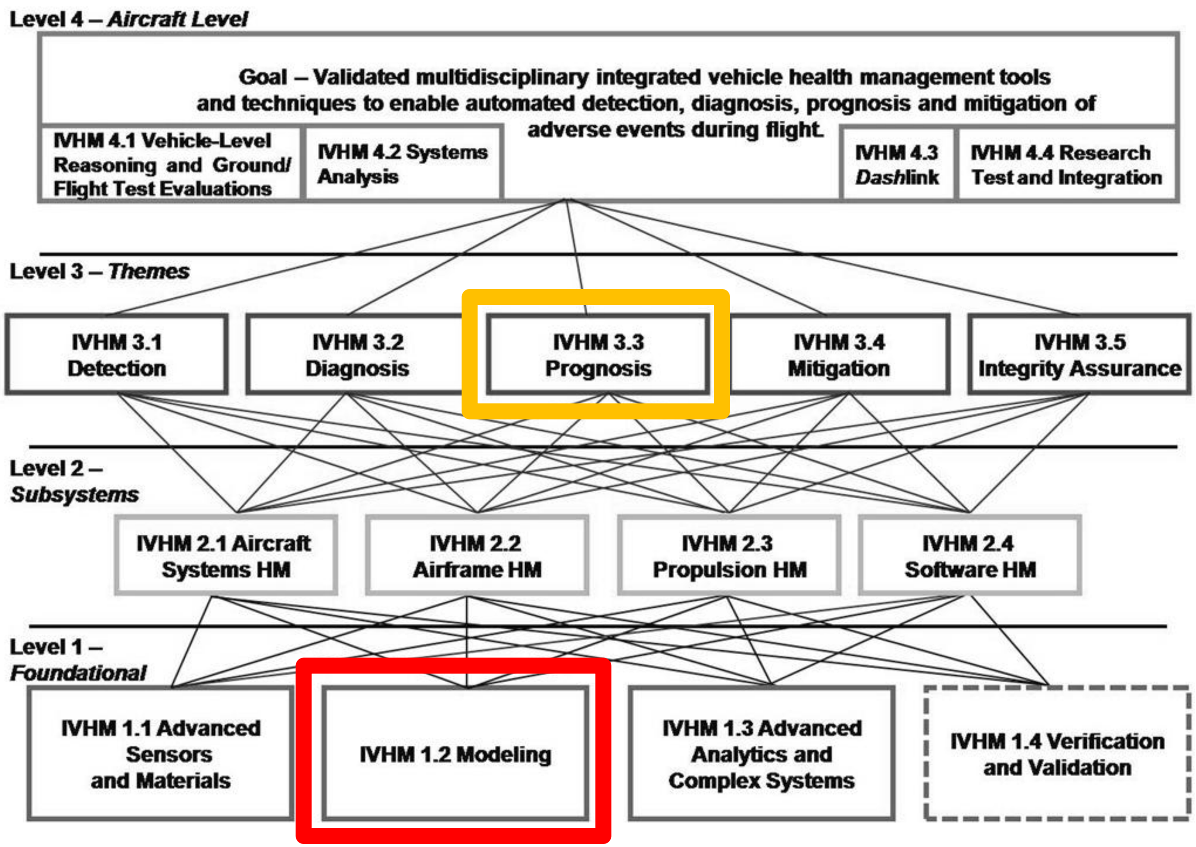
Outline

- Problem Statement
- Background
- IVHM milestones(s) being addressed
- Approach
- Results
- Conclusions
- Future Plans



Problem Statement

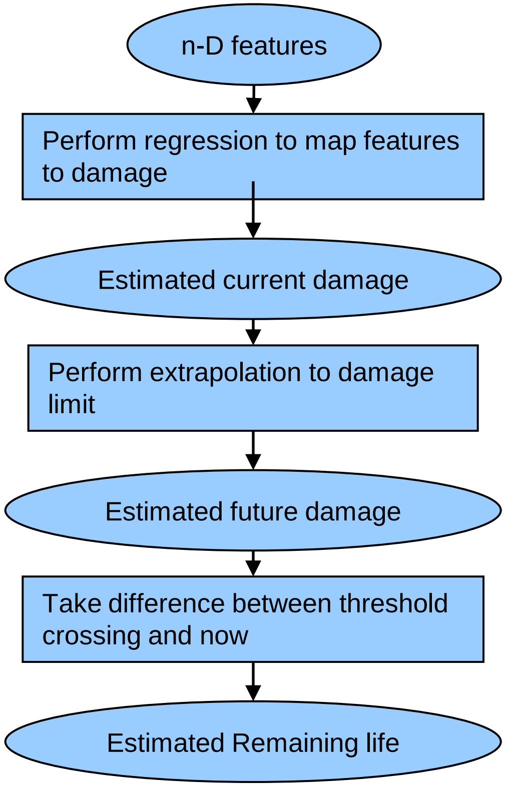
- Prognostics
  - Investigate algorithms that allow prediction of the time at which a component will no longer perform a particular function
  - Lack of performance is most often component failure
    - The predicted time becomes then the "remaining useful life" (RUL)
- State-of-practice and state-of-art
  - Data-driven techniques for prognostics based on machine learning
    - Statistical extrapolation
      - Polynomial regression
    - Probabilistic techniques
      - Gaussian process regression
      - Relevance vector machine
    - Neural networks
  - Model-based approaches slowly getting more traction
    - Improved understanding of the systems
    - Enhanced computational capabilities
- Challenges
  - Absence of sufficiently large data sets
  - Uncertainty management
  - Performance assessment

IVHM milestone

- The work is performed under task 1.2.3.2 “Develop and evaluate data-driven, physics-based and hybrid prognostic models and methodologies.“
  - Data-driven techniques investigated
    - Gaussian Process Regression
    - Relevance Vector Regression
    - Neural Networks
    - “Standard” regression techniques
  - Model-based techniques
    - Variations of Kalman Filters
      - Extended Kalman Filters
      - Unscented Kalman Filters
    - Variations of Particle Filters
      - Rao-Blackwellized Particle Filter
      - Fixed Lag Particle Filter

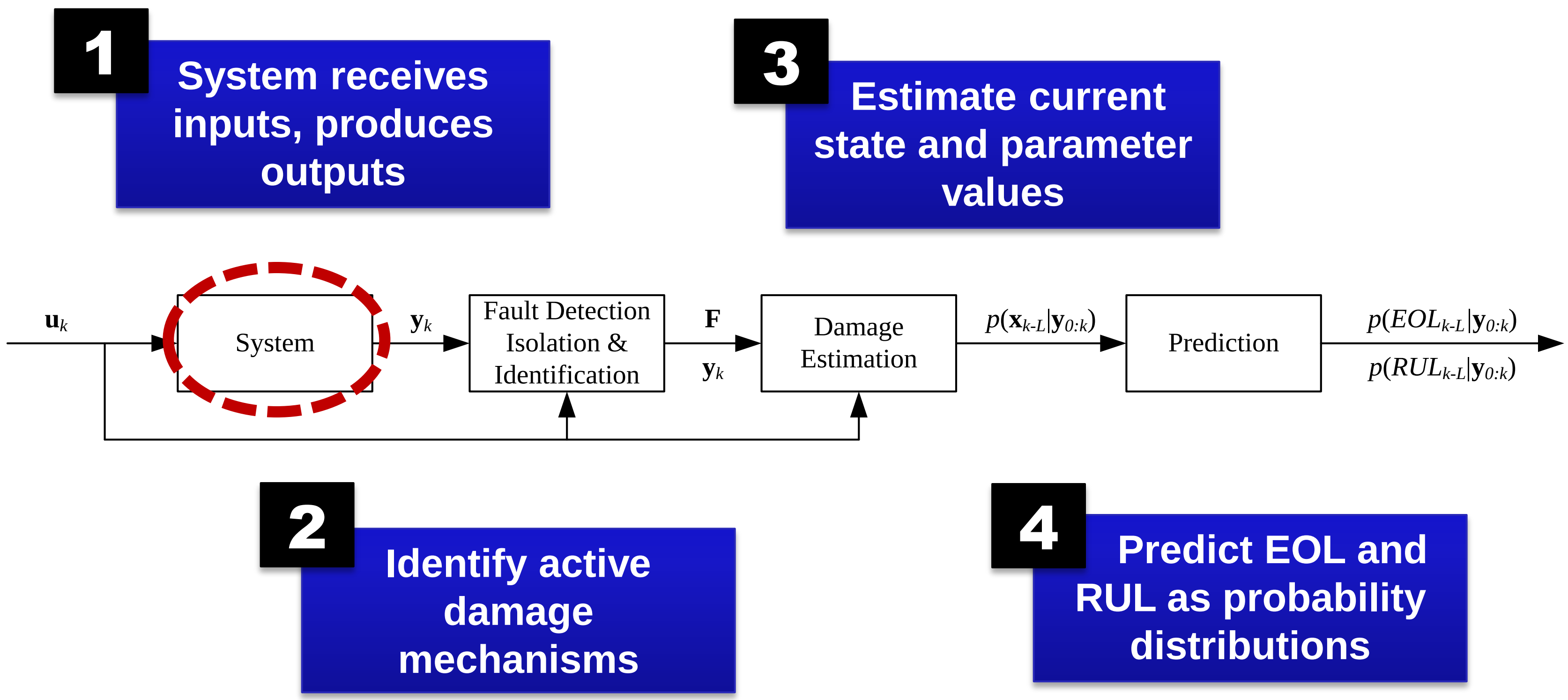
Background: Data-Driven Modeling

- Use run-to-failure data sets representing a range of operating conditions and fault modes
- Develop damage propagation model
  - by using suitable features and
  - learning characteristics such that one can
    - determine remaining life in a partial data set
- Advantage
  - No need to have a deeper understanding of the underlying physics of the process
- Limitations
  - Sufficient amounts of data for learning are hard to come by
    - Particularly for new systems
    - Or “fleets of size one”
  - Low confidence predictions
    - Rigorous integrated methods for uncertainty management not available
  - Methods often break under unexpected (unseen) situations
    - Changes in environmental and operational conditions
    - Material or process variations
    - Maintenance operations, self healing phenomena, etc.
  - Difficulty comparing results from different approaches
    - Lack of metrics



Background
Physics-Based Modeling

- Physics-based model of system
  - Describe the dynamics of the system under nominal operation using first principles (or other physics-based techniques)
- Physics-based damage propagation model
- Prediction algorithm



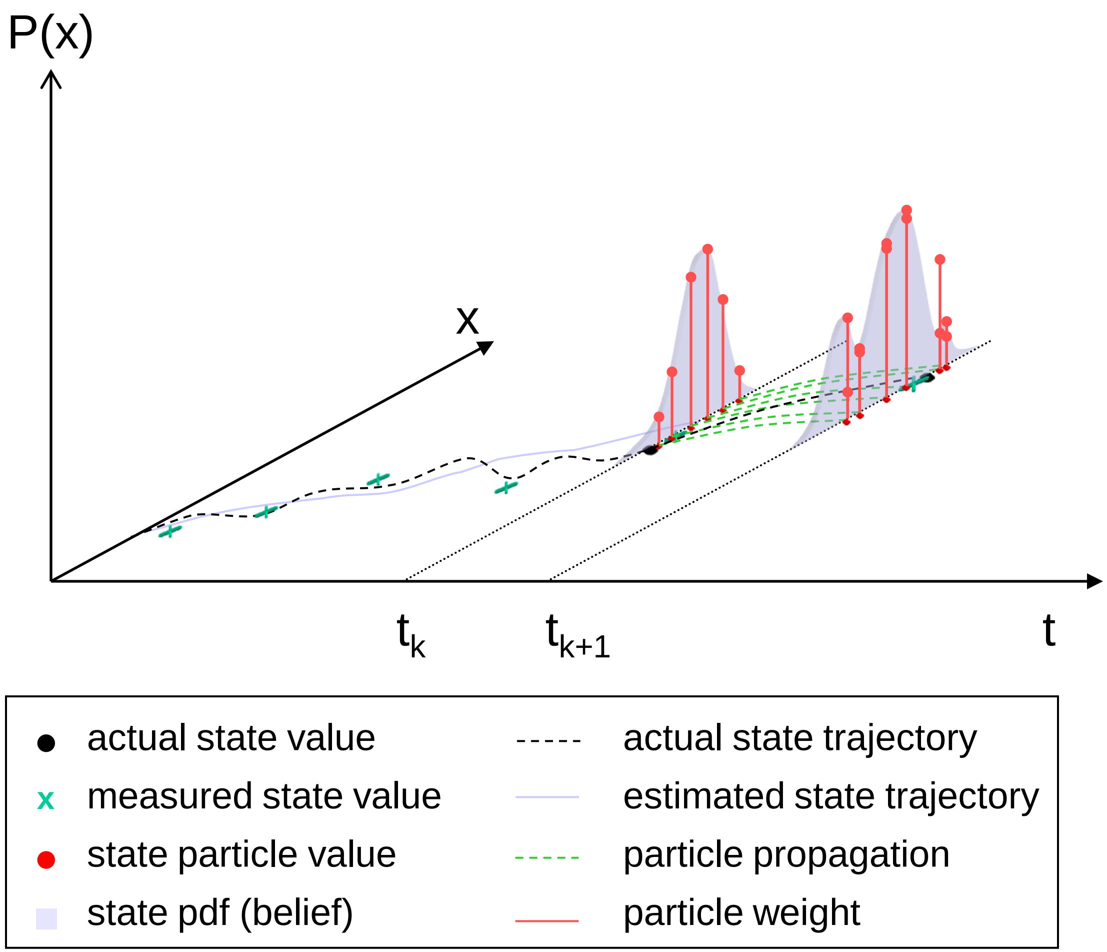
Approach: Particle Filtering

- Particle Filter offer a Bayesian framework that allows estimation of current state of damage and then propagate the damage into future without simplistic assumptions of Normality and model linearity in a rigorous statistical manner.

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

Approach: Particle Filtering

- Propagates particles (damage estimates) several steps ahead maintaining the statistical properties of the evidence (measurements) and characteristics of the dynamical system model



- Process steps:
  - 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
  - Repeat all steps above to propagate to next time index

Approach: Particle Filtering

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

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

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

x_k^i is a point in the state space

w_k^i is an importance weight associated with the point

Approach: Particle Filtering

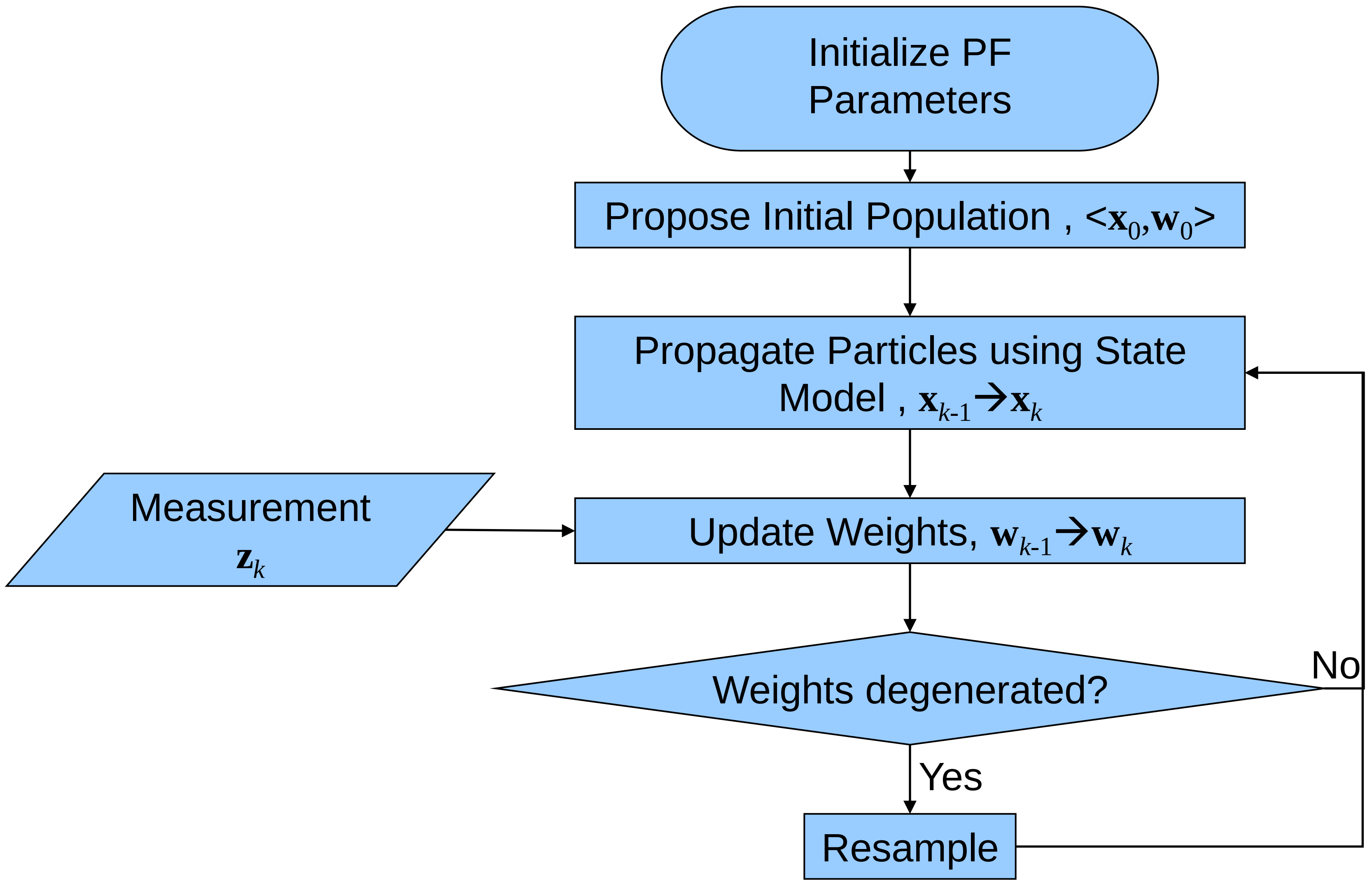
- Prediction step: use the state update model

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

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

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

Approach: Particle Filtering



Approach: Resampling

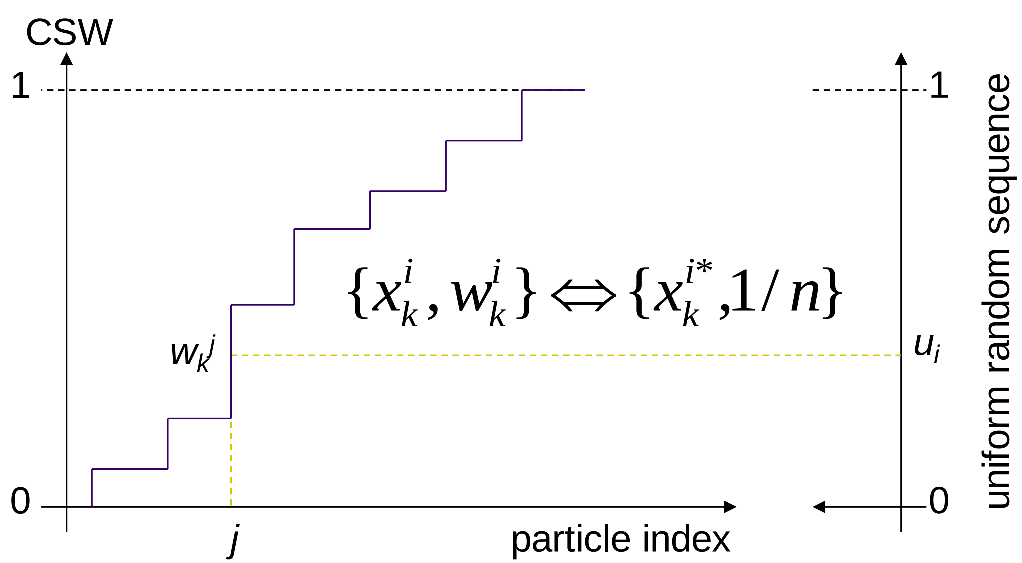
- Particle weights degenerate over time
  - measure of degeneracy: effective sample size

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

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

use normalized weights

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



Damage Growth Modeling

- Traditionally population growth models have been used for damage growth modeling
  - Arrhenius Model
  - Paris' Model
  - Coffin-Mason model

$$t_f = A\exp\left\{\frac{\Delta H}{kT}\right\}$$

$$\frac{da}{dN} = C\Delta K^m$$

$$N_f = Af^{-\alpha}\Delta T^{-\beta}G(T_{max})$$

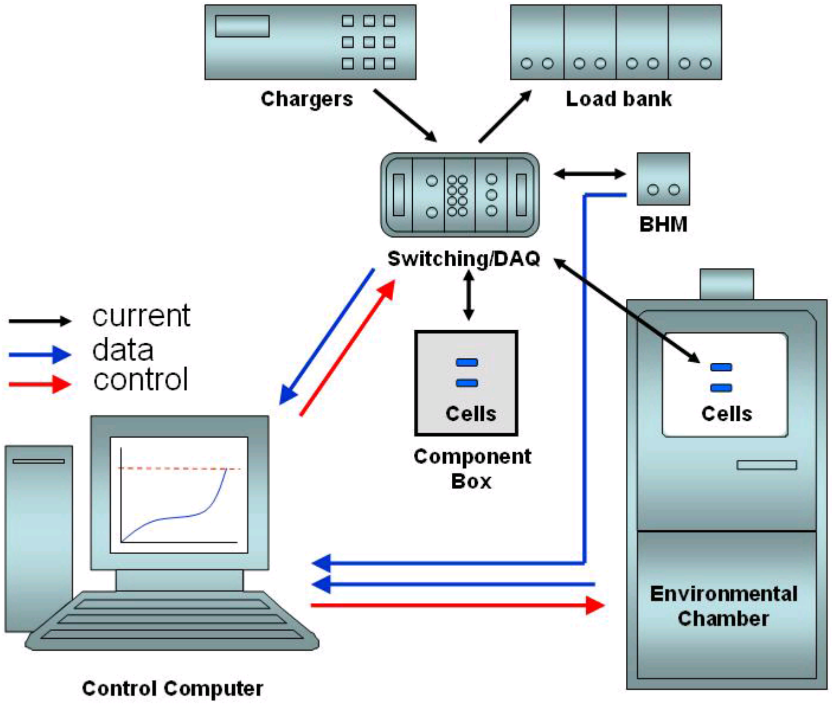
- Exponential based models
  - Explain general trend of fault growth
  - Fail to model several phenomena in different growth regimes
    - Fault growth characteristics change with the age of the system
      - Permanent wear sets in as batteries age and hence discharge dynamics changes
    - Self healing characteristics
      - Batteries recuperate charge when allowed to rest
      - Crack closure phenomenon tends to reduce effective crack size momentarily
      - Maintenance operations increase engine efficiencies
- Physics based models can incorporate multiple physical phenomena that actually take place and affect fault growth / ageing
- These models can be semi - empirical yet incorporate heuristics improving the accuracy and confidence in the predictions

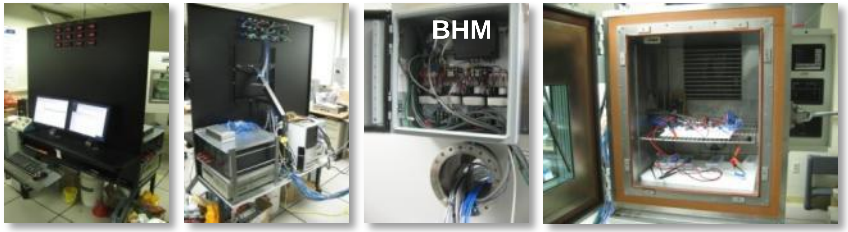
Hardware-in-the-Loop Test Bed

- Prognostics HIL test bed
  - To test prognostics algorithms with hardware in the loop
  - That mimics the complexities and issues encountered for a real system
- Such a system will support
  - Collection and dissemination of run-to-failure data
  - Development of metrics for prognostics
  - Algorithm development
  - Benchmarking of different approaches
  - Testing and validation of prognostic tools
- Requirements
  - Complexity high enough to showcase capabilities of more advanced algorithms
  - Can be failed in a safe manner
  - Aging process is repeatable
  - Small in size and cost effective
  - Aging dependency on environmental variables
  - Aging dynamics slow enough to be observable and fast enough for reasonable run-to-failure times

Hardware-in-the-Loop Testbed

- 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

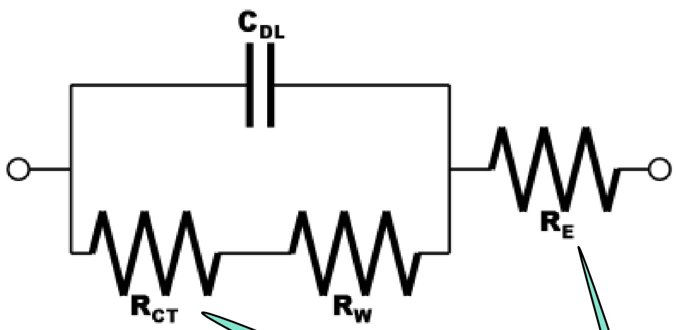




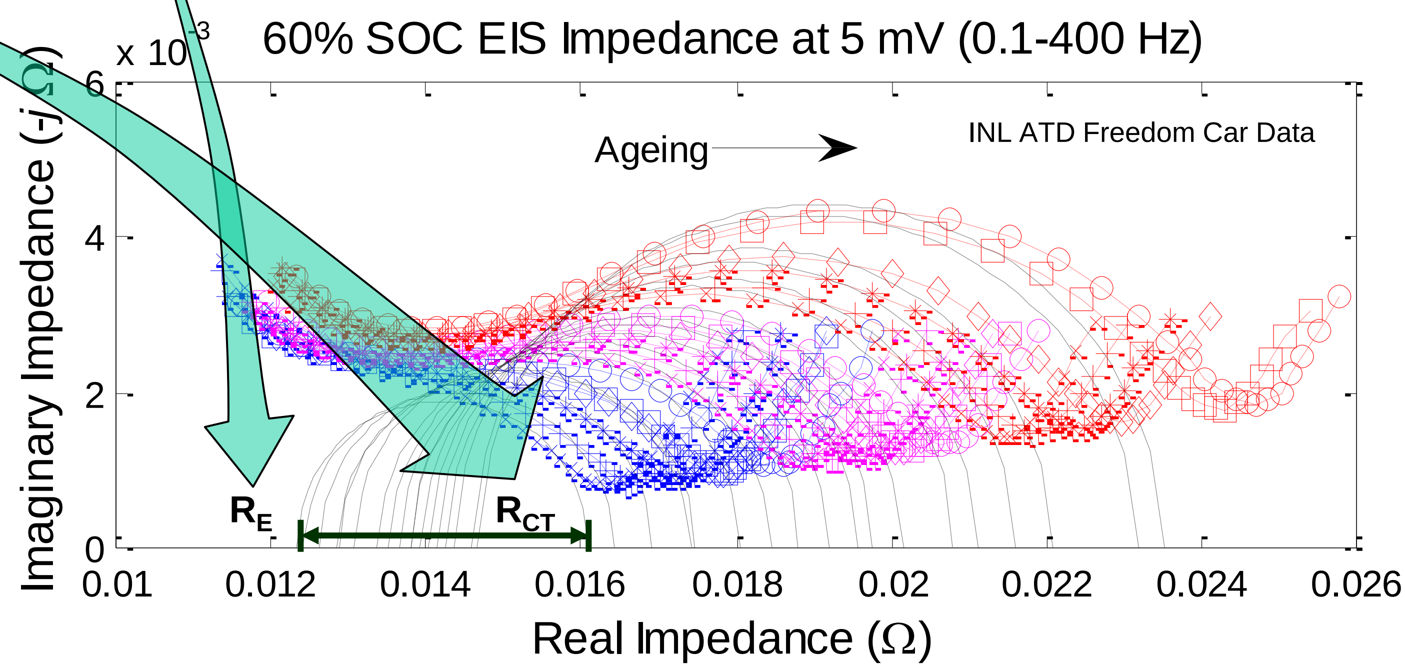
EIS: Electro-chemical Impedance Spectroscopy

Frequency Domain Modeling for Batteries

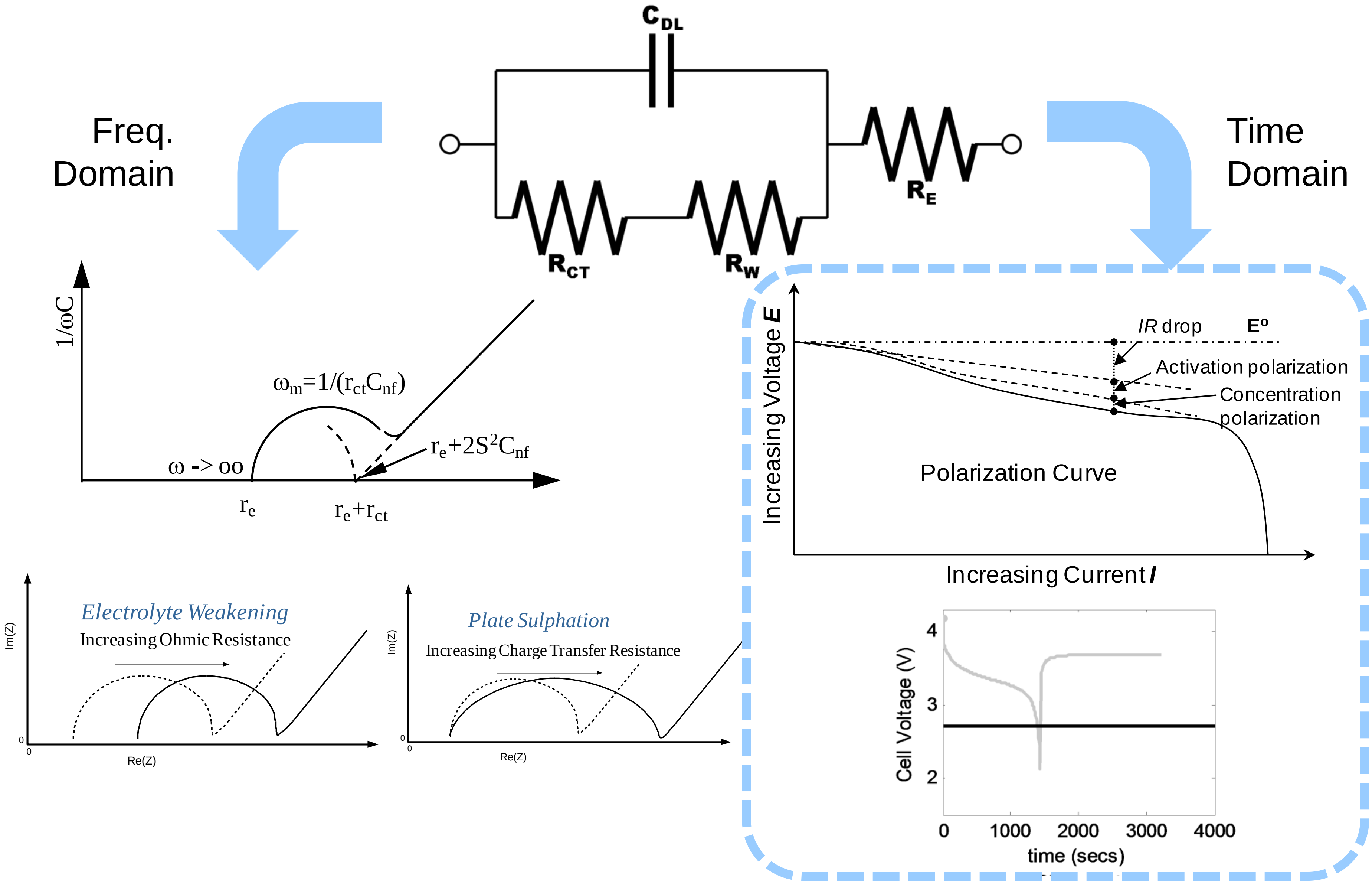
- Different aging effects have different signatures in the frequency domain analysis



- Electrolyte weakening causes increase in electrolyte resistance, R_E
- Passivation impedes charge transfer across the solid-electrolyte interface (SEI), which shows up as an increase in R_{CT}

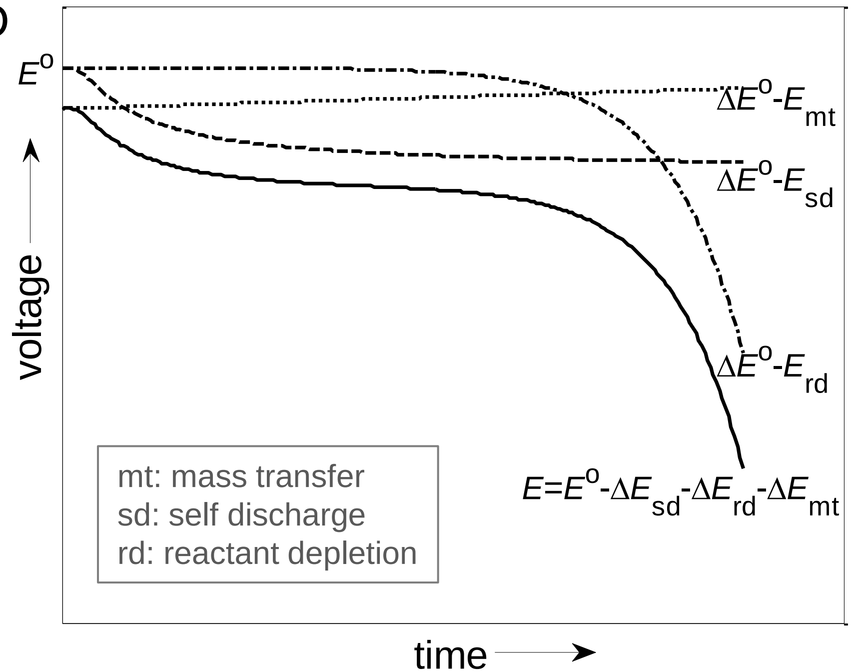


Approach: Modeling



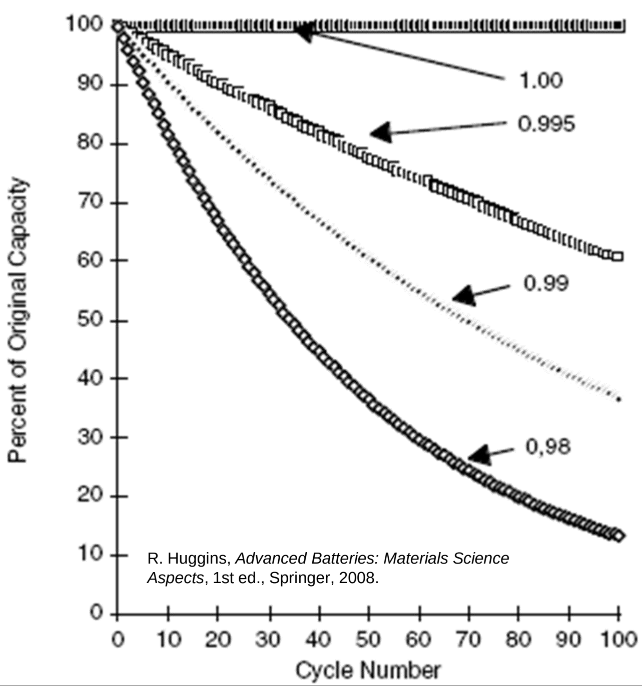
Approach: Modeling Damage Propagation

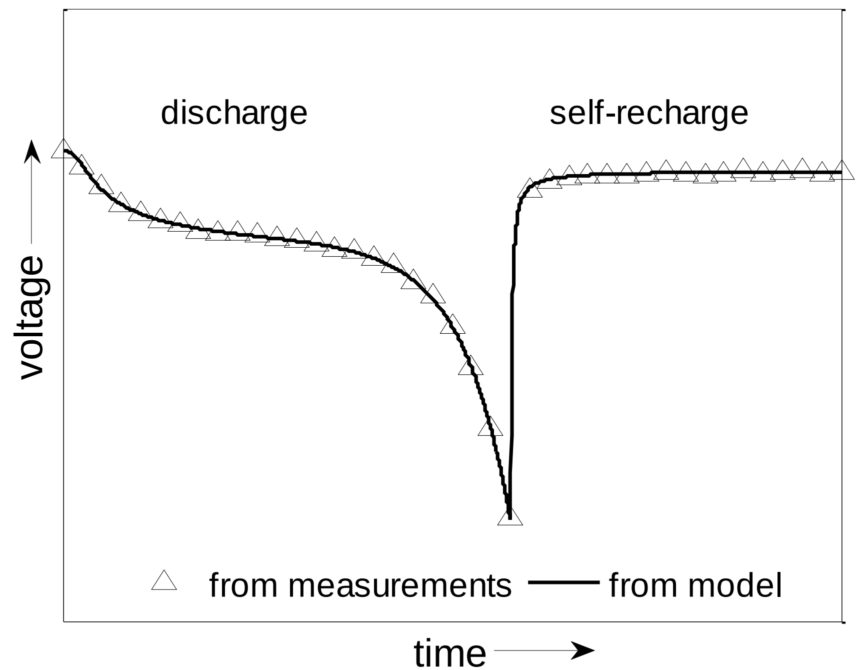
- Objective: Predict when Li-ion battery voltage will dip below 2.7V indicating end-of-discharge (EOD)
- Approach
  - Model non-linear electro-chemical phenomena that explain the discharge process
  - Learn model parameters from training data
  - Let the PF framework fine tune the model during the tracking phase
  - Use the tuned model to predict EOD



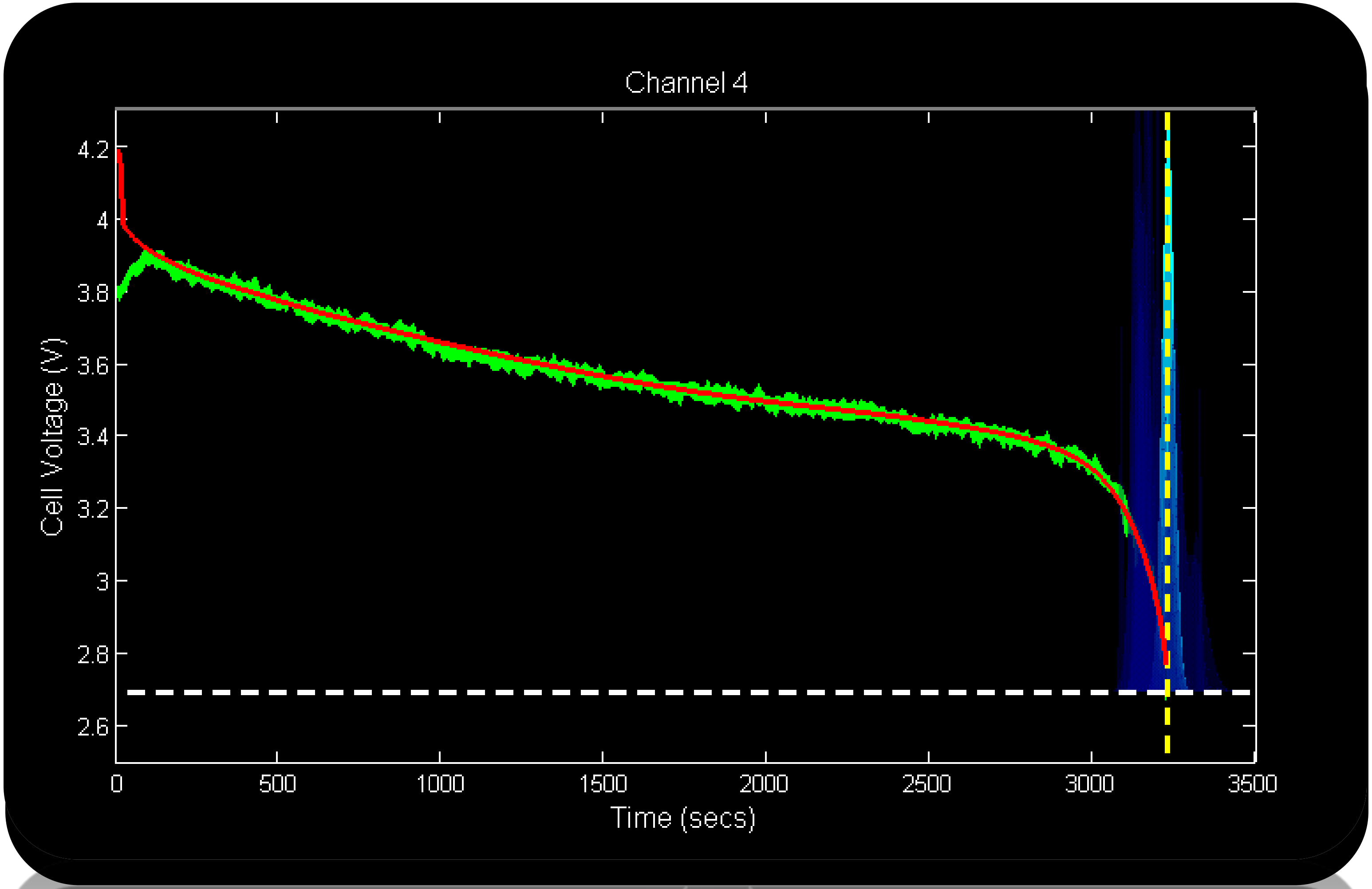
Approach: Modeling State of Life (SOL)

- Objective: Predict when Li-ion battery capacity will fade by 30% indicating life (End-of-Life)
- Approach
  - Model self-recharge and Coulombic efficiency that explain the aging process
  - Learn model parameters from training data
  - Let the PF framework fine tune the model during a few initial cycles
  - Use the tuned model to predict EOL

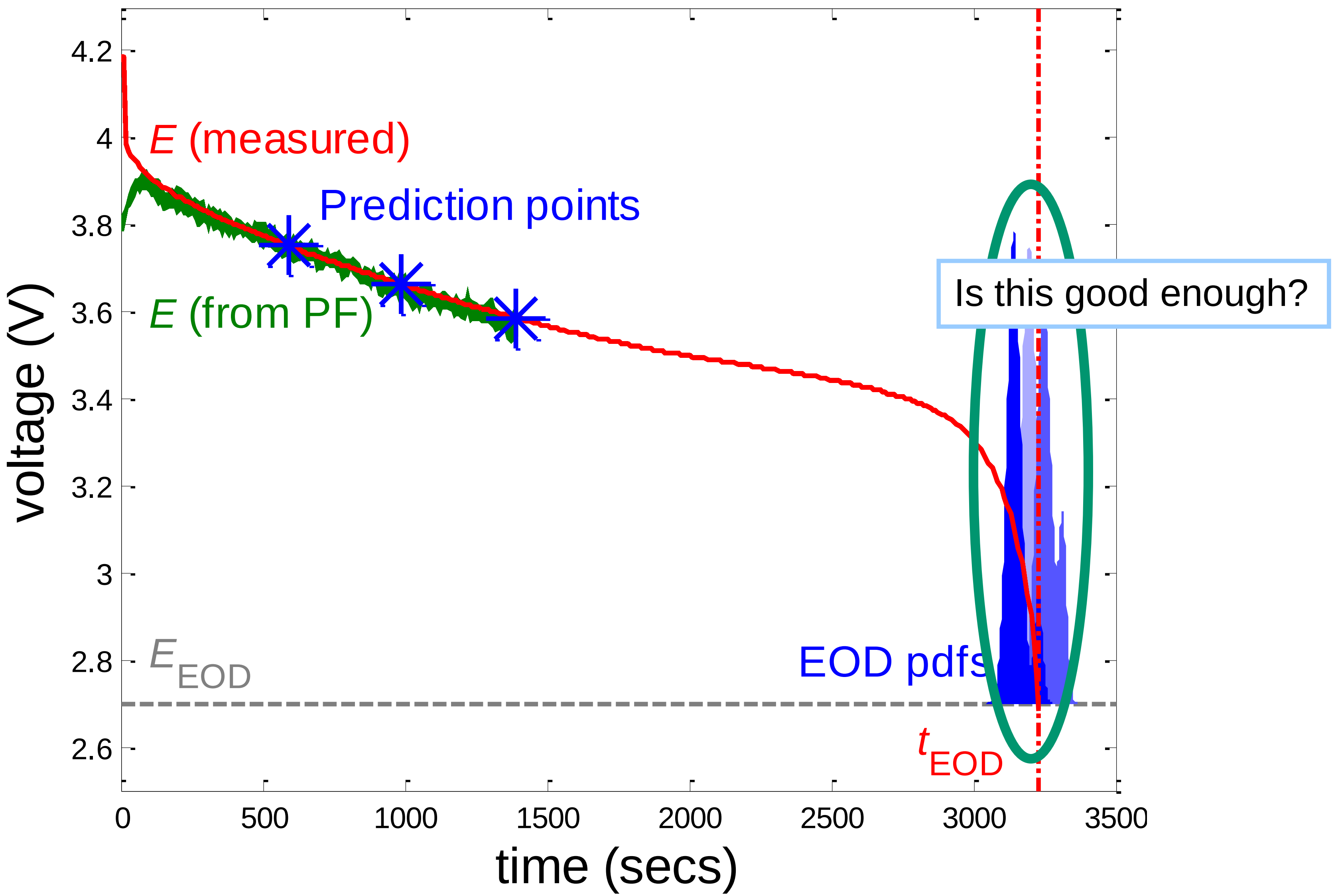




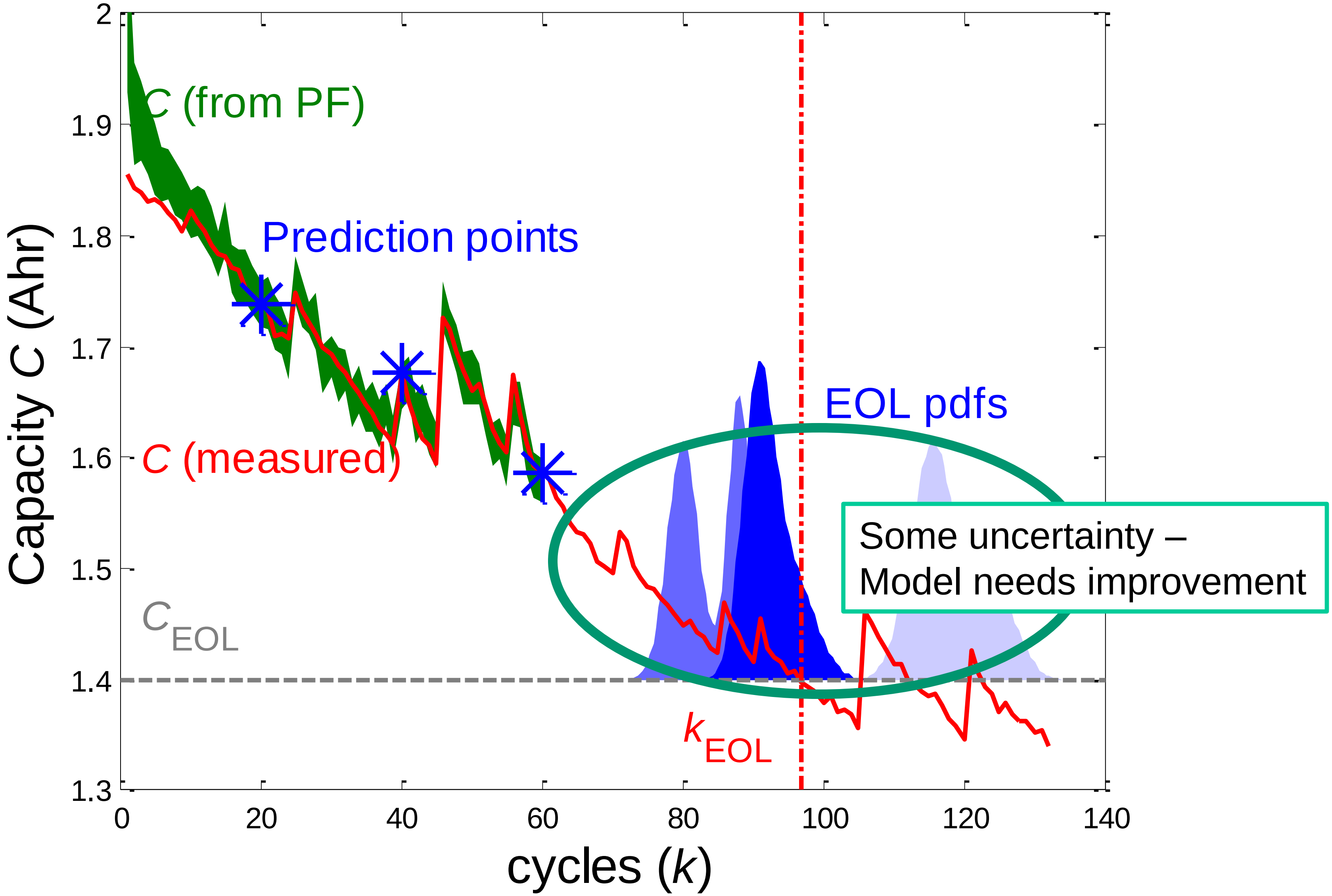
Results: Prognostics in Action



Results: SOC Prediction

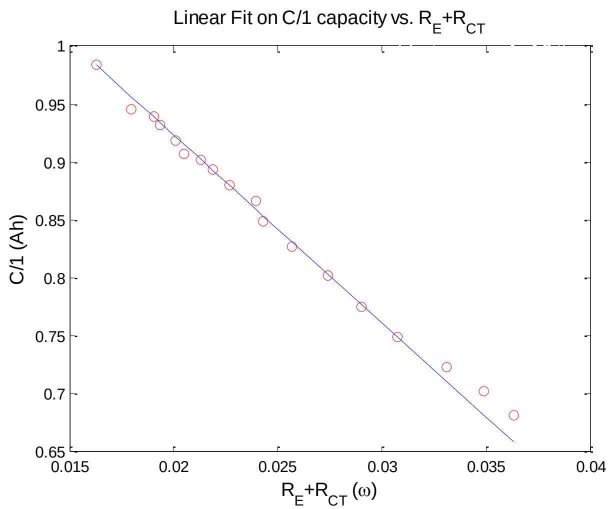


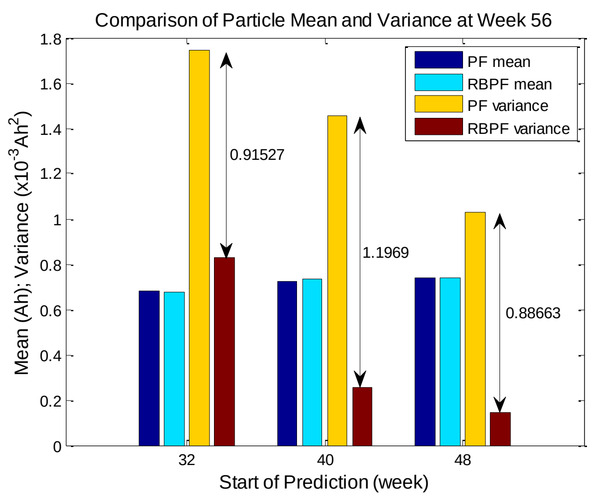
Results: SOL Prediction



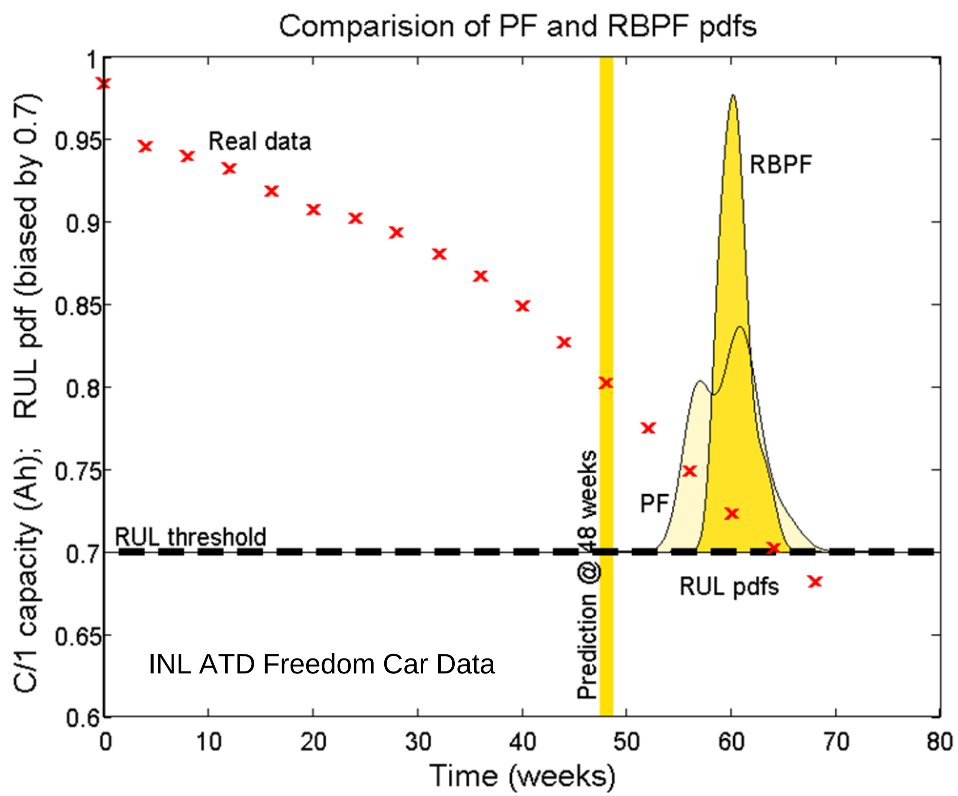
Uncertainty Reduction using RBPFs

- Domain knowledge can used in a Rao-Blackwellized Particle Filter (RBPF) to make the state estimate partially deterministic, thus reducing uncertainty





Training@25° C, Testing@45° C



Summary and Conclusions

- Presented work on algorithm development and model building for prognostics
  - Empirical model to describe battery behavior during individual discharge cycles as well as over its cycle life
  - Model has been tested using experimental data
  - Model has been used in a PF framework to make predictions of EOD and EOL effectively
  - Algorithms have been tested on other models
- Model can be applied to other battery types as long as effects specific to those chemistries are modeled as well (e.g. the memory effect in Ni-Cd rechargeable batteries)
- The PF prognosis framework allows explicit representation and management of uncertainty with mathematical guarantees of convergence
- HIL testbed built that allows assessment of different prognostic algorithms
  - Data sets available at https://dashlink.arc.nasa.gov/data/li-ion-battery-aging-datasets

Next Steps

- Assess impact of model fidelity improvement
  - Explicitly incorporate influence of factors like
    - Temperature
    - Load
    - Magnitude of Cycles
    - State of Charge (SOC) after charging
- Advanced filtering techniques (after the factors above are understood)
  - unscented PF
  - Rao-Blackwellized PF
- Explicitly assess impact of future load variations