Battery System Safety and Health Management for Electric Vehicles

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Content

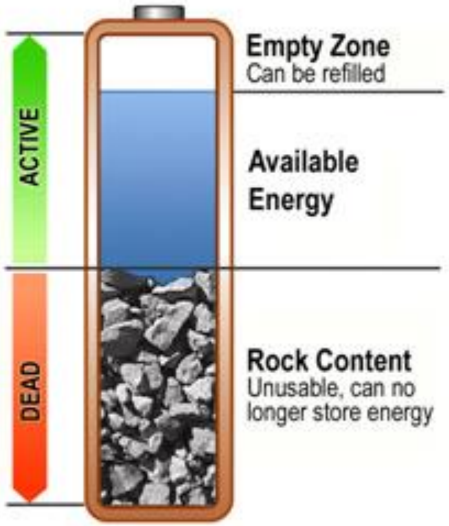
Motivation for Battery Safety

- Motivation:
  - ❖ Due to Li-ion batteries' highlighted advantages such as high energy density, slow self-discharging rate, and no memory effect, they become primary energy storage solutions to electric vehicles (EVs)
  - ❖ Safe and reliable operation of lithium-ion batteries is of vital importance, as unexpected battery failures could result in catastrophic accidents of EVs

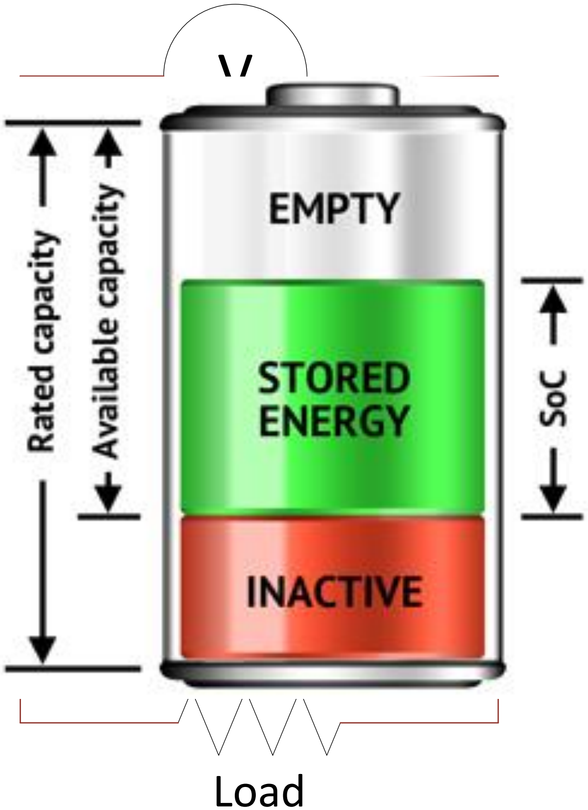
- Two tasks:
  - ❖ Battery health assessment: indicates the capability of the EVs
  - ❖ Battery failure diagnostics: avoid an catastrophic failure of a car

Li-ion Battery Health Assessment

- **System health assessment**: collects sensory signals from the system, extracts health-relevant features and system characteristics from the sensory signals
- Challenges:
  - system modeling is generally complicated and even incapable to access due to high dimensional I/O spaces and nonlinear processes of a complex system
  - high system dynamics increase the mutability of system inherent parameters that cause invalidation of original system models along a long time line



Battery System Basics



Measurements: current, voltage

SoC: the ratio of the stored energy to the rated capacity of a cell

$$SOC_k = SOC_{k-1} + \frac{\eta \Delta t}{C_{k-1}} i_{k-1}$$

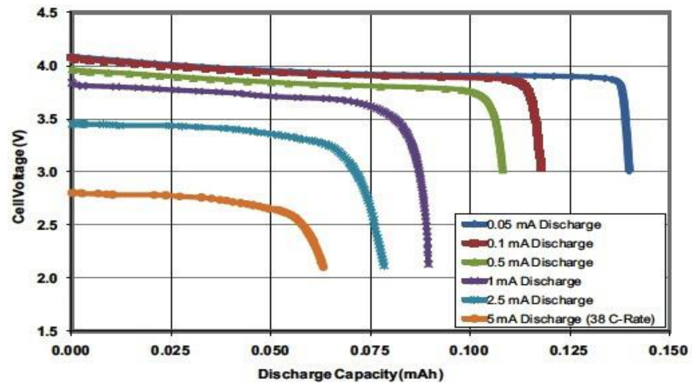
SoH: the ratio of the available capacity to the rated capacity after degradation of a cell

$$SoH_N = \frac{C_{available,N}}{C_{rated}}$$

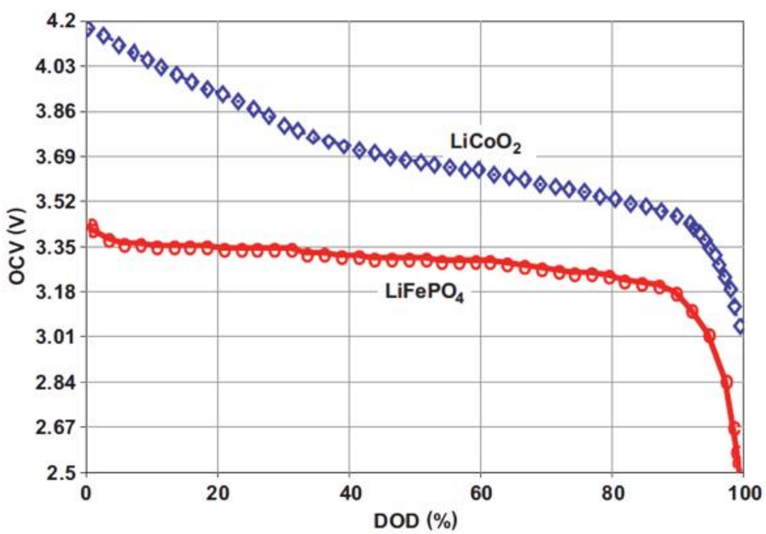
- SoC and SoH Estimations

State Transition: $x_k = \mathbf{F}\left(x_{k-1}, u_{k-1}, \theta_{k-1}\right) + w_k, \quad \theta_k = \theta_{k-1} + r_k$

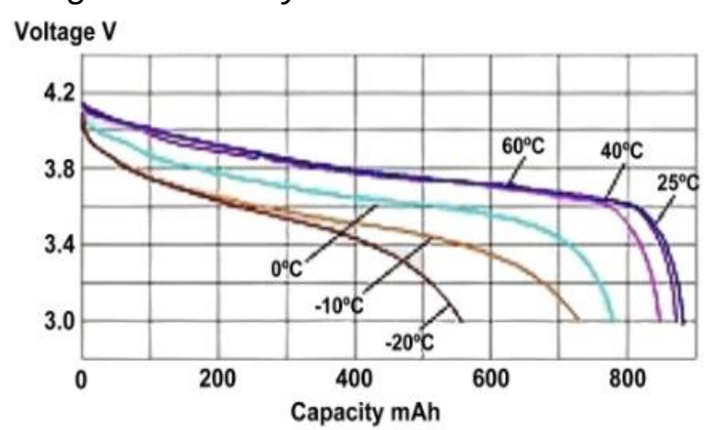
Measurement: $y_k = \mathbf{G}\left(x_k, u_k, \theta_k\right) + v_k$



* *Figure Courtesy of Infinite Power Solutions.*



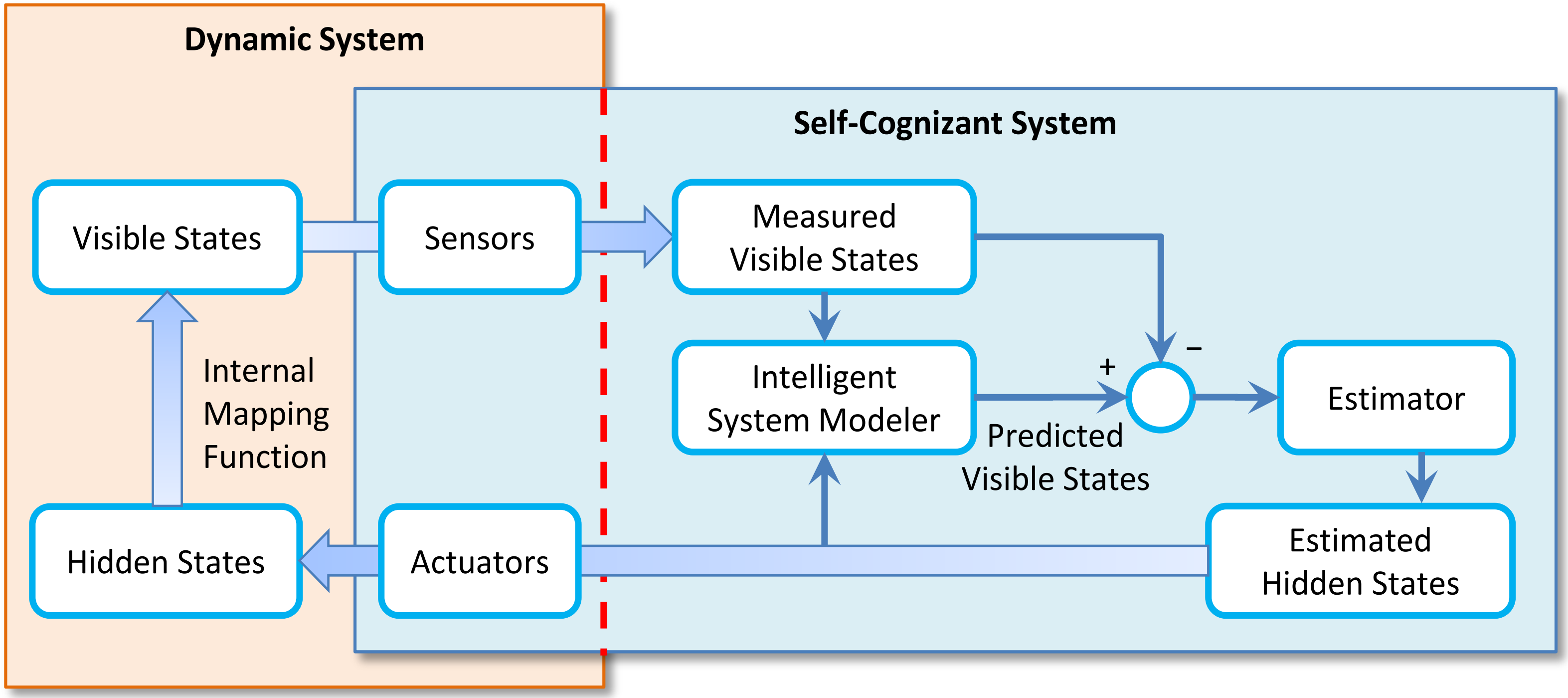
* *Figure Courtesy of Texas Instruments*



* *Figure courtesy of IBT Power*

Self-Cognizant Dynamic System (SCDS) Approach

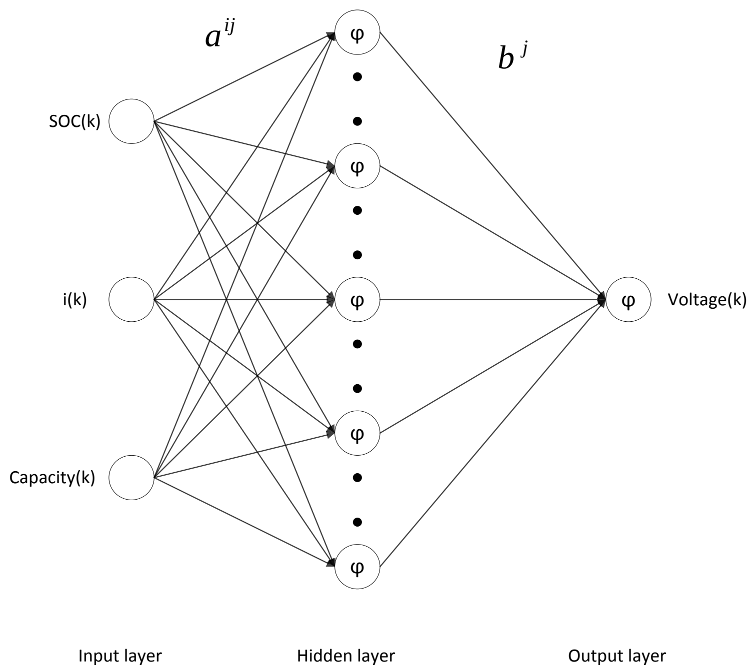
- The schematic diagram of a self-cognizant dynamic system



Intelligent System Modeler

- Battery terminal voltage modeling:

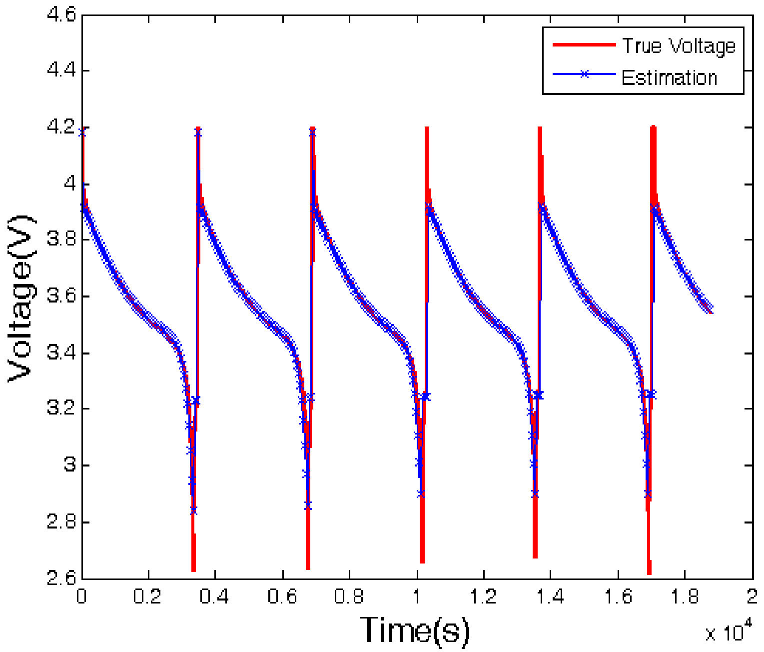
$$V_k = G(SOC_k, i_k, C_k)$$
$$\approx G_{NN}(SOC_k, i_k, C_k)$$



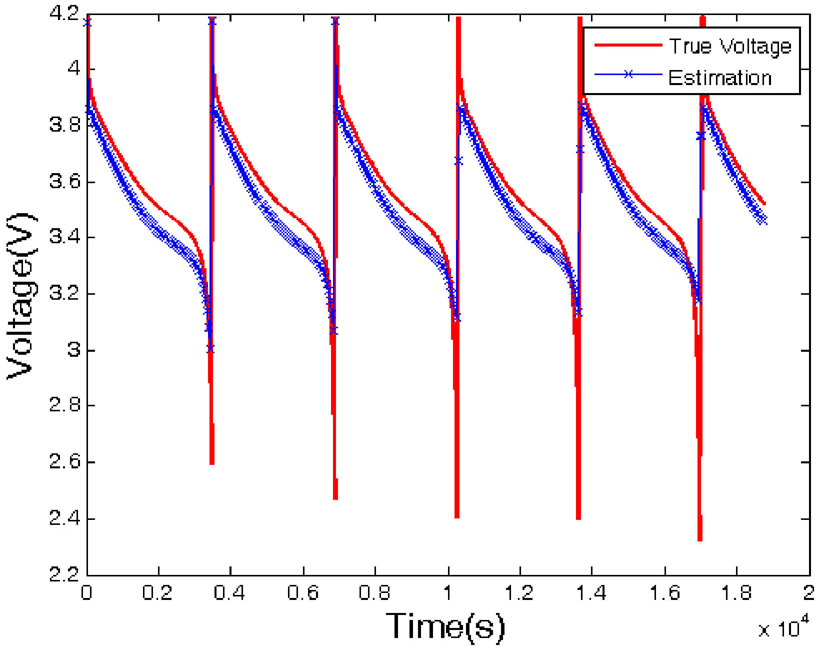
a^{ij}, b^{j}: the weights on the branches linking with input nodes, hidden nodes and output nodes
Transfer function φ is sigmoid function

Modeling of the Li-ion battery

- Battery 05 is employed to train the neural network



Battery 05



Battery 06

- Error of terminal voltage estimation by ANN

	Battery 05	Battery 06	Battery 07	Battery 18
RMS	0.0289	0.1034	0.1058	0.0871

Implementation of the SCDS Approach

- Developed battery system state-space model:

Transition: $$SOC_k = \mathbf{F}\left(SOC_{k-1},\ i_{k-1},\ C_{k-1}\right) + w_{k-1}$$

$$= SOC_{k-1} + \frac{\eta \triangle t}{C_{k-1}} i_{k-1} + w_{k-1}$$

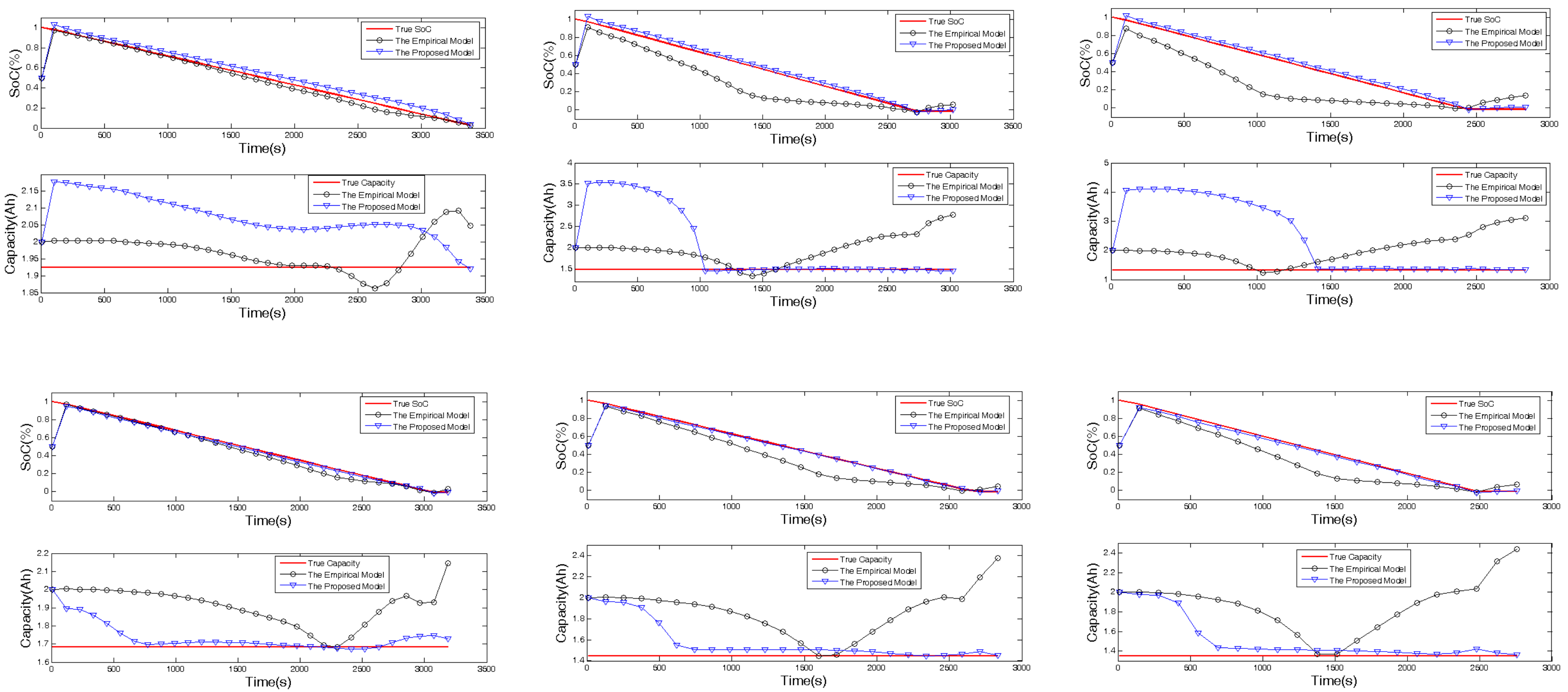
$$\boldsymbol{\theta}_k = \boldsymbol{\theta}_{k-1} + \mathbf{r}_{k-1} = [C_{k-1}, \mathbf{W}_{k-1}]^{\mathrm{T}} + \mathbf{r}_{k-1}$$

Measurement: $$y_k = \mathbf{G}\left(SOC_k, u_k, \boldsymbol{\theta}_k\right) + v_k$$

y_k : the terminal voltage
w_k and r_k : the process noise
v_k : the measurement noise
C_k: the maximum capacity
$\mathbf{W}_k$: the weights of FFNN

SCDS for SoC and SoH Estimation

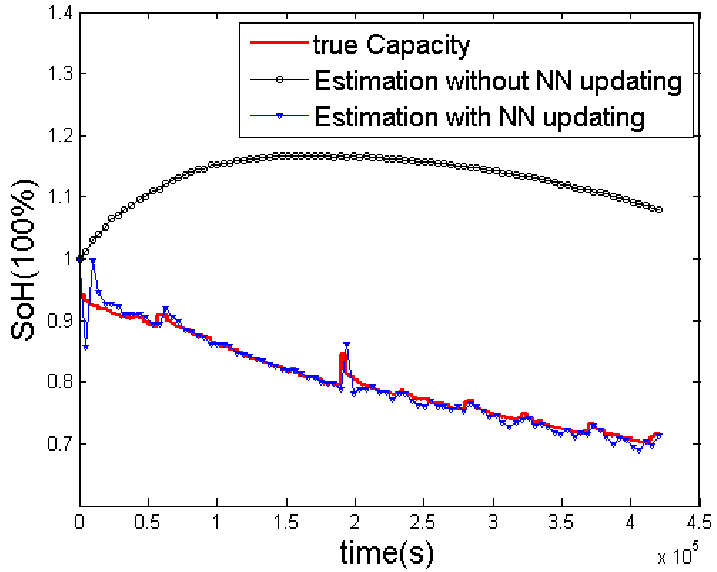
- The short-term SoC and SoH estimation

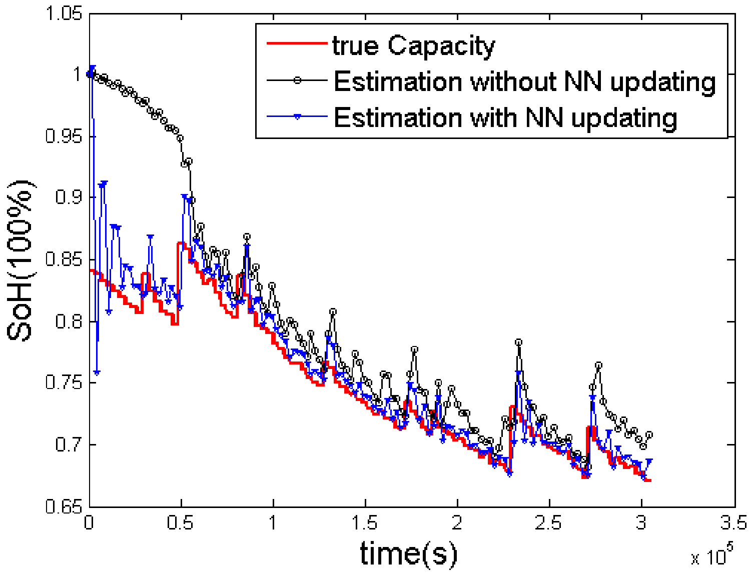


The 1st cycle **The 50th cycle** **The 100th cycle**

SCDS for SoC and SoH Estimation

- The long-term SoH estimation

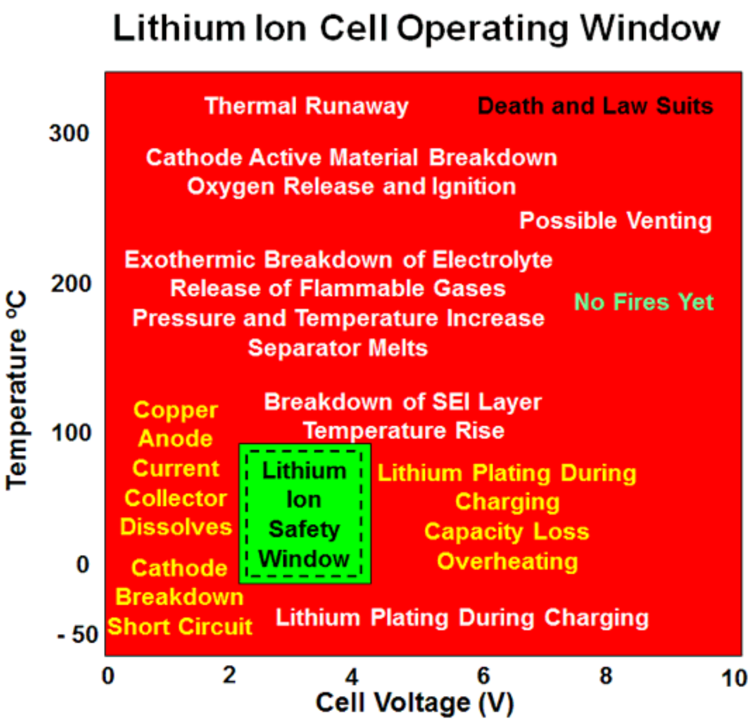




- Observations:
  - ❖ Capacity fade with hundreds of cycles
  - ❖ Ability to track the true capacity after initial cycles
  - ❖ Quick convergence from wrong initial guesses

Li-ion Battery Failure Diagnostics

Battery Failure diagnostics: identify characteristics of system failure by monitoring and estimating system states, and diagnose various failure modes



- Challenges:
  - how to locate characteristics of different system failure modes
  - how to model a rapidly varying system when normal system processes are out of control

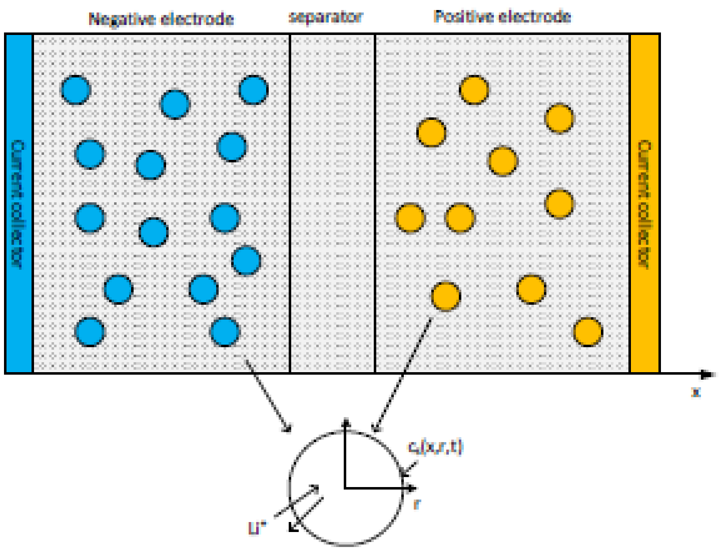
Li-ion Battery Failure Diagnostics: Li-plating

- Motivation:
  - ❖Li-plating is a typical and common failure mechanism that could lead to capacity fade due to active material loss, or even short circuit due to dendrites formation
  - ❖Li-plating happens under various operating conditions such as charging under low temperature or high current

- Objectives:
  - ❖Investigate Li-plating mechanism based on electrochemical principles
  - ❖Build criterions to judge Li-plating occurrence
  - ❖Predict the onset of Li-plating with estimation of current battery states

Reviews of the Electrochemical Model

- Li-ion battery physical internal structure:
  - ❖ Three domains: negative electrode, separator, positive electrode
  - ❖ Two phases: solid phase, electrolyte phase

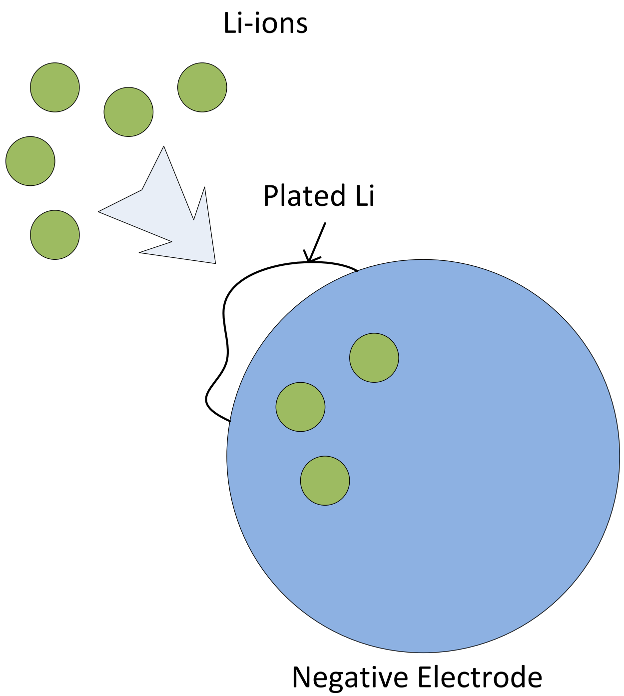


- Electrochemical Model
  - ❖ Based on ohmic porous electrode theory and Bulter-Volmer kinetics
  - ❖ A set of partial differential equations (PDEs) is used for modeling

$$C + xLi^{+} + xe^{-} \underset{\text{Discharge}}{\overset{\text{Charge}}{\rightleftharpoons}} CLi_{x}$$

$$LiCoO_{2} \underset{\text{Discharge}}{\overset{\text{Charge}}{\rightleftharpoons}} Li_{1-x}CoO_{2} + xLi^{+} + xe^{-}$$

Li-plating Mechanism



$$Li^{+} + e^{-} \rightarrow Li \downarrow$$

$$O + Li \downarrow \rightarrow Li - O$$

Possible side reactions for Li-plating

- The necessary assumptions for creating a Li-plating model
  - ❖ Only side reactions for Li-plating occur
  - ❖ The concentration gradient (or C-rate) on the surface of electrodes approximates to the extraction or intercalation rate

$$R_{ex} = \frac{\partial \overline{c}_{s,surf,p}}{\partial t} \qquad R_{in} = \frac{\partial \overline{c}_{s,surf,n}}{\partial t}$$

- The criterion of Li-plating occurrence $\left|R_{ex}\right| > \left|R_{in}\right|$

Important Coefficients Involved in Li-plating

- Diffusion coefficients in solid phase:[1]

  $D_{s,n} = 1.0e\text{-}14\ m^2/s$

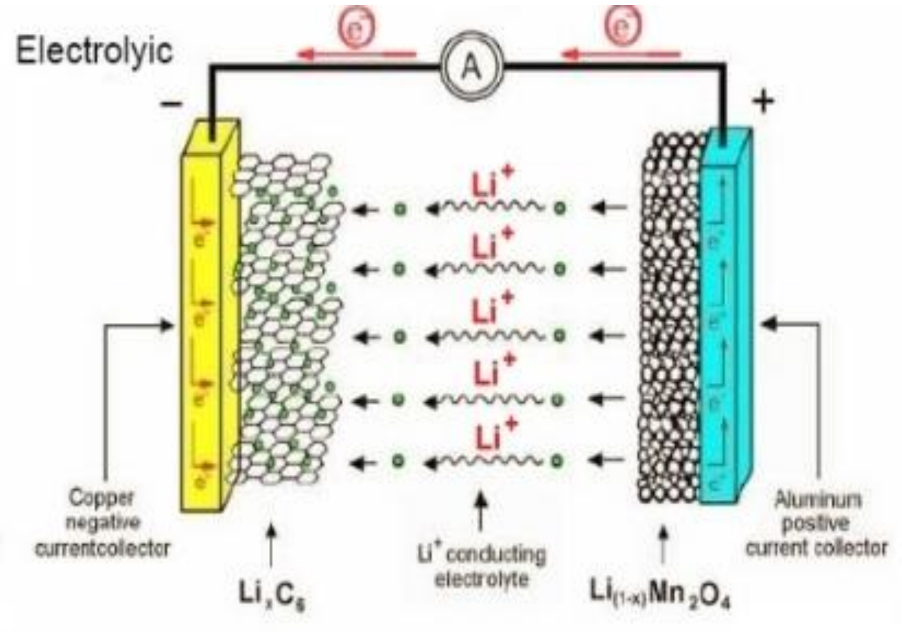
  range from $(10^{-10}\text{-}10^{-15})$

  $D_{s,p} = 3.9e\text{-}14\ m^2/s$

  range from $(10^{-12}\text{-}10^{-15})$

- Intercalation/extraction reaction rate: [2]

  $k_n = 5.0307*10^{-11}$ $mol/(L*s)/(mol/L)^{1.5}$



[1] M., Park, et. al., "A review of conduction phenomena in Li-ion batteries

[2] V. R., Subramanian, et. al., "Mathematical model reformulation for Lithium-ion battery simulations: Galvanostatic boundary conditions

Internal State Variable (ISV) Mapping Approach

- Problem Statement:

$$\mathscr{F}\left(x, t, \frac{\partial \mathbf{u}}{\partial x}, \frac{\partial \mathbf{u}}{\partial t}, \boldsymbol{\theta}\right) = 0 \xrightarrow{\text{estimate}} \boldsymbol{\theta}$$

- Rationale:

$$output: V(\mathrm{t}) = \Phi_{s,x=L}(\mathrm{t}) - \Phi_{s,x=0}(\mathrm{t})$$

$$\Rightarrow \quad L\Phi(x,t) = f(x,t,I(t),\boldsymbol{\theta}) \rightarrow \frac{\mathrm{d}\,\Phi_{x=L}(t)}{\mathrm{d}t} = f(t,I(t),\boldsymbol{\theta})$$

$$\Rightarrow \quad \Phi_{x=L,k} - \Phi_{x=L,k-1} = \Delta t \times f(I_k, \boldsymbol{\theta})$$

$$\Rightarrow \quad V_k = G(I_k, V_{k-1}, \boldsymbol{\theta})$$

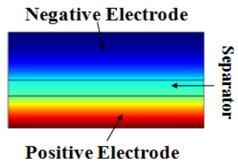
ISV Mapping Approach

Designed model parameters $\boldsymbol{\theta}$

Offline Stage
Online Stage

Simulation Model

Construct a simulation model in COMSOL

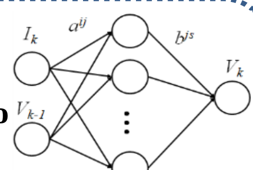


Experimental Data

Collect I-V data from battery electrical tests

Surrogate Model for Simulation I-V Data

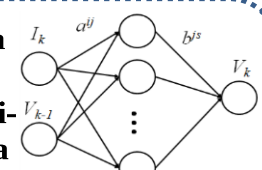
Construct a NN model from pseudo I-V data



$$\mathbf{W} = \left[a^{11}, \ldots, a^{ij}, b^{11} \ldots, b^{js} \right]$$

Surrogate Model for Experimental Data

Construct a NN model from experi-mental data



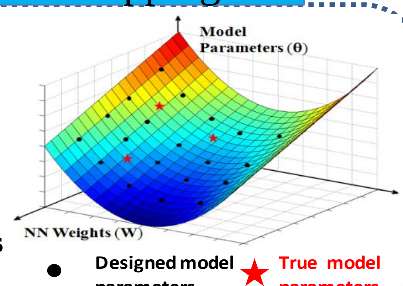
$$\mathbf{W}' = \left[a^{11}, \ldots, a^{ij}, b^{11} \ldots, b^{js} \right]$$

Construct a Kriging model

Map weights variable to true model parameters

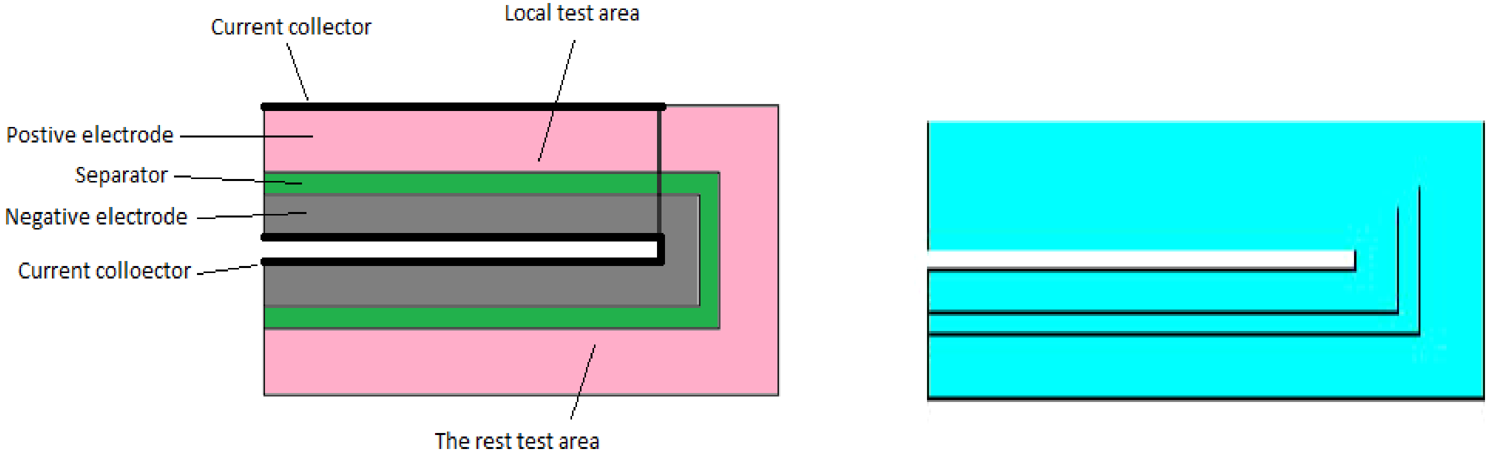
Kriging Model for ISV Mapping

Construct a mapping surface and obtain true model parameters



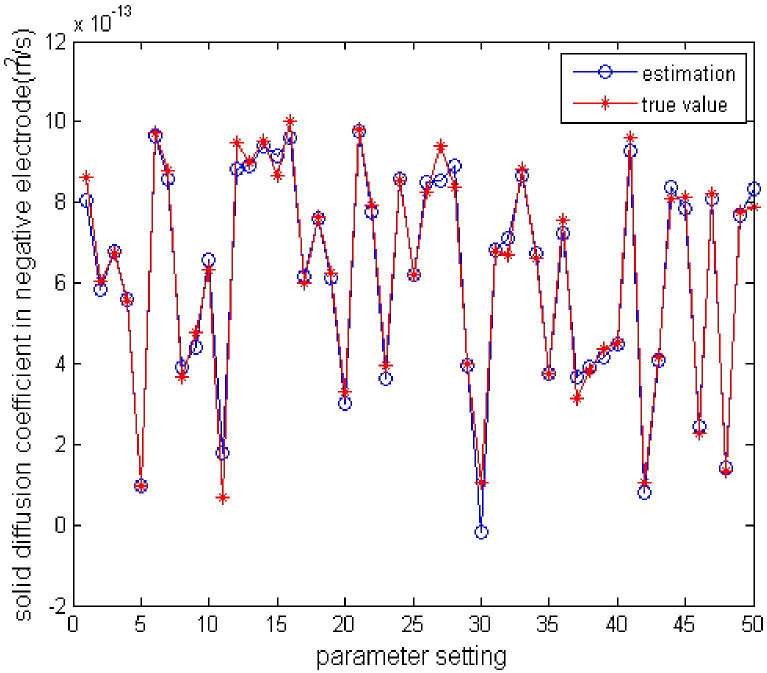
Battery Multi-physics Simulation

- The geometry of Li-ion battery 2D mode:

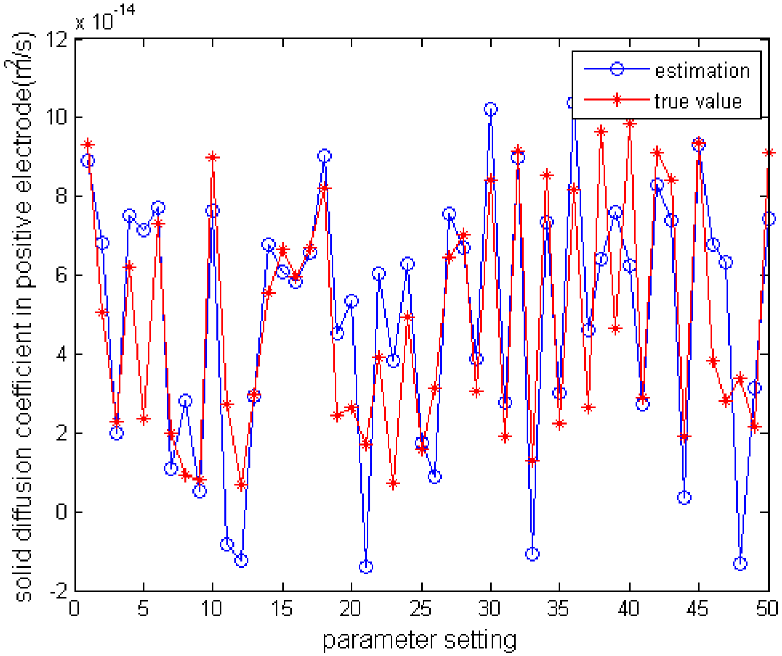


- To observe the Li-plating phenomenon at the specific area, the testing model is divided into the local test area and the rest area
- A set of V-I data under different parameters is generated as a training pool; another set of V-I data under random parameters is also generated to be online experimental data

ISV Mapping Validation



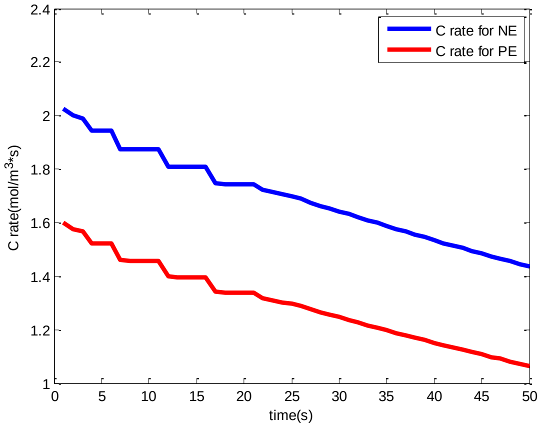
Estimation of diffusion coefficient in negative electrode

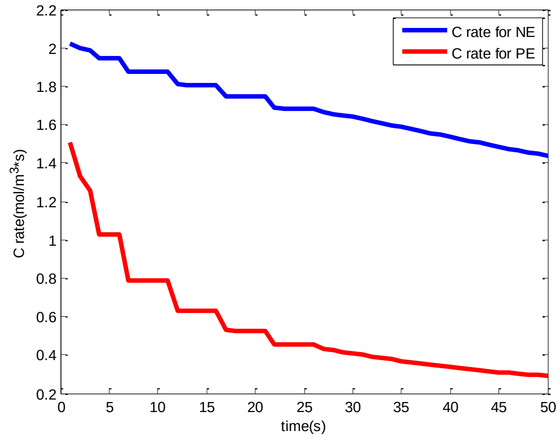


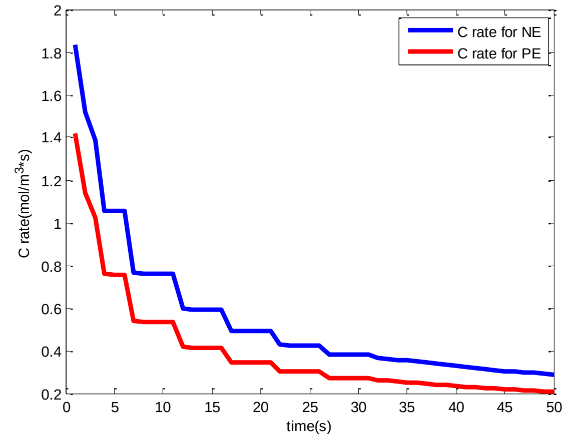
Estimation of diffusion coefficient in positive electrode

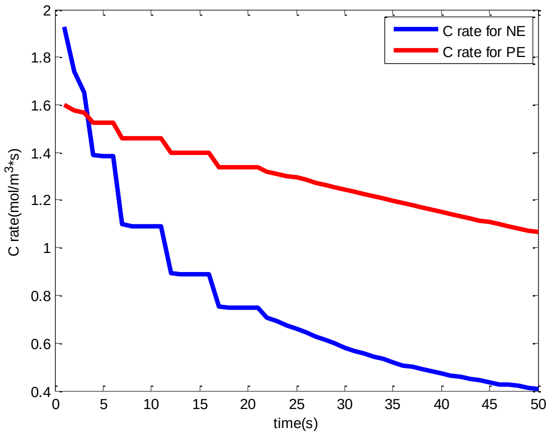
Li-plating Onset Diagnosis

- Getting estimation of D_n and D_p, we use different pairs of estimation to predict the concentration rate performance









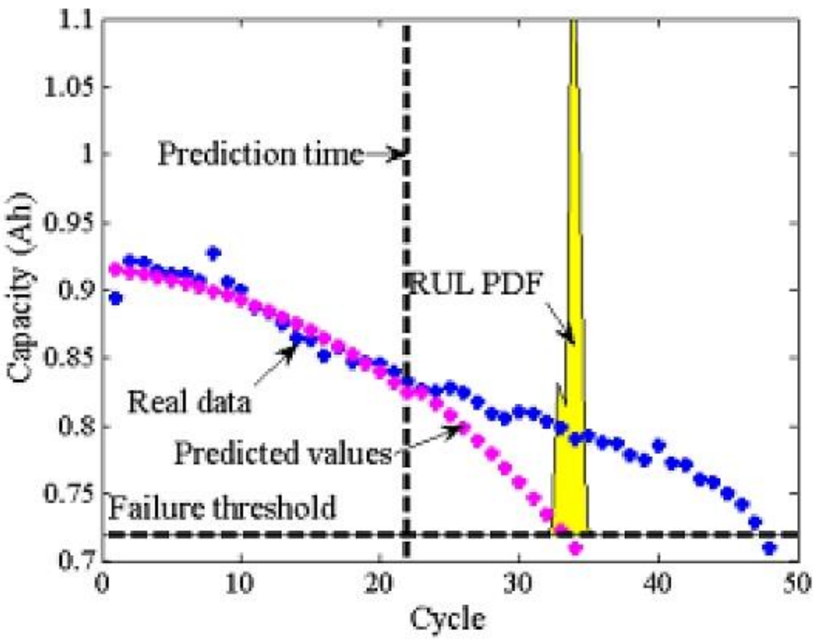
•C-rate for positive electrode **doesn't exceed** C-rate for negative electrode in the whole charge process

•C-rate for positive electrode **exceeds** C-rate for negative electrode in the whole charge process

•Li-plating occurrence at **t = 4s**

Future Work

Battery prognostics: capture the system degradation trend based on the current and previous health conditions of the system, and predict its future health condition and remaining useful life (RUL)



** Figure Courtesy of NASA Ames: Prognostics Center of Excellence (PCoE)*

- Challenges:
  - system degradation model is generally difficult to test and analyze
  - changes of operational and environmental parameters could significantly impact system degradation model

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