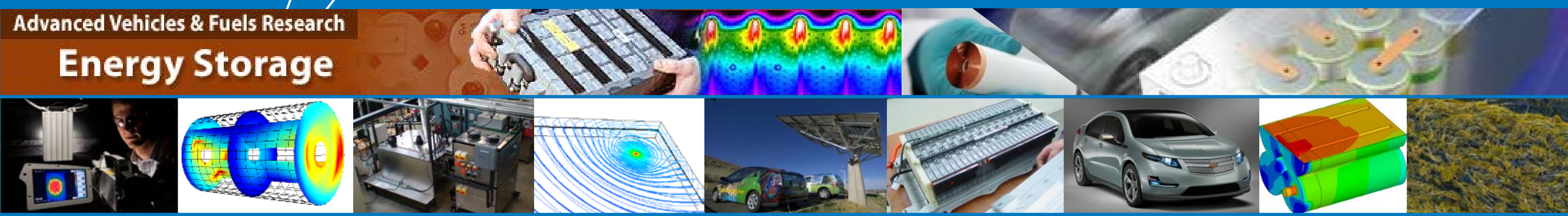
Models for Battery Reliability and Lifetime

Applications in Design and Health Management



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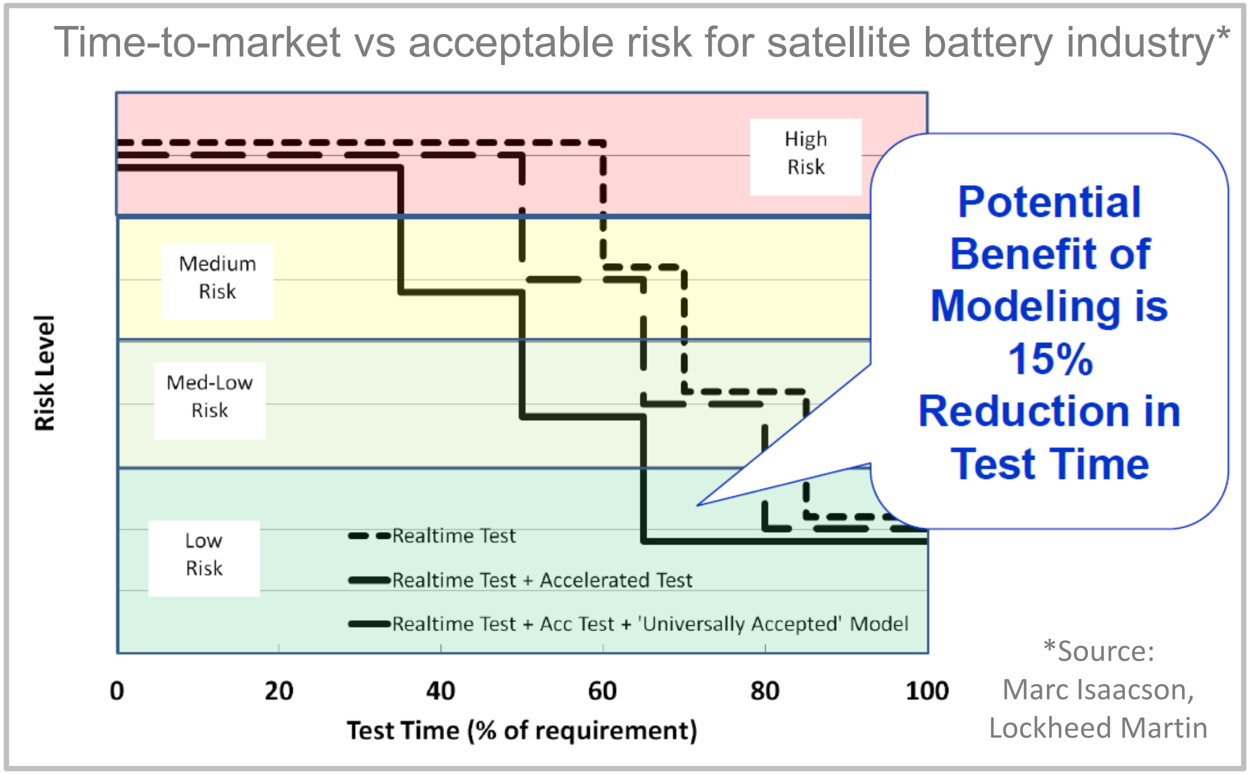
NREL/PR-5400-58550

Battery Congress • April 15-16, 2013 • Ann Arbor, Michigan

Better life prediction methods, models and management are essential to accelerate commercial deployment of Li-ion batteries in large-scale high-investment applications



OEM Goals:

- Optimize designs (size, cost, life)
- Minimize business & warranty risk
- Reduce time to market

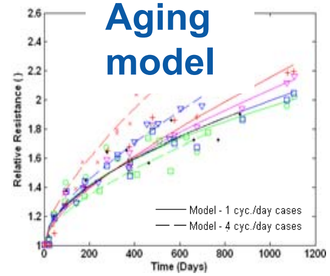
End User Goals:

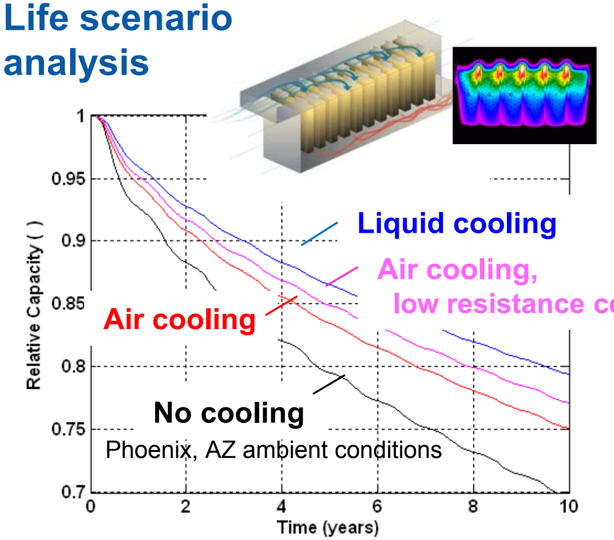
- Understand reliability and economics of new technologies
  (e.g., electric-drive vehicles vs. conventional vehicles)
- Manage assets for maximum utilization
  (e.g. route scheduling, charge control to optimize EV fleet life and cost)

NREL Research & Development Addressing Battery Lifetime

Life predictive modeling and battery system tradeoff studies

U.S. DEPARTMENT OF ENERGY | Energy Efficiency & Renewable Energy



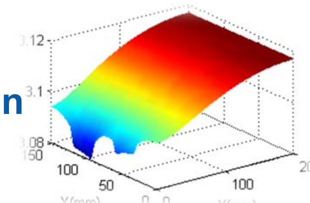


Computer-aided engineering of batteries (CAEBAT program)

U.S. DEPARTMENT OF ENERGY | Energy Efficiency & Renewable Energy

TARDEC The U.S. Army Tank Automotive Research, Development and Engineering Center

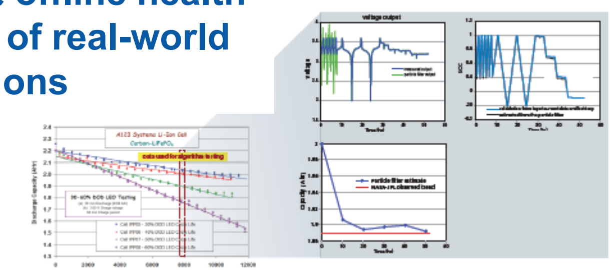
3D Multi-physics simulation



Battery health estimation & management (Laboratory-Directed R&D program)

NREL NATIONAL RENEWABLE ENERGY LABORATORY

Online & offline health tracking of real-world applications



Battery prognostic and electrochemical control (ARPA-E AMPED program)

arpa·e

Advanced battery management R&D with industry & university partners

Outline

Part 1: Battery Life Modeling

- Life Model Framework
- NCA Model
- FeP Model

Part 2: Life Model Application

- Life-Cycle Analyses
- Real-Time Health Management

NREL Life Predictive Model

Calendar fade
- SEI growth (possibly coupled with cycling)
- Loss of cyclable lithium
- a_1, b_1 = f(ΔDOD,T,V)

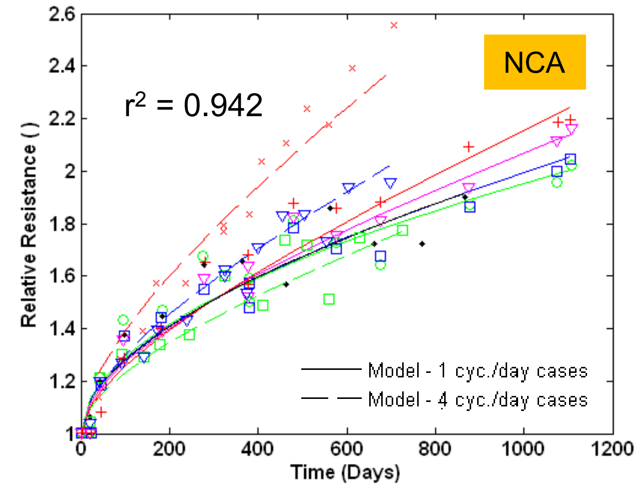
Cycling fade
- Active material structure degradation and mechanical fracture
- a_2, c_2 = f(ΔDOD,T,V)

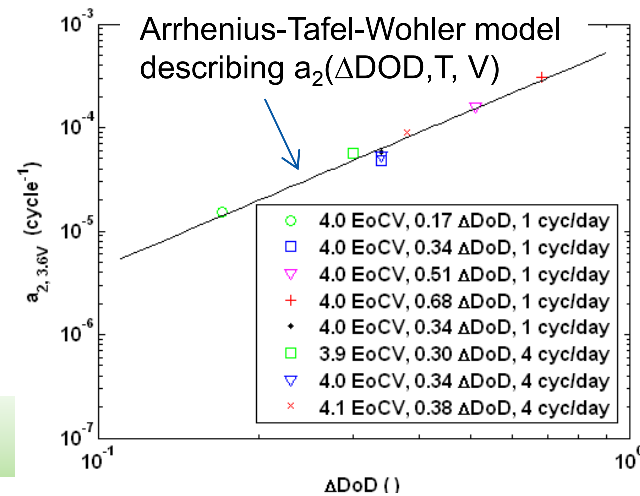
Relative Resistance $R = a_1 t^{1/2} + a_2 N$

Relative Capacity $Q = \min(Q_{Li}, Q_{sites})$

$Q_{Li} = b_0 + b_1 t^{1/2} + b_2 N$

$Q_{sites} = c_0 + c_2 N$





•Data shown above: J.C. Hall, IECEC, 2006.

Life model framework: Graphite/NCA example

Data

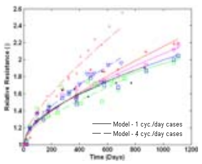
A. Resistance growth during storage
   Broussely (Saft), 2007:
   - T = 20°C, 40°C, 60°C
   - SOC = 50%, 100%

B. Resistance growth during cycling
   Hall (Boeing), 2005-2006:
   - DoD = 20%, 40%, 60%, 80%
   - End-of-charge voltage = 3.9, 4.0, 4.1 V
   - Cycles/day = 1, 4

C. Capacity fade during storage
   Smart (NASA-JPL), 2009
   - T = 0°C, 10°C, 23°C, 40°C, 55°C

   Broussely (Saft), 2001
   - V = 3.6V, 4.1V

D. Capacity fade during cycling
   Hall (Boeing), 2005-2006: (see above)



NCA

Regression

1. Fit local model(s)
2. Visualize rate-dependence on operating condition
3. Hypothesize rate-law(s)

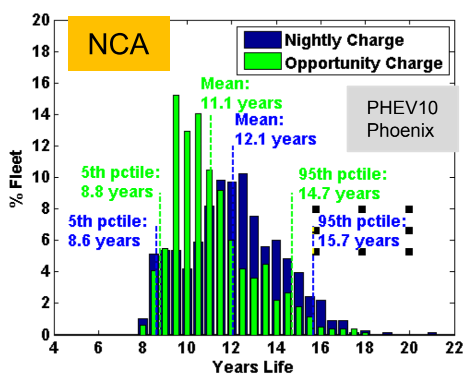
$$\theta_T = \exp\left[\frac{-E_a}{R}\left(\frac{1}{T(t)} - \frac{1}{T_{ref}}\right)\right] \quad \theta_V = \exp\left[\frac{\alpha F}{R}\left(\frac{V_{oc}(t)}{T(t)} - \frac{V_{ref}}{T_{ref}}\right)\right] \quad \theta_{\Delta DoD} = \left(\frac{\Delta DoD}{\Delta DoD_{ref}}\right)^{\beta}$$

4. Fit rate-laws(s)
5. Fit global model(s)

Select model with best statistics

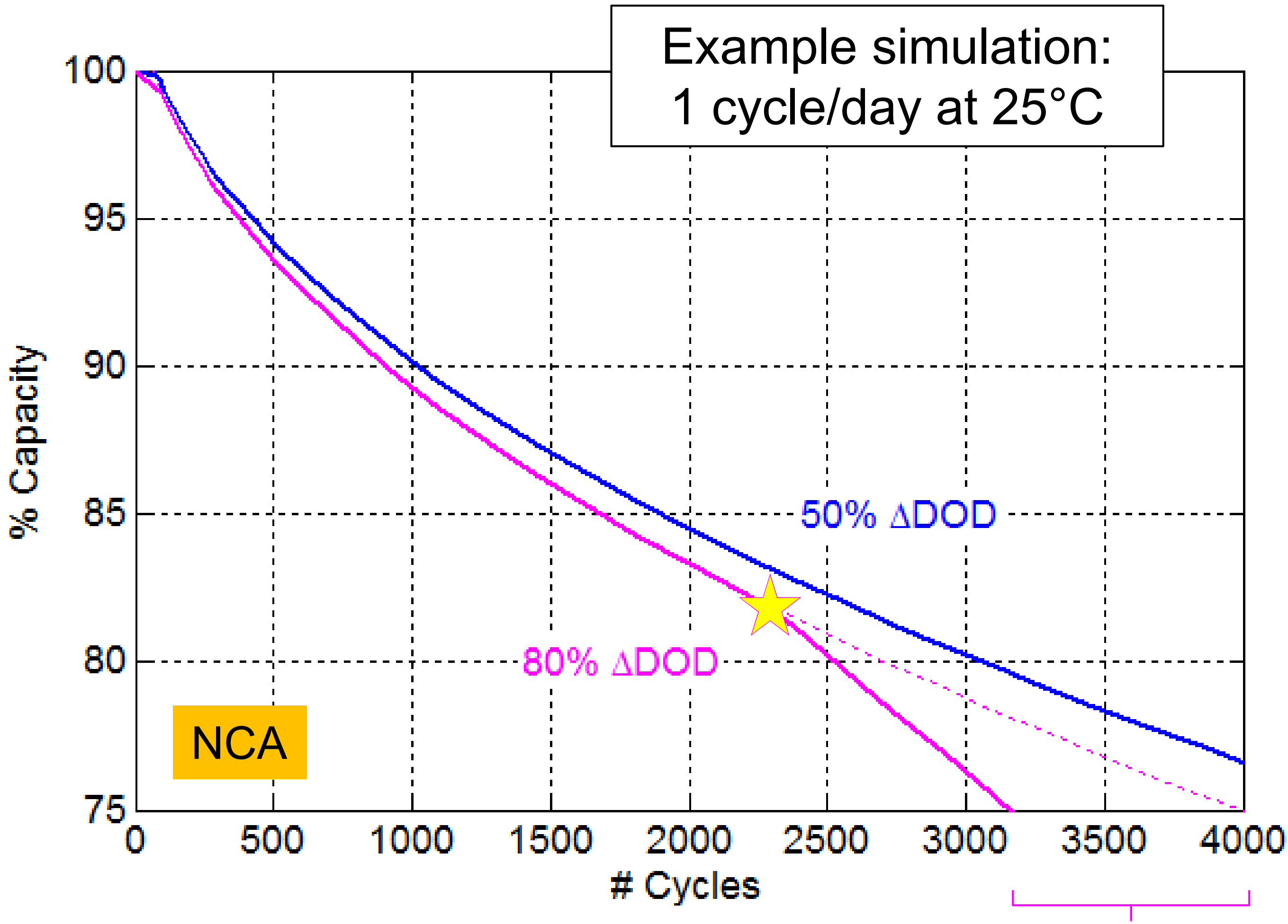
#	Storage Model	Parameters	RMSE (% capacity)	R2	Adjusted R2
7	q = 1 + b1*t^0.5	b1(T,Voc)	2.06	0.925	0.923
8	q = 1 + b1*t^z	b1(T,Voc), z	2.01	0.929	0.926
9	q = 1 + b1*t^z	b1(T,Voc), z(T)	2.03	0.929	0.925
10	q = 1 + b1*t.^0.5 + b2*t	b1(T,Voc), b2	1.99	0.930	0.927
11	q = 1 + b1*t.^0.5 + b2*t	b1(T,Voc), b2(T)	2.00	0.931	0.926
12	q = 1 + b1*t.^0.5 + b2*t	b1(T,Voc), b2(T,Voc)	1.87	0.941	0.936

Predictive model



Knee in curve important for predicting end of life

(Hypothesis based on observations from data)



<u>50% DOD:</u>
Graceful fade (controlled by lithium loss)

<u>80% DOD:</u>
Graceful fade transitions to sudden fade ~2300 cycles (transition from lithium loss to site loss)

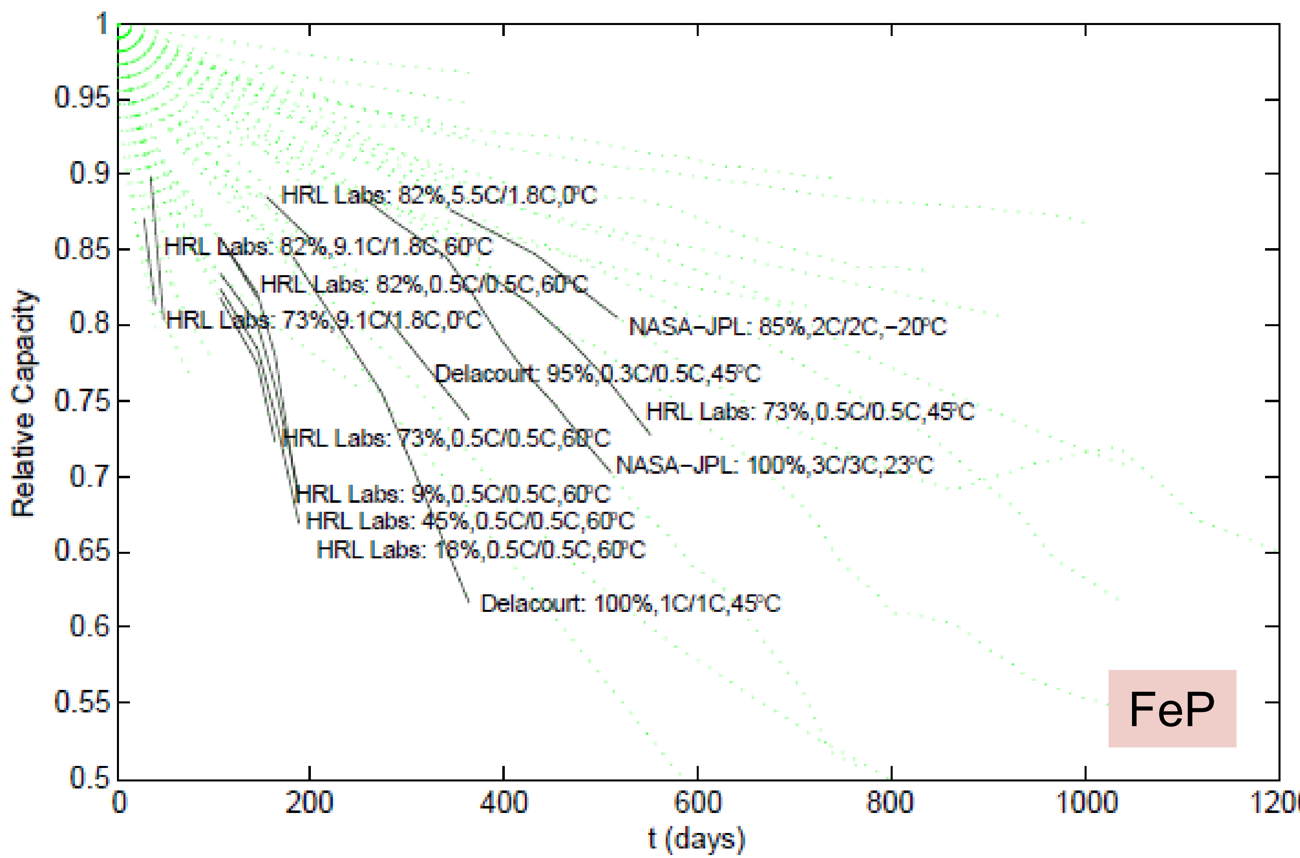
Life over-predicted by 25% without “knee”

Iron-phosphate (FeP) Life Model

Estimated $2M data collection effort of other labs has been leveraged for this analysis (DOE, NASA-JPL, HRL & GM, Delacourt, CMU, IFP)

	Temperature							
DOD	-20°C	0°C	15°C	25°C	30°C	45°C	60°C	C-rate
0				Delct 1		Delct 5		Storage, 50%
				Delct 2		Delct 6		Storage, 100%
95				Delct 3		Delct 7		LEO or EV cycle
60				NASA 4				
50				NASA 5				
40				NASA 6				
30				NASA 7				
100								C/2
90							HRL 1q	
80						HRL 18	HRL 7	
50							HRL 6	
20							HRL 5	
10							HRL 4	
100				Delct 4		Delct 8		1C
				NASA 1				
90								
80								
50								
20								
10								
100	NASA 9			NASA 2		NASA 8		2C
90							HRL 2q	
80								
50			HRL 10			HRL 9		
20								
10							HRL 8	
100				NASA 3				3C
90								
80								
50								
20								
10								
100								6C
90		HRL 12						
80						HRL 11		
50								
20								
10						HRL 13		
100								10C
90							HRL 3q	
80		HRL 17 c2				HRL 15		
50			HRL 14					
20								
10							HRL 16	

Capacity fade with "knee" region highlighted



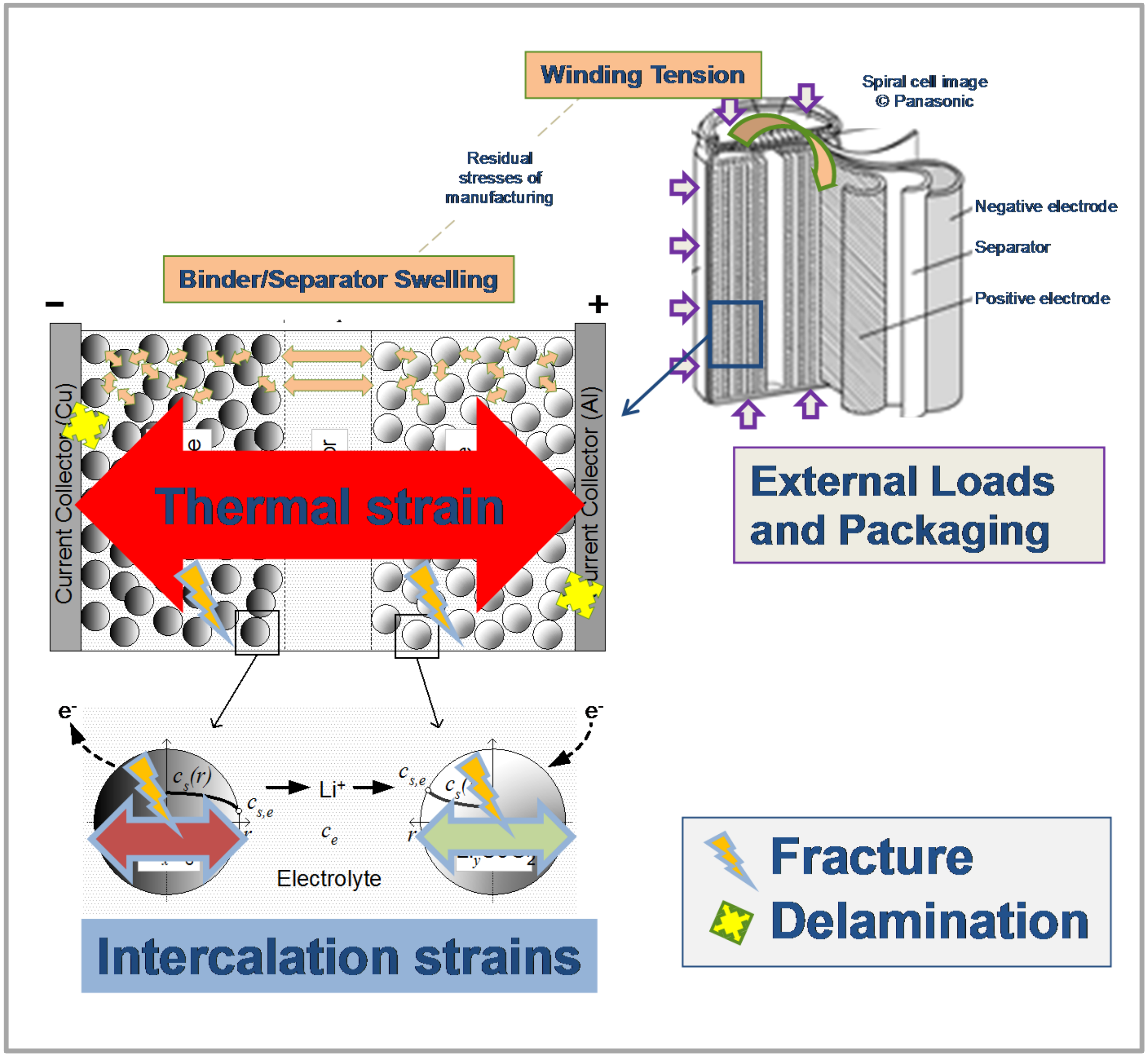
A123 ANR-26650-M1

- Li_xC_6/Li_yFePO_4
- 2.3 Ah, $3.3V_{nominal}$

Active site loss controlled mainly by mechanical-driven cycling fade

Hypothesis for active site loss dependence on operating parameters:

- C-rate (intercalation gradient strains)
- DOD (bulk intercalation strains)
- Low T (exacerbates Li intercalation-gradients)
- High T (exacerbates binder loss of adhesion)
- ΔT (thermal strains)



Hypothesized Active Site Loss Model

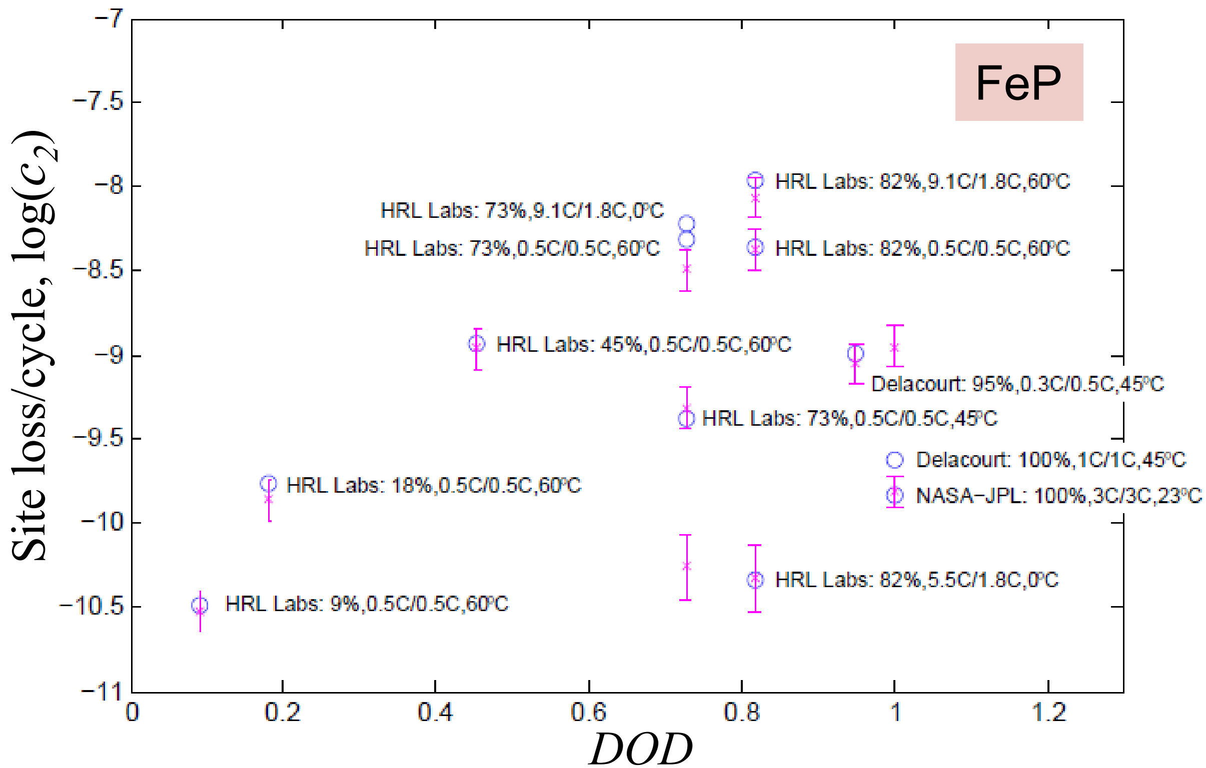
$$q = \min(q_{Li}, q_{sites}).$$

$$q_{Li} = b_0 + b_1 t^z + b_2 N \qquad q_{sites} = c_0 + c_2 N$$

$$c_2 = c_{2,ref}\left\{ \underbrace{\exp\left(\frac{-E_a^{\text{binder}}}{R}\left(\frac{1}{T}-\frac{1}{T_{ref}}\right)\right)}_{\text{accelerated binder failure at high T}} \left[\underbrace{m_1\, DOD}_{\text{bulk intercalation strain}} + \underbrace{m_2\, \Delta T}_{\text{bulk thermal strain}} \right] + \underbrace{m_3 \exp\left(\frac{-E_a^{\text{intercal.}}}{\mathrm{R}}\left(\frac{1}{T}-\frac{1}{T_{ref}}\right)\right)\left(\frac{C_{rate}}{C_{rate,ref}}\right)\left(\sqrt{\frac{t_{pulse}}{t_{pulse,ref}}}\right)}_{\text{intercalation gradient strain, accelerated by low temperature}} \right\}.$$

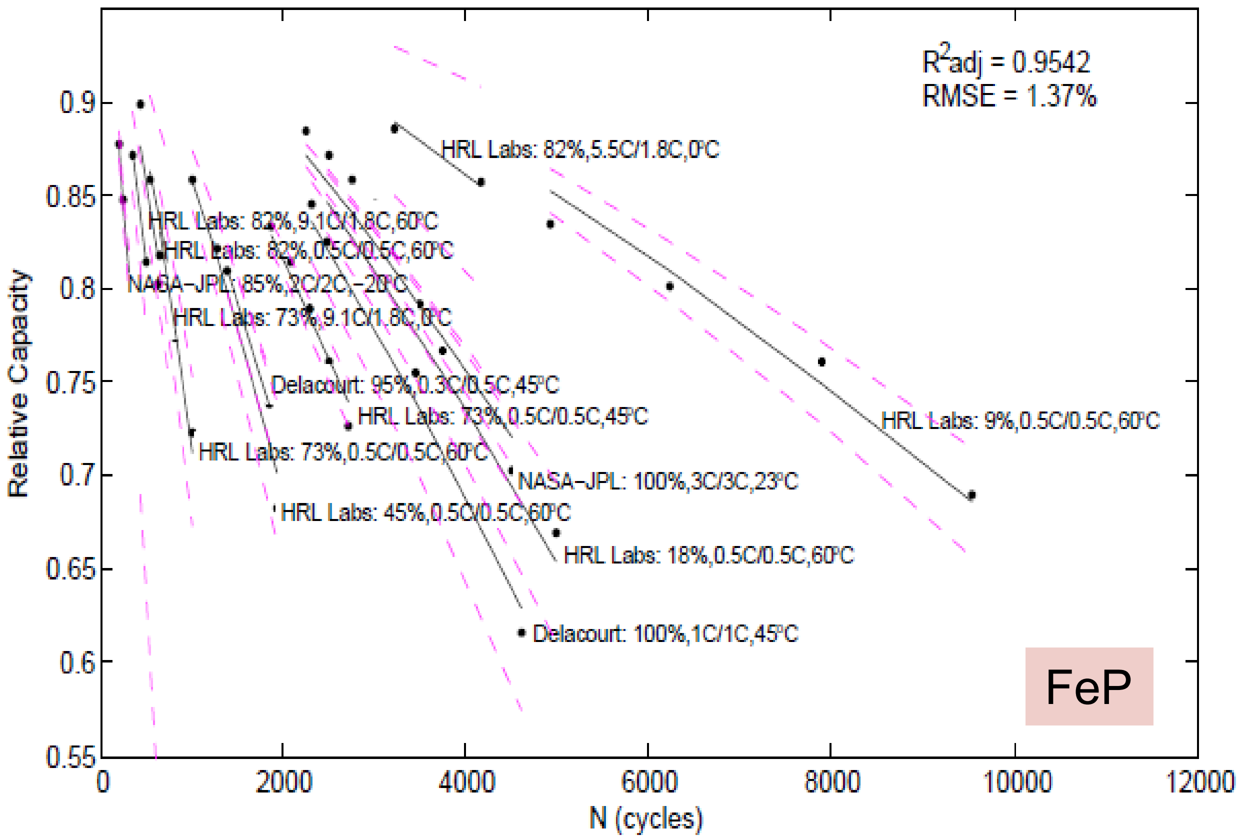
Blue symbols are site-loss rates for each individual aging condition

Purple symbols are global rate-law model across all aging conditions



FeP model comparison with knee data

Global model compared with 13 aging conditions from 0°C to 60°C



Active site loss *(at room temperature, 1C charge/discharge, 100% DOD reference conditions)*

- 83% due to bulk volumetric expansion/contraction of the active material*
- 13% due to particle fracture owing to intercalation stress at high C-rates
- 4% due to temperature swings encountered by the cell

* This dominant aging term correlates with Amp-hour throughput, often used as a proxy for aging

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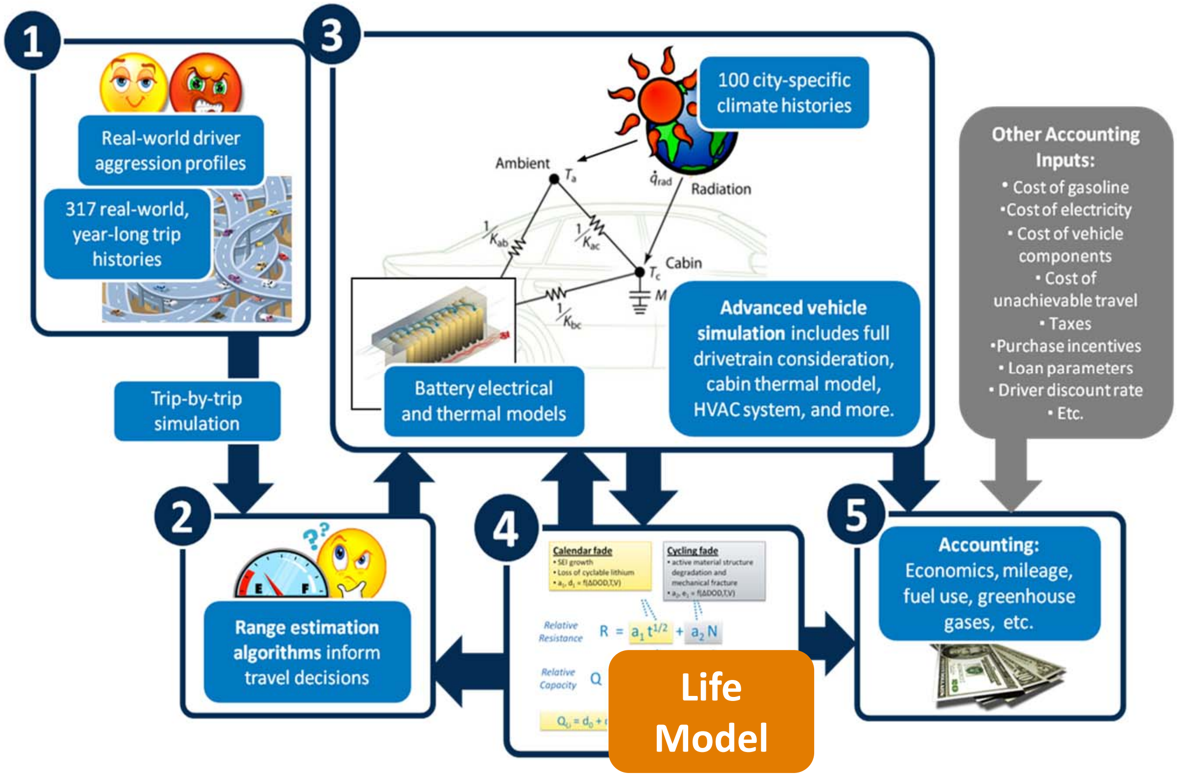
Automotive Analyses: Battery Ownership Model

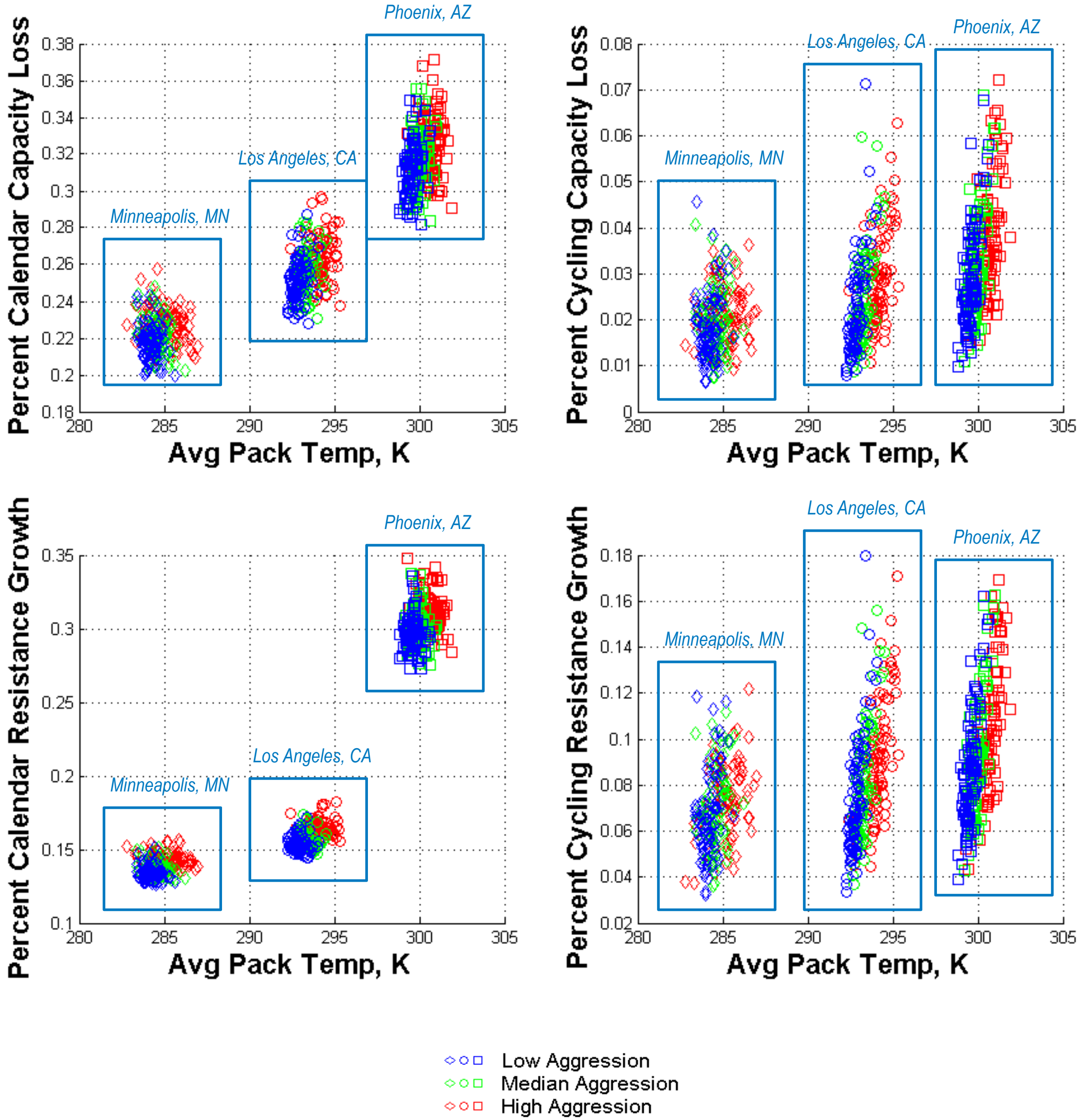
Objective: Identify cost-effective pathways to reduce petroleum use and carbon footprint via optimal use of vehicular energy storage systems

Approach:

- Trip-by-trip simulation of hundreds of real-world, year-long, vehicle-specific drive patterns in real climates
- Model driver behavior, road loads, auxiliary loads, vehicle cabin thermal response, and **battery electrical, thermal, and <u>life</u> response**



Automotive Analyses: Battery Ownership Model



A recent study of climate, trip history, and driver aggression shows how these factor affect battery state of health after 10 years in a BEV75

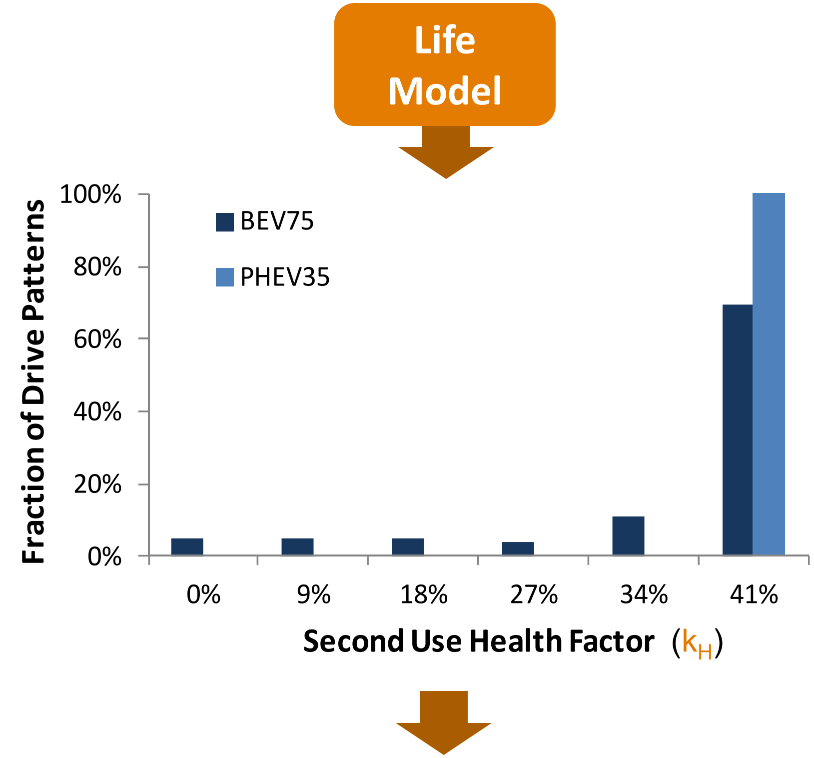
- 317 different real-world trip histories
- 3 different driver aggression levels
- 3 different climates

- **Findings:** Climate has the largest effect on battery wear, followed by trip history

Battery Second-Use Analyses

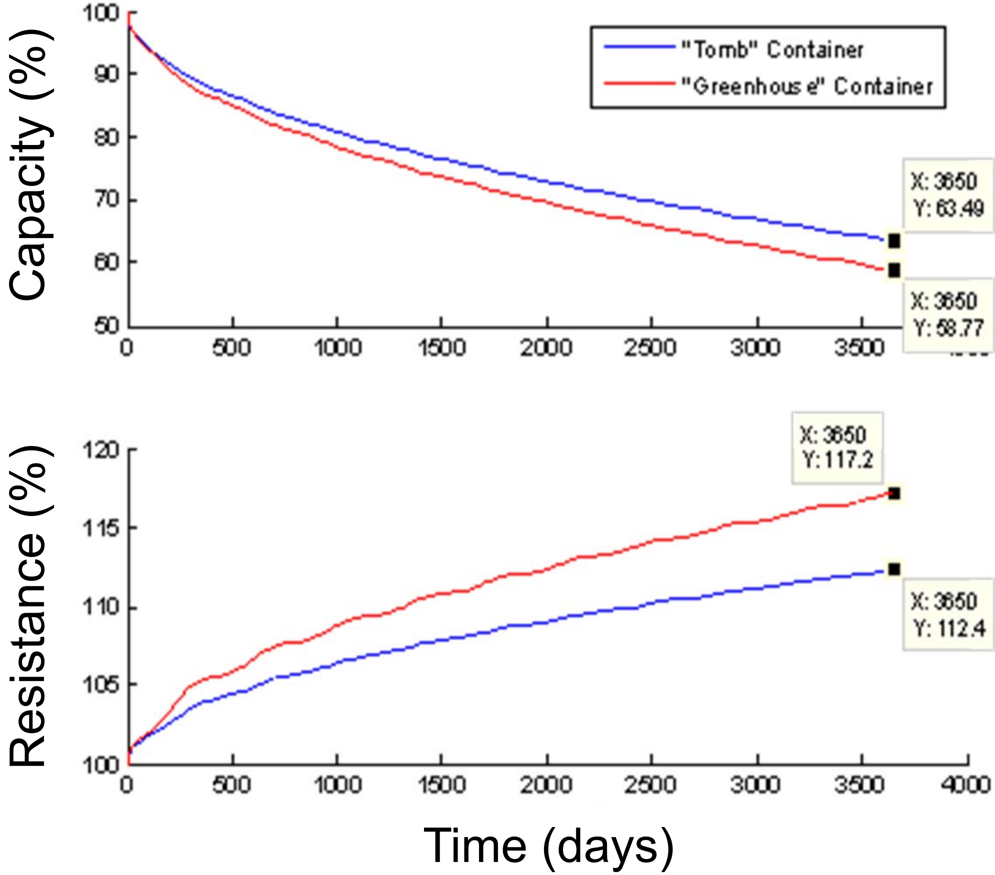
Battery state of health is critical to determining the technical capability and performance of a second-use battery

Our second-use analyses incorporate the life model to calculate a health factor that becomes a major determinant in second-use feasibility



$$\text{Second-Use Battery Selling Price} = k_U k_H c_N$$

Grid Analyses: Community Energy Storage



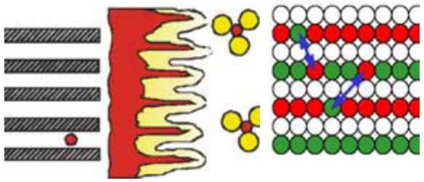
Analyzed the long-term effects of two different community energy storage system configurations in a real-world climate

- **"Tomb" configuration**: insulated from ambient temperature and solar irradiation, strong connection to soil temperature.
- **"Greenhouse" configuration:** Strong connection to ambient temperature, large effect of irradiation.
- **Duty Cycle:** Daily 60% DOD peak-shaving event
- **Climate:** Los Angeles, CA
- **Findings:** The difference in long-term wear between the two system configurations is small for this combination of climate and duty cycle

Time-scales: Control & Estimation

Control

Figures: Vetter, J. Power Sources (2005)



Side reaction limits

Particle stress limits

NREL PIX 19243

Available energy

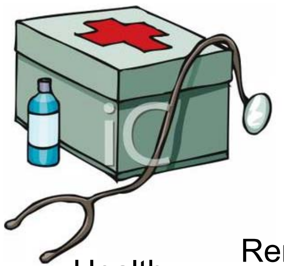
Available power

NREL PIX 20041

Prognostic-based charging

NREL PIX 10925

Prognostic-based V2G

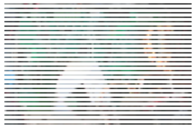


Health

Remaining life

Application

Embedded control



NREL PIX 19358

Performance

NREL PIX 19243

Commute

NREL PIX 24515

Charge

NREL PIX 20040

Grid

NREL PIX 10928

Environment

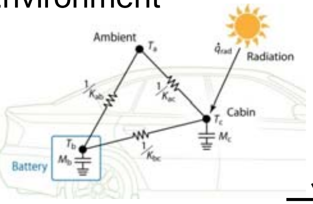


Figure: Dean Arnmstrong

2nd Use

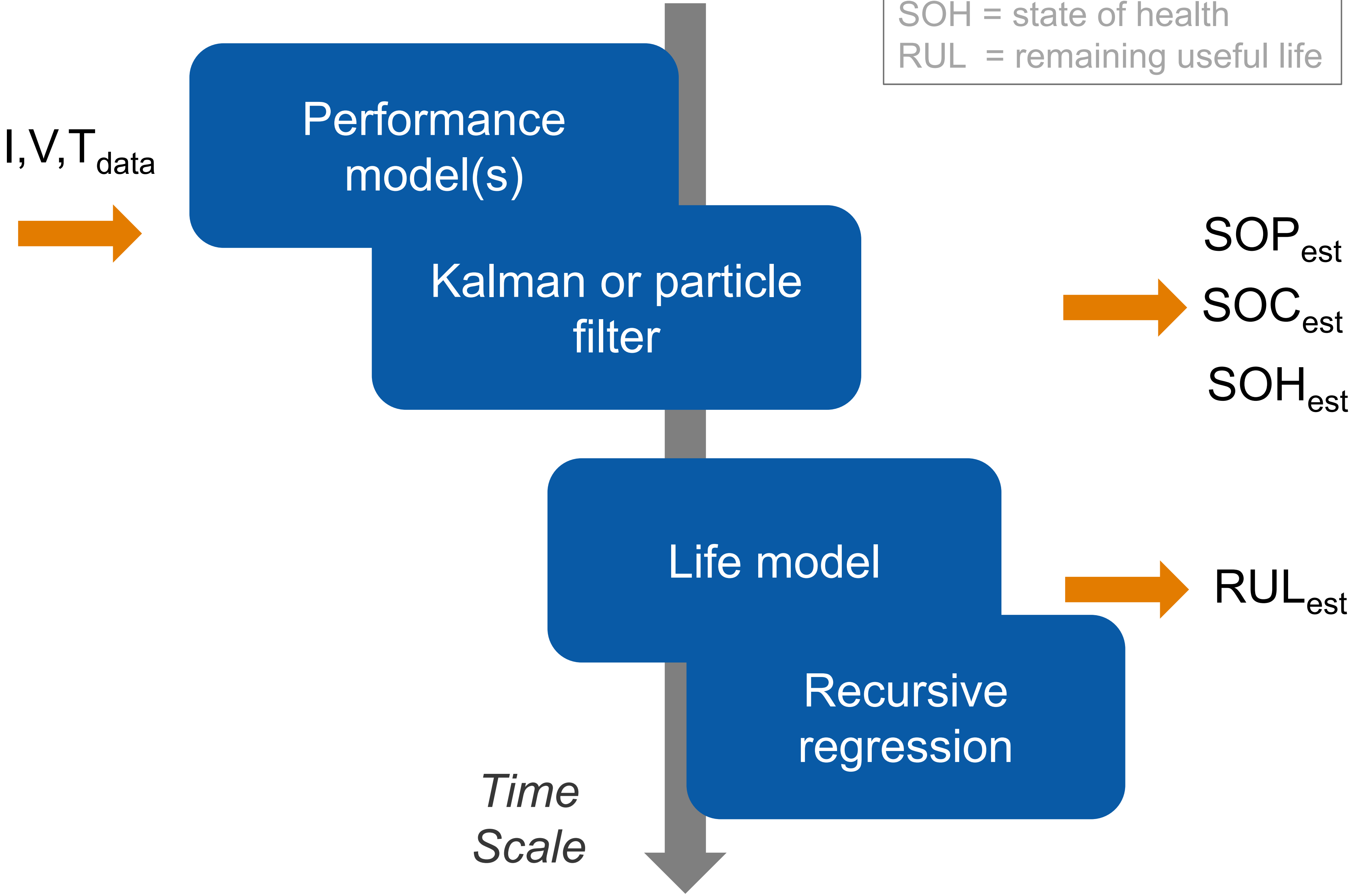
NREL PIX 18660

10^{-3} 10^{0} 10^{3} 10^{6} 10^{9}

[*seconds*]

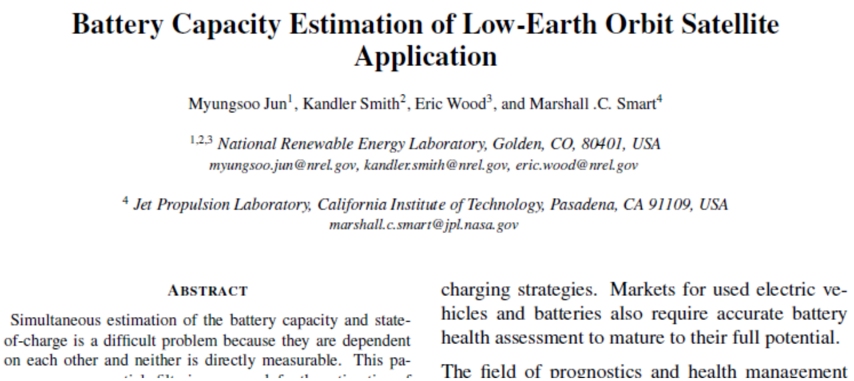
Algorithm topology

SOP = state of power
SOC = state of charge
SOH = state of health
RUL = remaining useful life



Diagnostic Example (online)

Particle filter + circuit model: Estimates both SOC & capacity within 2% of actual



Battery Capacity Estimation of Low-Earth Orbit Satellite Application

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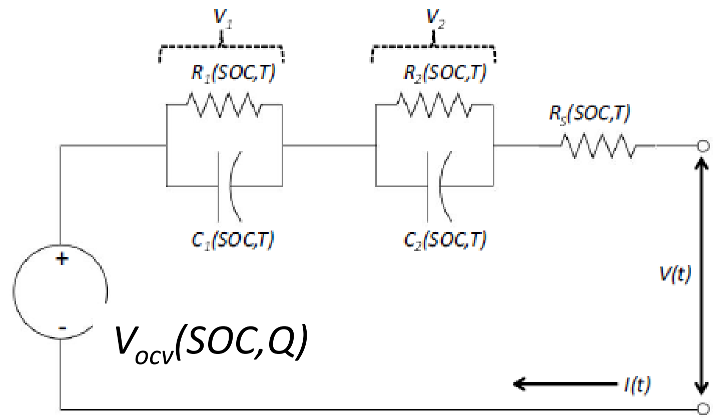
ABSTRACT

Simultaneous estimation of the battery capacity and state-of-charge is a difficult problem because they are dependent on each other and neither is directly measurable. This pa-

charging strategies. Markets for used electric vehicles and batteries also require accurate battery health assessment to mature to their full potential.

The field of prognostics and health management



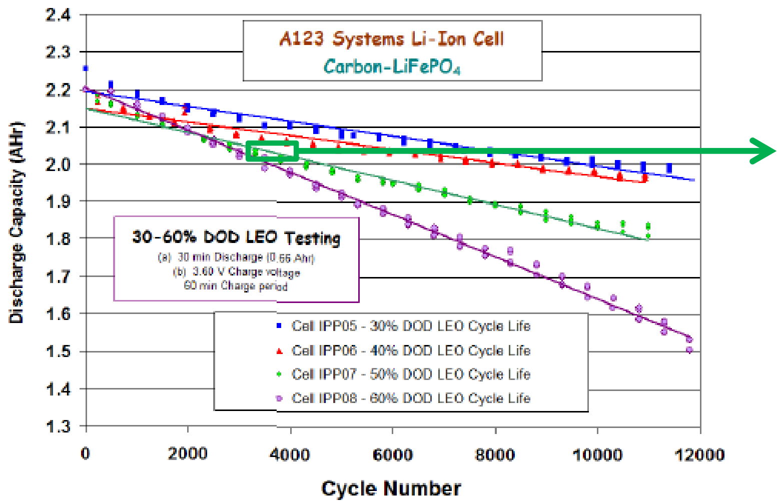


Figure 2. Capacity loss during partial DOD cycling of A123 $LiFePO_4$-based cells (Courtesy Jet Propulsion Laboratory)

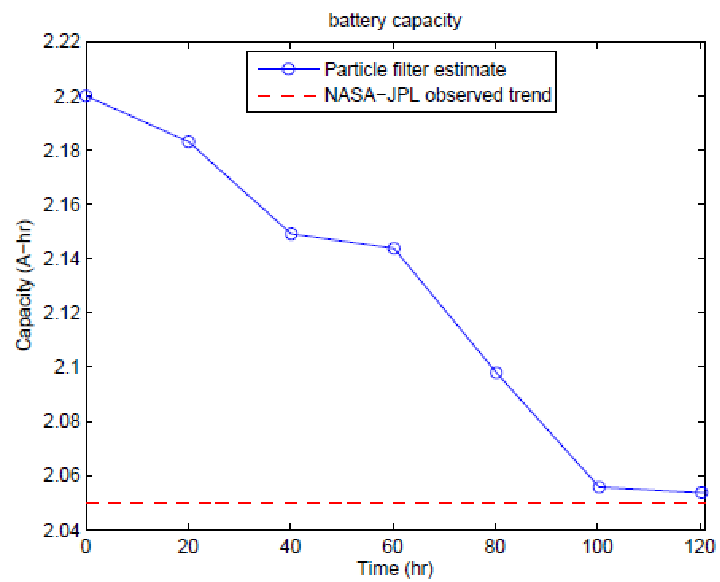
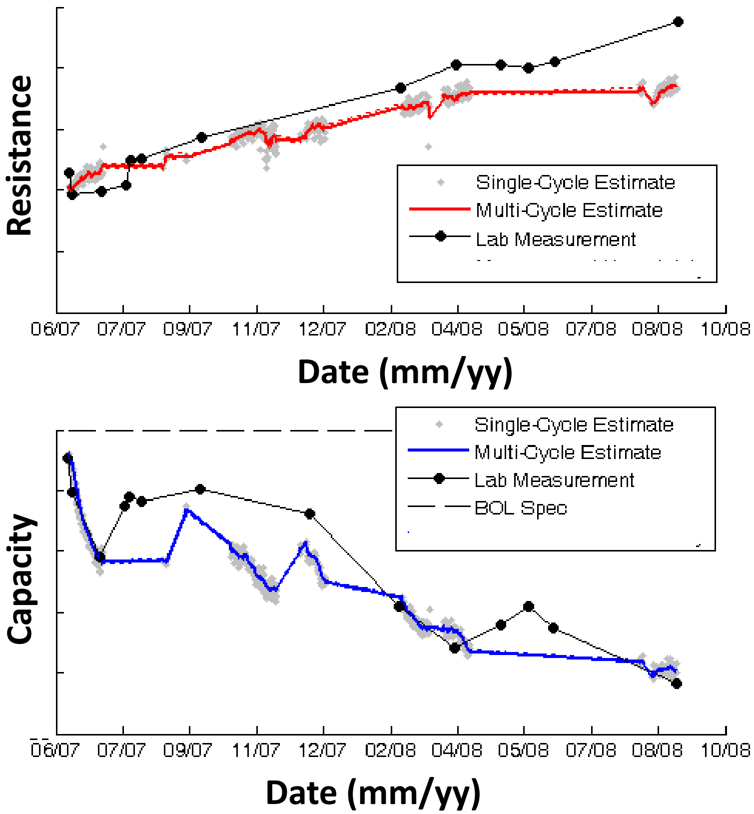


Figure 5. Battery capacity estimation

Diagnostic Example (vehicle fleet analysis)

Estimation of Total Capacity and DC Resistance using in-service (partial discharge) I,V,T data

Validation of algorithm with SCE/Saft Lab Data



Diagnostic Analysis Tools also being applied to

- **EV MD delivery vehicle fleet (200+ vehicles, ~1.5 yrs data)**
- **Hybrid fuel cell vehicles (40 vehicles, ~5 yrs data)**

Figure credits: Eric Wood

ARPA-E AMPED: Three Projects in Battery Management

Advanced Management and Protection of Energy Storage Devices

- Develop advanced sensing and control technologies to provide new innovations in safety, performance, and lifetime for grid-scale and vehicle batteries.

Eaton Corporation

Project: Downsized HEV pack by 50% through enabling battery prognostic & supervisory control, while maintaining same HEV performance & life

NREL: Life testing/modeling of Eaton cells; controls validation on Eaton HEV packs

Utah State/Ford

Project: 20% reduction in PHEV pack energy content via power shuttling system and control of disparate cells to homogenous end-of-life

NREL: Requirements analysis; life model of Ford/Panasonic cell; controls validation of Ford PHEV packs

Washington Univ.

Project: Improve available energy at the cell level by 20% based on real-time predictive modeling & adaptive techniques

NREL: Physics-based cell-level models for MPC; implement WU reformulated models on BMS; validate at cell & module level

Summary

Capable battery life models can be built today, but rely heavily on empirical life test data.

Application of life models can be used to optimize design (offline) and maximize asset utilization (online).

NREL is pursuing battery life models with physics-based descriptions of degradation mechanisms that could both reduce time-to-market and advise longer-life cell designs.

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Boeing – John C. Hall

S. California Edison – Naum Pinsky, Loic Gaillac