

# Quadruple Adaptive Observer of the Core Temperature in Cylindrical Li-ion Batteries and their Health Monitoring

*Xinfan Lin, Hector E. Perez,  
Jason B. Siegel, Anna G. Stefanopoulou*

Dept. of Mechanical Engineering  
University of Michigan, Ann Arbor

*Yonghua Li, R. Dyche Anderson*  
Ford Motor Company

June. 27, 2012

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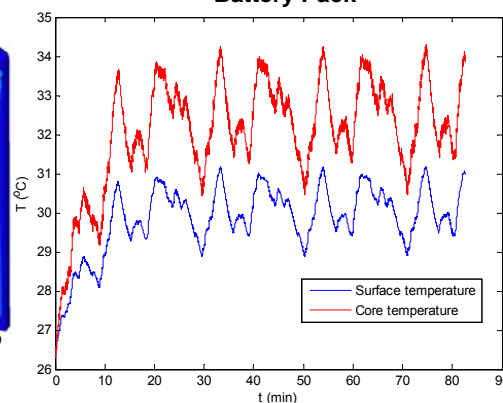
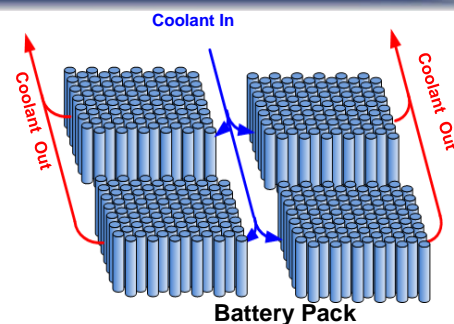
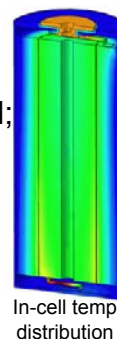
## Background

### Thermal Management for Li ion batteries

- Safety: overheating, thermal runaway
- Performance:  
Aging, efficiency, self-discharge...
- Basis: temperature monitoring

### State of Art: temp monitoring

- Detailed PDE: accurate but complicated;  
not suitable for onboard bat pack
- Single state: oversimplified  
 $T_c \gg T_s$  (high C-rate)
- Two-states lumped model:  $T_c$  and  $T_s$   
Park, Jaura, Ford, SAE2003

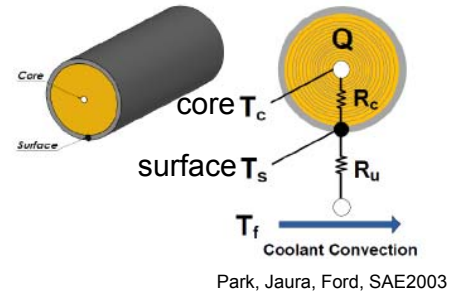




## Background

### Problem: determining parameters

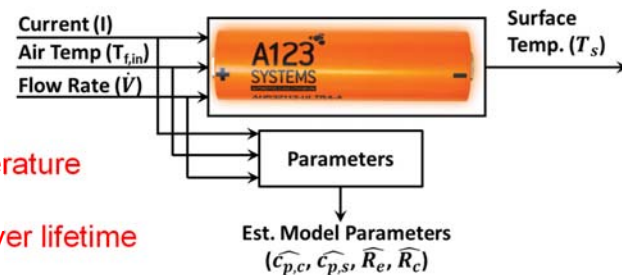
- Thermal/electrical resistance, heat capacity...
- Calculation based on component properties:
  - approximation, not accurate
  - complicated structure and interfaces
- Designed experiments beforehand
  - degradation: internal resistance change
  - biased estimation due to parameter drift



Two states thermal model

### Online identification

- Based on onboard signals
  - current, flow temperature, surface temperature
- Parameter real-time update: accurate over lifetime
- Health monitoring: resistance growth



Online parameter Identification

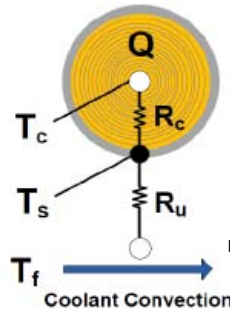
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## Content

- Background
- Battery Thermal Model and Online Identification
- Experimental Validation
- Identification of Time-varying  $R_e$
- Conclusion and Future Work

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Park, et al. 2003 SAE

Two states thermal model

States:

- $T_c$ , core temperature
- $T_s$ , surface temperature

Inputs:

- $I$ , current
- $T_f$ , coolant temperature

Output :

- $T_s$ , surface temperature

Core temperature dynamics

$$C_c \frac{dT_c}{dt} = I^2 R_e + \frac{T_s - T_c}{R_c}$$

Surface temperature dynamics

$$C_s \frac{dT_s}{dt} = \frac{T_f - T_s}{R_u} - \frac{T_s - T_c}{R_c}$$

Parameters:

- $C_c$ , core heat capacity
- $C_s$ , surface heat capacity
- $R_e$ , internal resistance (SOC, temperature dependent)
- $R_c$ , conduction resistance
- $R_u$ , convection resistance (coolant flow velocity dependent)

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$$s^2 T_s - s T_{s,0} = \underbrace{\frac{R_e}{C_c C_s R_c}}_{\alpha} I^2 + \underbrace{\frac{1}{C_c C_s R_c R_u}}_{\beta} (T_f - T_s) - \underbrace{\left( \frac{C_c + C_s}{C_c C_s R_c} + \frac{1}{C_s R_u} \right)}_{\gamma} (s T_s - T_{s,0})$$

Parametric model

- Laplace transform to the original ODEs
- Parameters lumped to  $\alpha$ ,  $\beta$ ,  $\gamma$
- Regressors: measured signals

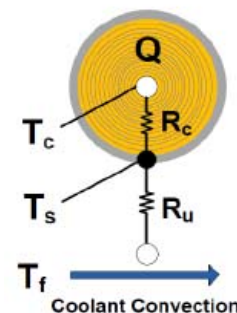
Identifiability Analysis

- Only  $\alpha$ ,  $\beta$ ,  $\gamma$  identifiable
- 5 physical parameters vs 3 equations
- Need priori knowledge of two parameters
- $C_c$ ,  $C_s$ : constant among cells, over lifetime
- 4 regressors vs 4 equations:

coolant velocity varying &  $R_u$  pre-calculated

Parameter reformulation:

- Solve  $R_e$ ,  $R_c$ ,  $R_u$  from  $\alpha$ ,  $\beta$ ,  $\gamma$
- Constant  $R_e$ : temp dependent (later)



Two states thermal model

$$\begin{cases} (C_c + C_s) C_s \beta R_u^2 + C_s \gamma R_u + 1 = 0 \\ R_c = \frac{1}{\beta C_s C_c R_u} \\ R_e = C_c C_s \alpha R_c \end{cases}$$

Parameter reformulation

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# Identification Design

## Least square algorithm

- Noise reduction
- On-line Recursive

$$s^2 T_s - s T_{s,0} = \underbrace{\frac{R_e}{C_c C_s R_c}}_{\alpha} I^2 + \underbrace{\frac{1}{C_c C_s R_c R_u}}_{\beta} (T_f - T_s) - \underbrace{\left( \frac{C_c + C_s}{C_c C_s R_c} + \frac{1}{C_s R_u} \right)}_{\gamma} (s T_s - T_{s,0})$$

Parametric Model

## Identification

- Signal Filtering
- Normalization
- Regression

$$\begin{aligned} \theta &= [\alpha \quad \beta \quad \gamma]^T & \dot{\theta} &= P \frac{\varepsilon \phi}{m^2} \\ \phi &= \left[ \frac{I^2}{\Lambda} \quad \frac{T_f - T_s}{\Lambda} \quad \frac{s T_s - T_{s,0}}{\Lambda} \right]^T & P &= -P \frac{\phi \phi^T}{m^2} P \\ z &= \frac{s^2 T_s - s T_{s,0}}{\Lambda} & \varepsilon &= z - \theta^T \phi \\ & & m^2 &= 1 + \phi^T \phi \end{aligned}$$

Online least square ID algorithm

## Adaptive Monitoring

- Real time parameter update
- Closed loop observer:  $T_s$  feedback
- Fast convergence, noise suppression

$$\begin{aligned} C_c \frac{d\hat{T}_c}{dt} &= I^2 \hat{R}_e + \frac{\hat{T}_s - \hat{T}_c}{\hat{R}_c} + l_1 (T_s - \hat{T}_s) \\ C_s \frac{d\hat{T}_s}{dt} &= \frac{T_f - \hat{T}_s}{\hat{R}_u} - \frac{\hat{T}_s - \hat{T}_c}{\hat{R}_c} + l_2 (T_s - \hat{T}_s) \end{aligned}$$

Adaptive monitoring of battery core temperature

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## Content

- Background
- Battery Thermal Model and Online Identification
- **Experimental Validation**
- Identification of Time-varying Re
- Conclusion and Future Work

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## Experimental Results

### Experimental setup

- Battery Cycler
- Thermal Chamber
- A&D test control system
- Flow chamber
- A123 26650 LiFePO4

Battery Cycler

Thermal Chamber

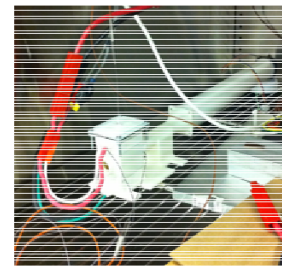
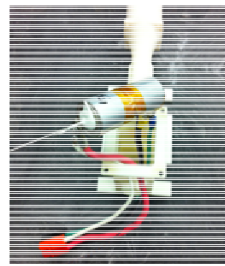


### Temperature sensing

- Thermocouples on casing, core, flow
- Core sensor installation
  - Argon-filled glove box
  - Drilled to the central cavity
  - Inserted thermocouple
  - Sealed



Installation of thermocouple



Flow chamber



## Drive cycle and PE analysis

### Drive cycle

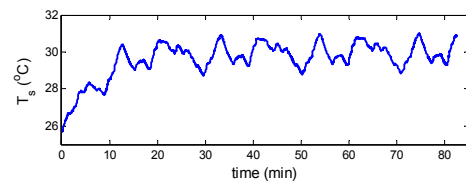
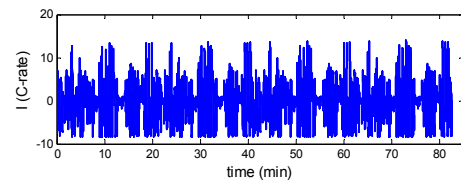
- Scaled Urban Assault Cycle (Lee 2011)
- Hybrid electric military vehicle
- Fixed flow,  $R_u$  to be identified
- Re constant: small temp variation

### Persistent excitation

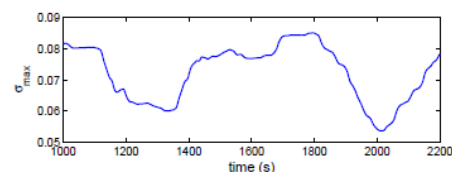
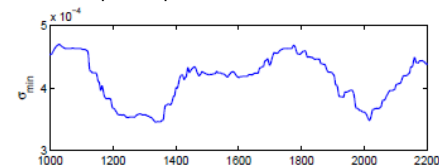
- Prerequisite for identification
- $U(t)$ : integration of regressors
- PE condition:  $U(t)$  bounded by  $\alpha_0$  and  $\alpha_1$
- $\alpha_0$  and  $\alpha_1$  by eigen values of  $U(t)$

$$\alpha_1 I_M \geq U(t) = \frac{1}{T_0} \int_t^{t+T_0} \phi(\tau) \phi^T(\tau) d\tau \geq \alpha_0 I_M \quad \forall t \geq 0$$

$$\phi = \left[ \frac{I^2}{\Lambda} \quad \frac{T_f - T_s}{\Lambda} \quad \frac{sT_s - T_{s,0}}{\Lambda} \right]^T$$



Input-output: measured  $T_s$  and  $I$



Eigen values of  $U(t)$



## Experimental Results

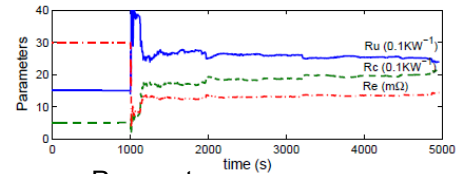
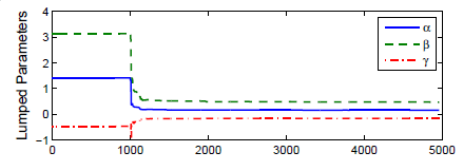
### Parameter convergence

- Current  $I$  and  $T_s$  for Identification
- Convergence of lumped and physical para
- $R_e$  constant: small temp variation

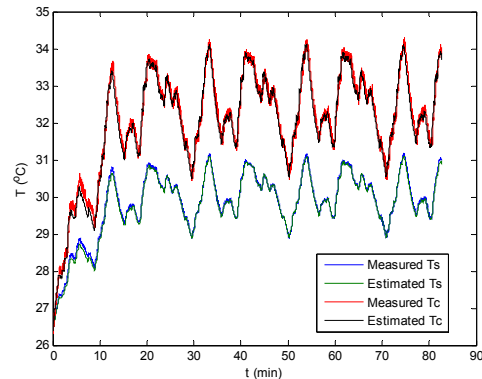
### Validation

- $T_s$  used for ID
- $T_c$  estimated by identified parameters
- Good Match of  $T_c$

$C_s$ (J/K)	$C_c$ (J/K)	$R_u$ (K/W)	$R_c$ (K/W)	$R_e$ (mOhm)
4.5	67	3.03	1.83	11.4



Parameter convergence



Temperature Validation

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# Non-constant Re?

## Varying Re

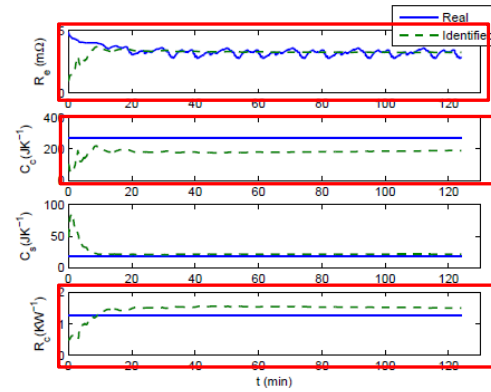
- Temp: larger Re for lower temp

$$R_e = R_{e0} \exp\left(\frac{T_{ref}}{T_c}\right)$$

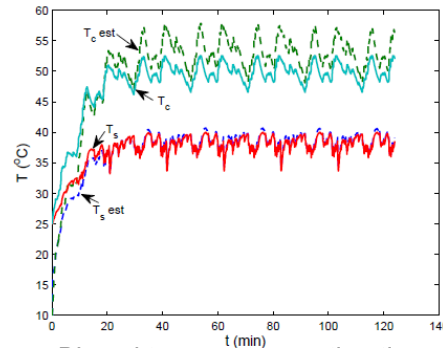
- SOC dependent

## Pure Least Square Algorithm (Simulation)

- Converge to average Re
- Biased ID of other Parameters
- Small error in Surface temp
- Significant errors in Core temp



Biased Parameter estimation



Biased temperature estimation 13/18



# RLS with Non-uniform Forgetting Factors

## RLS with Forgetting factors

- Moving window on data
- New data favored over old
- Decaying exponentially

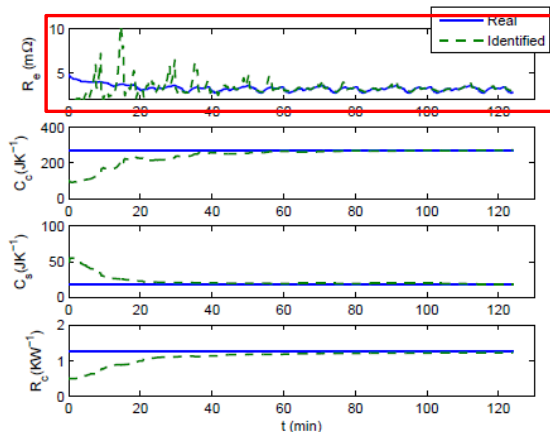
$$\dot{P}(t) = \eta^T P(t) \eta - P(t) \frac{\phi(t) \phi^T(t)}{m^2(t)} P(t)$$

$$J(\theta) = \frac{1}{2} \int_0^t e^{-\beta(t-\tau)} \frac{[z(\tau) - \theta^T(t) \phi(\tau)]^2}{m^2(\tau)} d\tau$$

$$\eta = \begin{bmatrix} \eta_1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

## Results

- Identified Re follows the real (simulated)
- Unbiased ID for other parameters
- Correct Core temp estimation



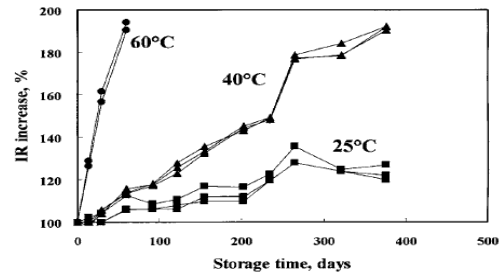




## State of Health Monitoring

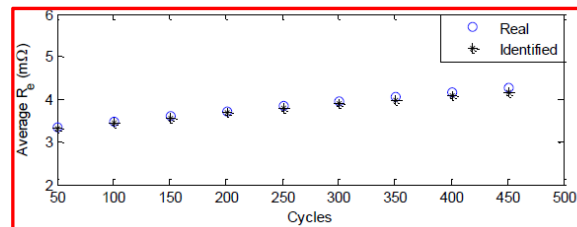
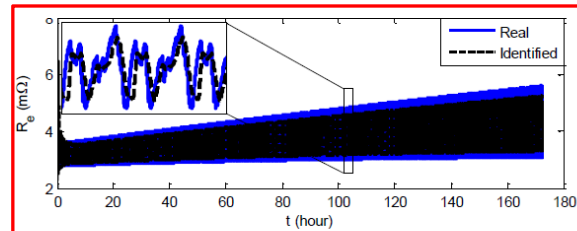
### Battery Degradation

- Aging/Abuse...
- Capacity Fade
- Growth in Internal Resistance (Yoshida 2006, etc).
- State of health monitoring



### Degradation detection

- Simulated growing resistance
- Exaggerated/Accelerated simulation
- Long term resistance growth can be captured for SOH evaluation



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## Conclusion and Future Work

### Parameter ID and Adaptive monitoring

- Online recursive parameter ID for the two state battery thermal model
  - Validated by experiments with surface and core temperature measurement
- Identification of varying internal resistance  $R_e$ 
  - Application of forgetting factors
  - Verified by simulation
- SOH evaluation by detecting resistance growth
  - Verified by simulation

### Battery Thermal Pack monitoring

- Pack model by scaling up the single cell models
- Considering Cell to cell conduction and convection
- Observability analysis and sensor deployment
- RHEVE 2012/OGST

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# Thank you!

## Q&A

### Acknowledgement:

U.S. Army Tank Automotive Research,  
Development, and Engineering Center (TARDEC)  
and  
Automotive Research Center (ARC), a U.S. Army center  
of excellence in modeling and simulation of ground vehicles

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