The Role of Battery Management in Electric Vehicles

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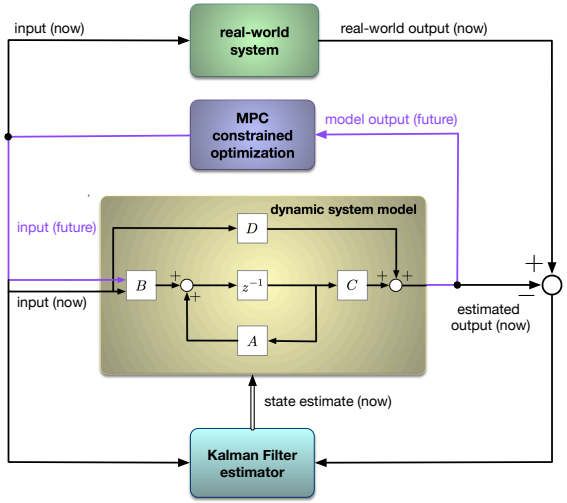
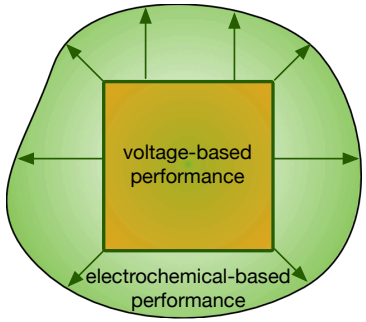
Topics for today's lecture

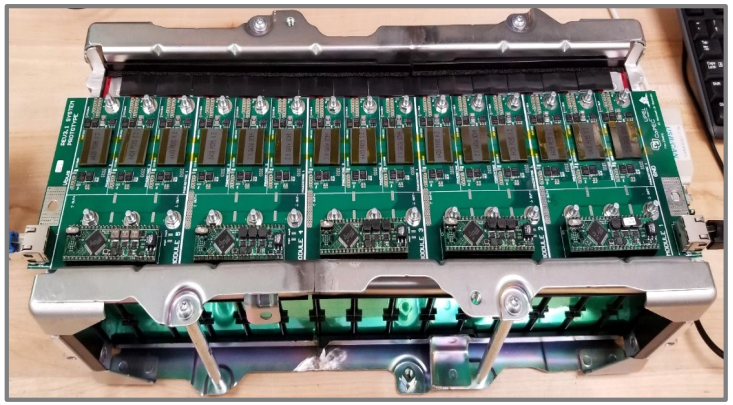
- **Part 1:** Lithium-ion battery cell models
  - **Topic 1.1:** Equivalent-circuit cell models
  - **Topic 1.2:** Parameter identification for equivalent-circuit models
  - **Topic 1.3:** Physics-based cell models
  - **Topic 1.4:** Parameter identification for physics-based models
- **Part 2:** Algorithms for battery management systems
  - **Topic 2.1:** Estimating state-of-charge
  - **Topic 2.2**: Estimating state-of-power





Role of Battery Management in Electric Vehicles

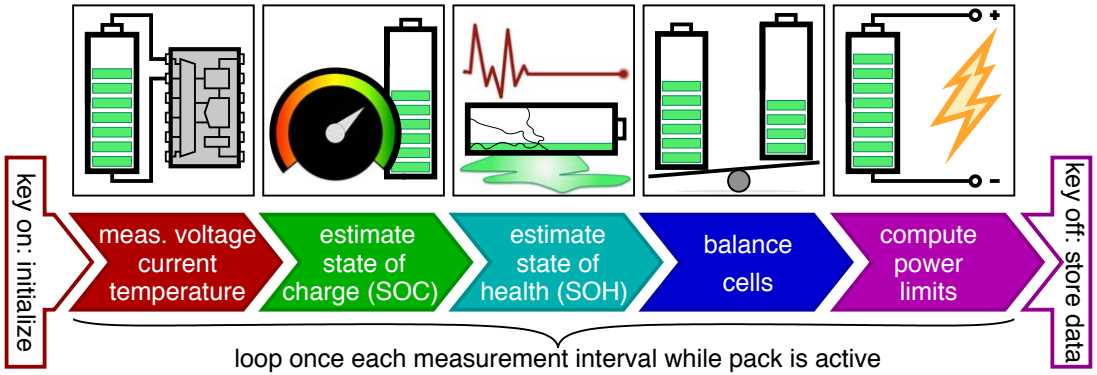
- Primary purposes of battery management are:
  - **Ensure** safe vehicle operation — **detect** unsafe operating conditions and **take action**
  - **Protect** individual cells from damage (abuse/ failure cases), and prolong the life of the battery (normal operating cases)
  - **Maintain** the battery pack in a state where it can fulfill its functional design requirements



  - **Prolong** the life of the battery under normal operating conditions
    - Inform vehicle controller on how to make *best* use of the battery pack (e.g., power limits, charge control, etc.)
- Battery management is accomplished by a battery management system (BMS) – an embedded device installed on-board the vehicle

Battery Management Functions

- A BMS continually makes physical measurements of voltage, current, & temperature, and runs **algorithms** to:
- Determine battery pack:
  - **State-of-Charge** (**SOC)**
  - **State-of-Health** (**SOH)**

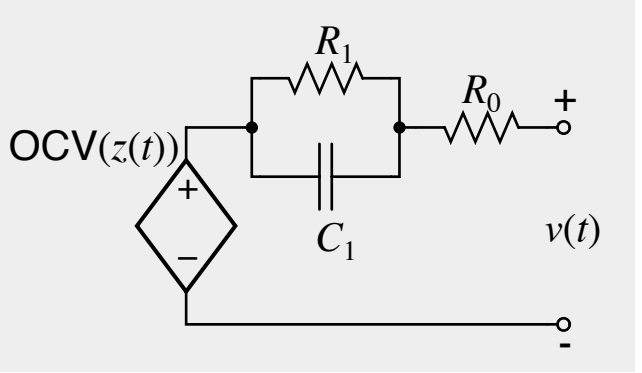


- Determine which cells must be **balanced**
- Compute available **energy** and **State-of-Power (SOP)** of the pack
- The most accurate and robust algorithms rely heavily on mathematical equations, or models, that describe battery cell operation

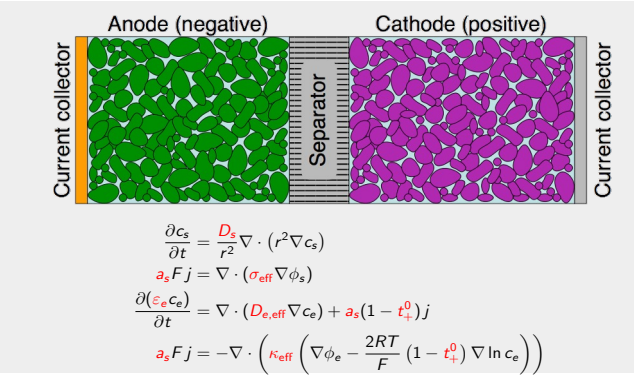
Part 1
Lithium-ion Battery Cell Models

Battery Cell Models

- Equivalent circuit models (ECM) –built from common circuit elements
  - OCV a function of cell state-of-charge
  - Ohmic series resistance R_0
  - Polarization time constants caused by diffusion - similar to parallel resistor-capacitor circuit $R_1||C_1$



- Physics-based models (PBM) – built from first-principles electrochemical equations
  - Enforce conservation of mass & charge
  - Capture reaction kinetics
  - Convey underlying processes involved in dynamic behavior

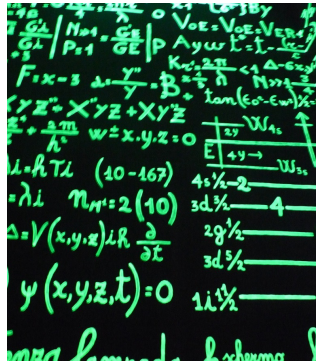


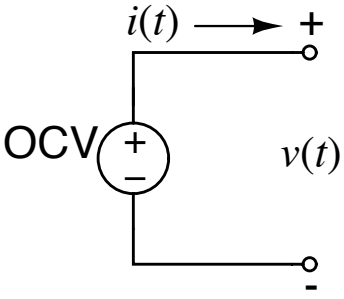
Topic 1.1

Equivalent-Circuit Cell Models

Equivalent-circuit Models; Open-circuit Voltage

- Models are sets of equations that describe something
- We may develop simple battery models by building up behavioral/ phenomenological analogs using **common circuit elements**
- Resulting "equivalent circuit" models (ECMs):
  - Help give feeling for how cells respond to different usage scenarios
  - Are the basis for most BMS algorithms currently employed in industry
- We start with the simplest possible model: *ideal voltage source*
- In this model, $v(t) = \mathrm{OCV}$ (open-circuit voltage)
  - Voltage is constant: not a function of past cell usage or electrical current
- This model is over-simplified, but provides a good starting point
  - Fundamentally, batteries ***do*** supply a voltage to a load
- And, when the cell is unloaded and in complete equilibrium (i.e., "open-circuit"), the voltage is fairly predictable
- An ideal voltage source will be part of our ECM





State of Charge and Total Capacity

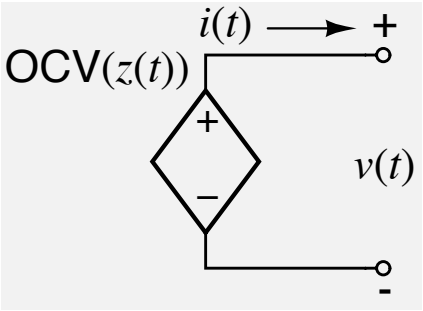
- When a cell is fully charged, its open-circuit voltage is higher than when it is discharged
- So, we can improve our model by including dependence on a cell's charge status
- We define unitless *state of charge* (SOC) $\boldsymbol{z(t)}$ of a cell to be:
  - $\boldsymbol{z(t) = 100\%}$ when the cell is fully charged
  - $\boldsymbol{z(t) = 0\%}$ when the cell is fully discharged
- Also define *total capacity* $\boldsymbol{Q}$ (thermodynamic reversible capacity, measured in Ah or mAh) to be total amount of charge removed when discharging from $z(t) = 100\%$ to $z(t) = 0\%$

- Can model SOC as:
  $\dot{z}(t) = -i(t)/Q$
  $v(t) = \mathrm{OCV}(z(t)),$
  where $\dot{z} = \mathrm{d}z/\mathrm{d}t$ and sign of $i(t)$ is positive on discharge

- In discrete time, if we assume that $i(t)$ is constant over the sampling interval Δt:

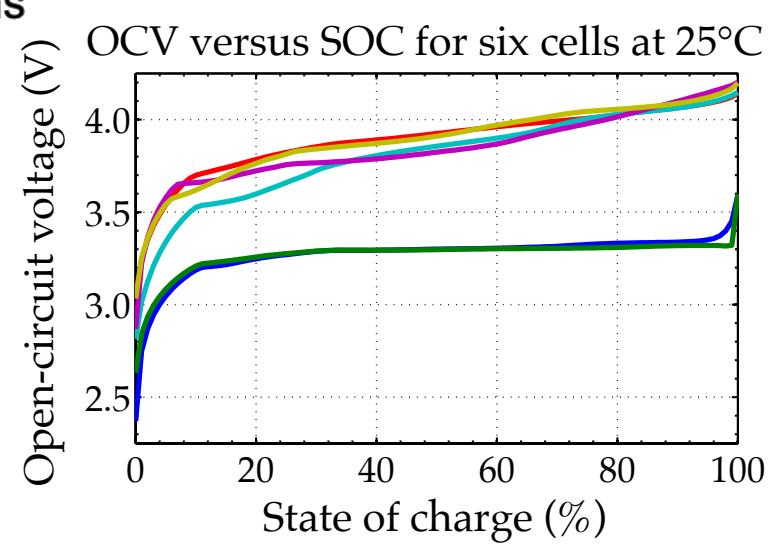
$$z[k+1] = z[k] - \frac{\Delta t}{Q} i[k]$$

$$v[k] = \mathrm{OCV}(z[k])$$



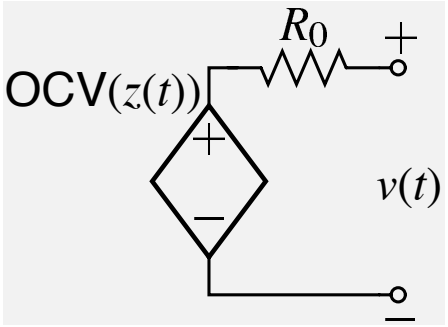
Coulombic Efficiency; Open-circuit Voltage

- Cells are not perfectly efficient: we can model this by writing $\dot{z}(t) = -i(t)\eta(t)/Q$ or in discrete-time, $z[k+1] = z[k] - \eta[k]i[k]\Delta t/Q$
  - ***"Coulombic efficiency"*** $\eta[k] \leq 1$ on charge, as some charge is typically lost due to unwanted side reactions
  - We usually model $\eta[k] = 1$ on discharge
- Coulombic (or charge) efficiency ≠ energy efficiency
  - Coulombic efficiency = (charge out)/(charge in), often around 99% in Li-ion
  - Energy efficiency = (energy out)/(energy in), is often closer to 95% due to resistive heat loss
- OCV plotted vs. SOC for six lithium-ion chemistries
- Note: OCV is also a function of **temperature** — we can include that in the model as $\mathrm{OCV}(z(t), T(t))$.

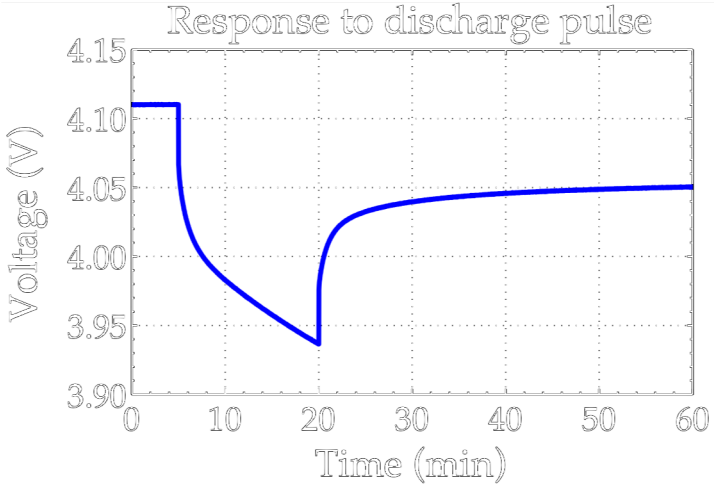


Polarization: Ohmic and Diffusion Voltages

- Polarization is a difference between terminal voltage and OCV due to passage of current
- For example, a cell's voltage drops when the cell is under load
- This can be modeled, in part, as a resistance in series with the ideal voltage source: $v(t) = \mathrm{OCV}\big(z(t)\big) - i(t)R_0$
  - $v(t) > \mathrm{OCV}(z(t))$ on charge,
  - $v(t) < \mathrm{OCV}\big(z(t)\big)$ on discharge
- Power dissipated by R_0 as heat: energy efficiency imperfect

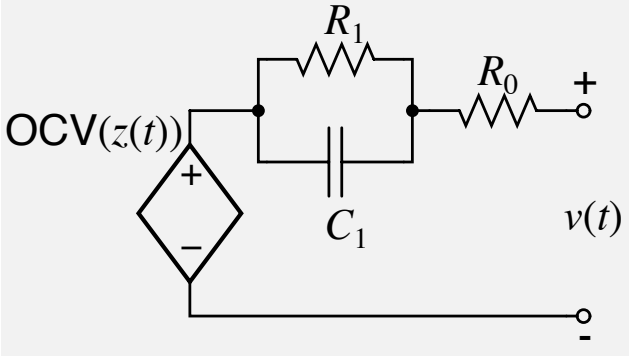


- R_0 models *instant* voltage change due to a current step
- In practice, we also observe a *dynamic* response: a response that evolves over time due to a current step
- Caused by slow diffusion processes in the cell; we refer to this slowly-changing voltage as a <u>diffusion voltage</u>

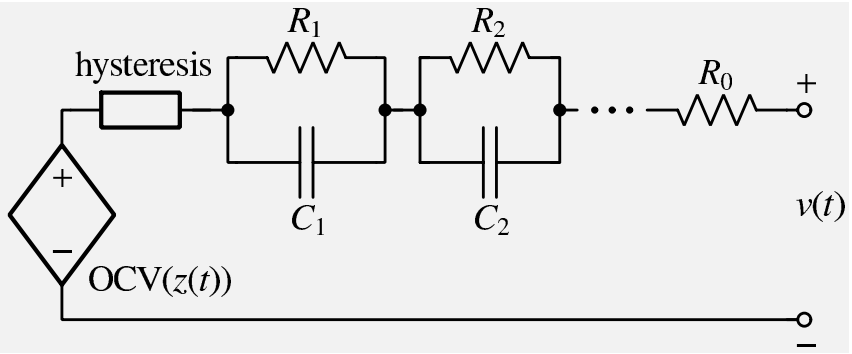


Thévenin Model

- Diffusion voltages can be closely approximated in a circuit using one or more parallel resistor-capacitor sub-circuits
- Cell voltage in "Thévenin model" is now:
  $v(t) = \mathrm{OCV}\big(z(t)\big) - v_{C_1}(t) - R_0 i(t)$
- Process to identify parameter values from test data is simpler if we write voltage in terms of element currents instead:
  $v(t) = \mathrm{OCV}\big(z(t)\big) - R_1 i_{R_1}(t) - R_0 i(t)$

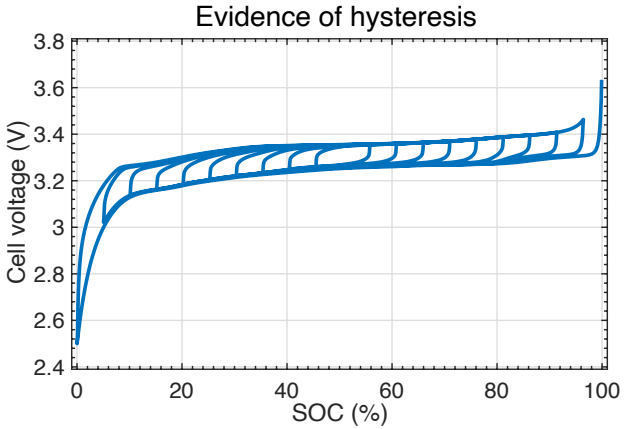


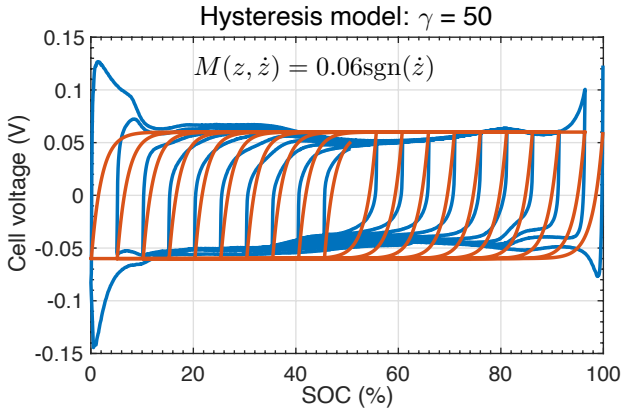
- Standard circuit rules can be used to find differential equations for capacitor voltage or diffusion-resistor current
- Additional R-C pairs can be added to the model to improve modeling fidelity (in theory, an infinite number are needed, but we can do quite well with only a few)



Experimental Evidence of Hysteresis

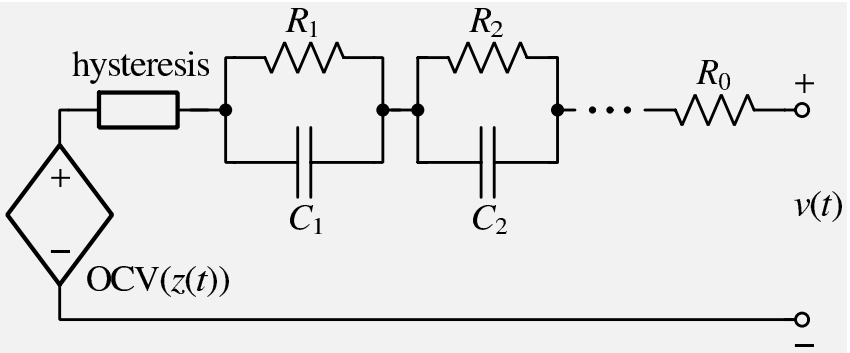
- If a cell is allowed to rest long enough, diffusion voltages decay to zero, so *model* voltage decays to the OCV
- In a real cell, this doesn't happen; i.e., for every SOC, we find a range of possible stable "OCV" values - *hysteresis*
- Ignoring hysteresis causes large prediction errors
- Note distinction between hysteresis and diffusion voltages:
  - Diffusion voltages change directly with time but hysteresis voltages change when SOC changes
- Can visualize hysteresis more clearly when we subtract OCV
- Appears there is a maximum plus/minus hysteresis, may be SOC dependent; limit is positive if cell presently charging; otherwise, negative: $M(z,\dot{z})$
- Hysteresis "decays" toward $M(z,\dot{z})$ at a rate that depends on closeness to that amount: indicates a differential equation in z





Enhanced self-correcting model

- Hysteresis can be modeled as first-order ODE
- R-C and hysteresis equations can be converted to discrete time for computer implementation
- Note that multiple R-C pairs can be included in the model



- Final form of ECM is a time-varying nonlinear discrete-time state-space structure (with appropriate substitutions of elements in matrices):

$$\underbrace{\begin{bmatrix} z[k+1] \\ i_R[k+1] \\ h[k+1] \end{bmatrix}}_{x[k+1]} = \underbrace{\begin{bmatrix} 1 & 0 & 0 \\ 0 & A_{RC} & 0 \\ 0 & 0 & A_H[k] \end{bmatrix}}_{A[k]} \underbrace{\begin{bmatrix} z[k] \\ i_R[k] \\ h[k] \end{bmatrix}}_{x[k]} + \underbrace{\begin{bmatrix} -\eta[k]\Delta t/Q & 0 \\ B_{RC} & 0 \\ 0 & A_H[k]-1 \end{bmatrix}}_{B[k]} \underbrace{\begin{bmatrix} i[k] \\ \text{sign}(i[k]) \end{bmatrix}}_{u[k]}$$

$$v[k] = \text{OCV}(z[k], T[k]) + Mh[k] - \sum_{R_j} R_j i_{R_j}[k] - R_0 i[k]$$

Topic 1.2

Parameter Identification for Equivalent-Circuit Cell Models

Characterizing Cell OCV

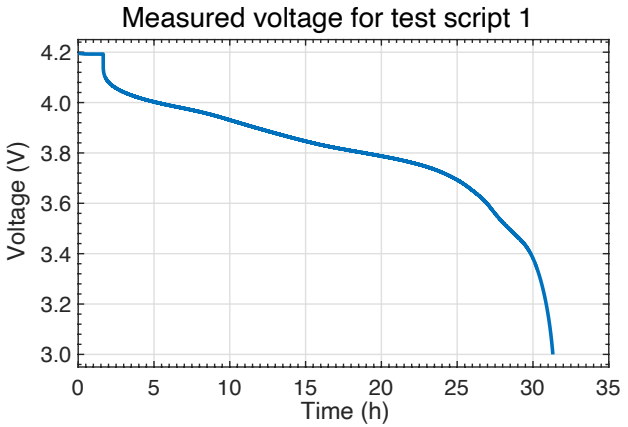
- **System ID** involves characterizing OCV and the dynamic aspects of the model separately
- Laboratory test steps to collect data for the OCV relationship:

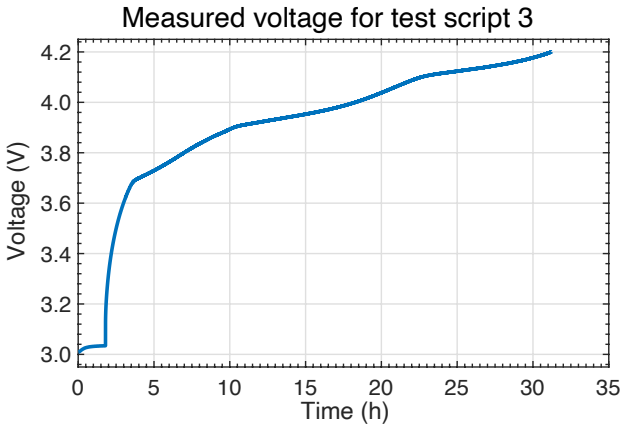
  Script 1: Soak cell at test temperature; discharge from 100% SOC to $v_{\min}$ (note: this is not the same thing as 0% SOC)

  Script 2: Soak cell at 25 ºC; dis/charge cell to 0% SOC (OCV is now $v_{\min}$)

  Script 3: Soak cell at test temperature; charge from 0% SOC to $v_{\max}$ (not 100% SOC)

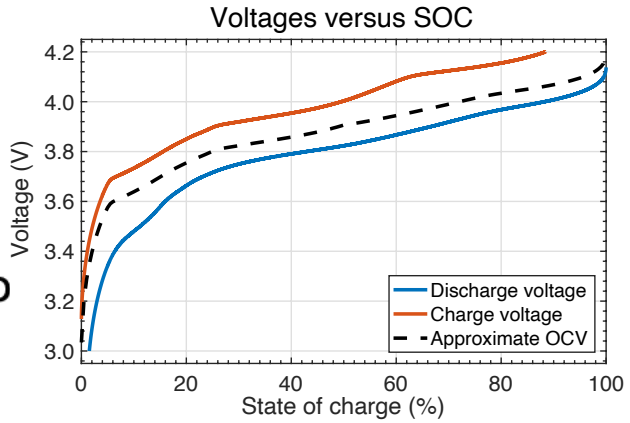
  Script 4: Soak cell at 25ºC; dis/charge cell to 100% SOC (OCV is now $v_{\max}$)
- Carefully considering the meaning of each of these steps, we can also compute coulombic efficiency and total capacity





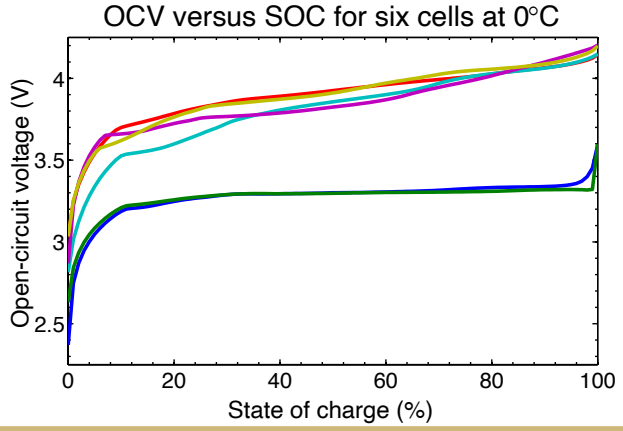
Processing OCV-test Data

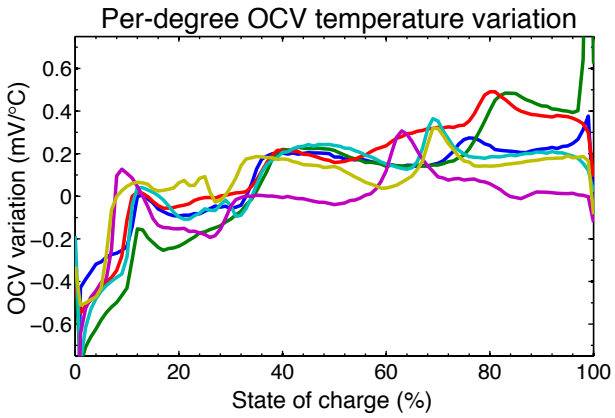
- Data processing recognizes that SOC at the beginning and end of the set of four scripts is 100%; using the SOC equation, we can determine coulombic efficiency and total capacity
- We can then determine SOC for every test point
- We need to create a way to solve the "missing data problem" to interpolate approximate OCV vs. SOC for every temperature



- OCV vs. SOC at individual temperatures is regressed to a simple linear model to find the final relationship:

$$\mathrm{OCV}\big(z(t),T(t)\big) = \mathrm{OCV0}\big(z(t)\big) + T(t)\times\mathrm{OCVrel}\big(z(t)\big)$$





Characterizing model dynamic parameter values

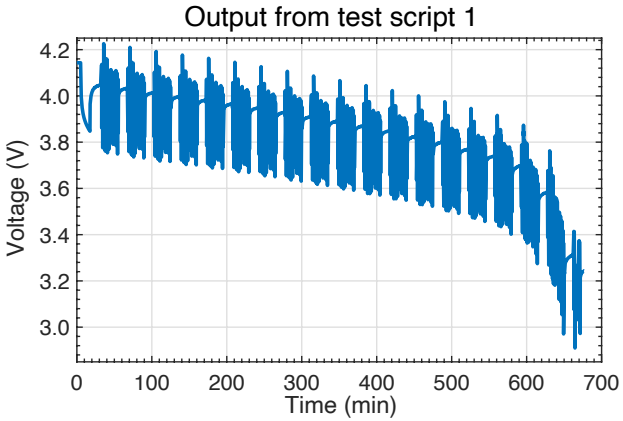
- Test steps for dynamic testing:

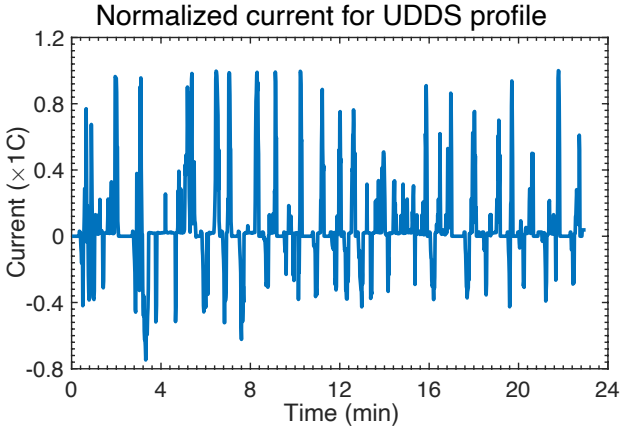
  Script 1: Soak cell at test temperature; discharge a small amount to avoid overvoltage later in test; execute dynamic profiles over SOC range of interest

  Script 2: Soak cell at 25 ºC; dis/charge cell to 0% SOC (OCV equal to $v_{\min}$)

  Script 3: Soak cell at 25 ºC; charge cell to 100% SOC (OCV equal to $v_{\max}$)

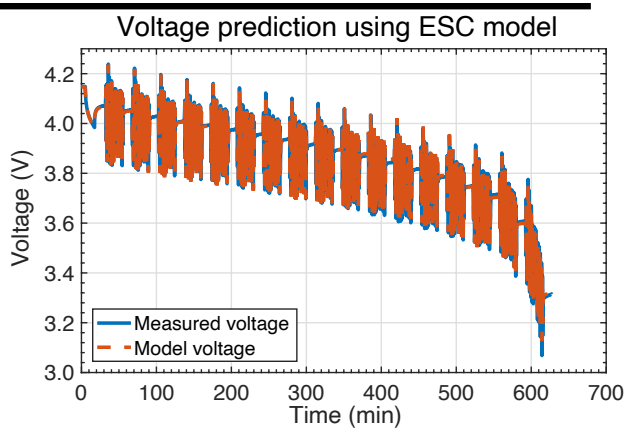
- Dynamic test script should resemble final usage scenario as much as possible since we are regressing the model parameters to fit measured data (and the model has error)
- We often use standard "urban dynamometer driving schedule" tests when fitting models for automotive purposes

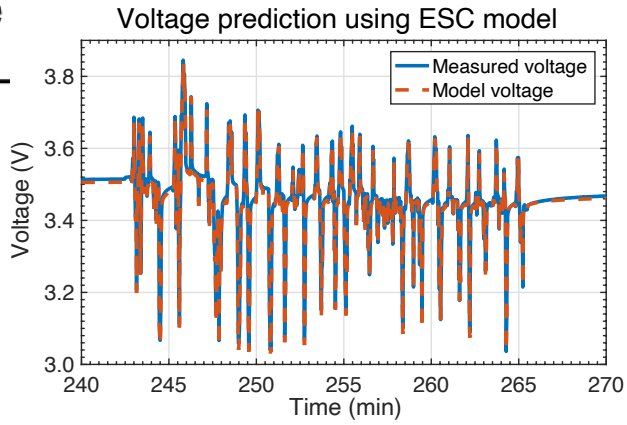




Processing model dynamic parameter values

- The dynamic data $\{i[k], v[k]\}$ are used to identify all ESC model parameter values (except OCV vs. SOC relationship)
  1. Compute η and Q directly from data
  2. Compute $z[k]$, $\mathrm{OCV}(z[k])$ for every data sample; subtract OCV from $v[k]$
  3. Use *subspace system ID* to find RC time constants
  4. Compute $i_R[k]$ for every data sample
  5. *Guess* value for γ; using γ, compute $h[k]$ for every sample
  6. "Unexplained" part of voltage is now linear in parameters—solve for these parameter values using least squares
  7. Compute rms voltage-prediction error of present model
  8. Adapt γ to minimize error, iterating 5–8 until convergence
- Good models often have less than 5mV rms error, although models are often usable even up to 25mV or so



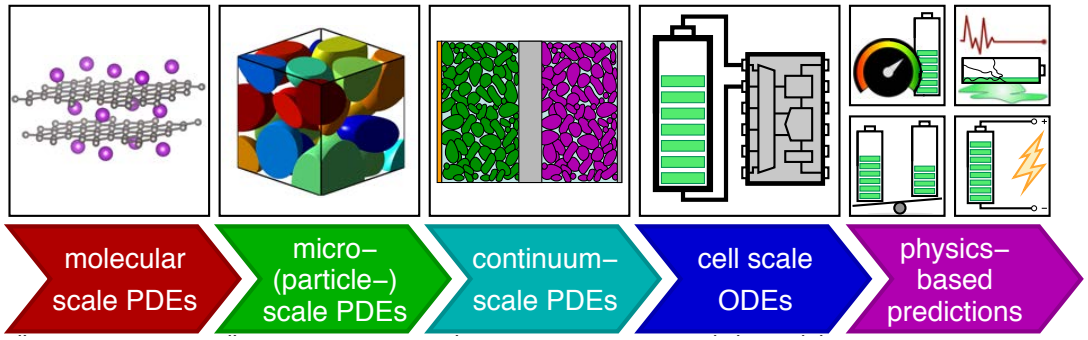


Topic 1.3

Physics-Based Cell Models

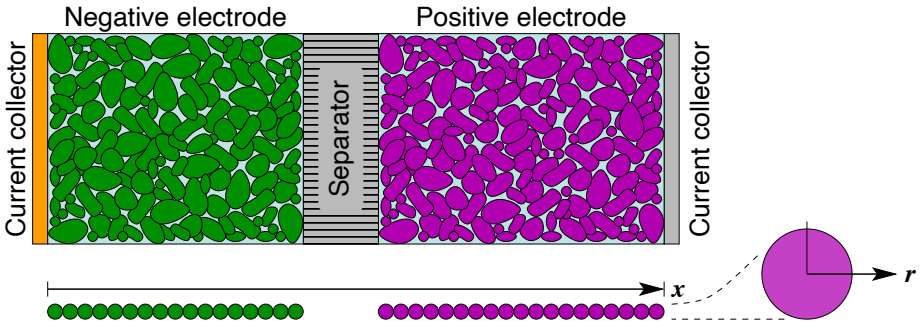
Physics-based models (PBMs)

- ECMs can predict input-output well, but PBMs are needed to understand (and ultimately control) cell aging
- Following variables are of interest:
  - Potential in solid, $\phi_s(x,t)$
  - Potential in electrolyte, $\phi_e(x,t)$
  - Concentration of Li in solid, $c_s(x,r,t)$, particularly at surface of solid, $c_{s,e}(x,t)$
  - Concentration of Li in electrolyte, $c_e(x,t)$
  - Rate of lithium movement between phases, $j(x,t)$
- Models can be developed at different length scales, varying from molecular to continuum
- Smaller length scales allow understanding the effects of localized flaws and fine details; larger length scales homogenize to enable faster computation
  - Presently, continuum-scale models can (often) run in real time on desktop PCs; smaller length scales need more time or supercomputers



Continuum-scale P2D model

- Continuum "porous electrode" "pseudo-2d" models use physics to derive equations for all internal cell processes using coupled PDEs
- Solving the PDEs (and associated boundary conditions) determines all internal and external variables of interest



$$\frac{\partial c_s}{\partial t} = \frac{D_s}{r^2}\nabla \cdot \left(r^2 \nabla c_s\right)$$ ***[diffusion of lithium in solid electrode particles]***

$$a_s F j_n = \nabla \cdot \left(\sigma^{\text{eff}} \nabla \phi_s\right)$$ ***[charge balance in particles; electron current]***

$$\frac{\partial(\varepsilon_e c_e)}{\partial t} = \nabla \cdot \left(D_e^{\text{eff}} \nabla c_e\right) + a_s(1 - t_+^0) j_n$$ ***[diffusion of lithium in electrolyte]***

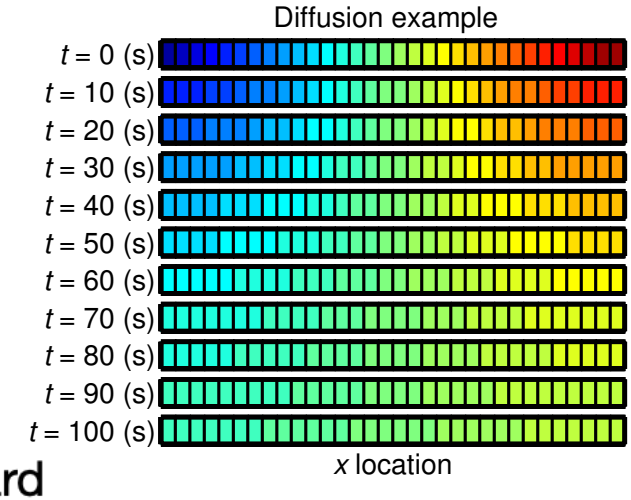
$$a_s F j_n = -\nabla \cdot \left(\kappa^{\text{eff}} \left(\nabla \phi_e - \frac{2RT}{F}\left(1 - t_+^0\right)\left(1 + \frac{d \ln f_\pm}{d \ln c_e}\right)\nabla \ln c_e\right)\right)$$ ***[ion current]***

$$j_n = k_0 \left(c_{s,e}\right)^{\alpha_c} \left(c_{s,\max} - c_{s,e}\right)^{\alpha_a} \left(c_e\right)^{\alpha_a} \left(\exp\left(\frac{\alpha_a F}{RT}\eta\right) - \exp\left(-\frac{\alpha_a F}{RT}\eta\right)\right)$$ ***[reaction rate]***

$$\eta = \phi_s - \phi_e - U_{\text{ocp}}(c_{s,e}) - j_n F R_{\text{film}}$$

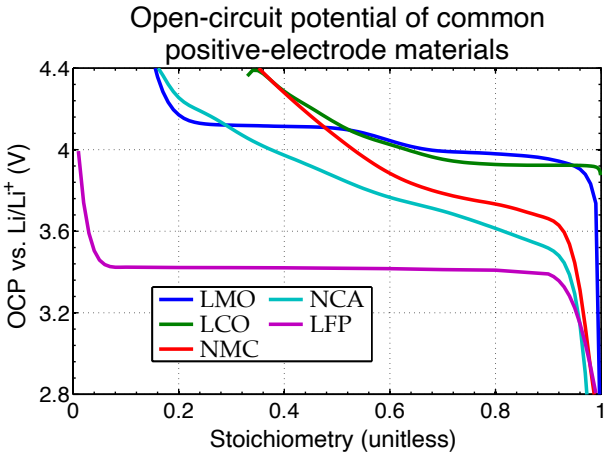
1-d diffusion example

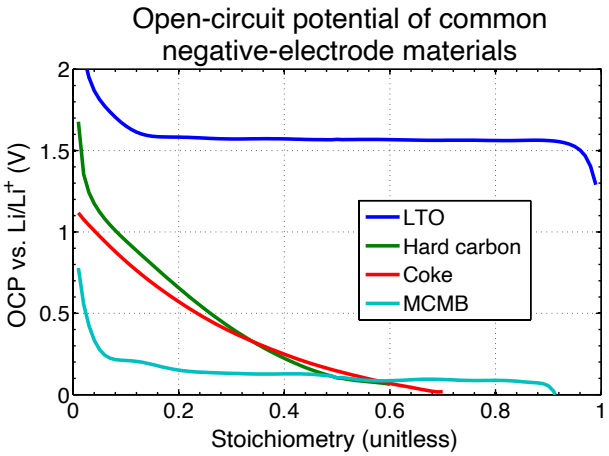
- Most model equations are principally diffusion equations:
  $\frac{\partial c(x,t)}{\partial t} = \nabla \cdot \left(D \nabla c(x,t)\right) + f(x,t)$
  where c is a quantity that diffuses, f is a forcing function
- To help visualize diffusion, let's consider the special case of 1-d diffusion: in 1-d, divergence is a first derivative so
  $$\frac{\partial c(x,t)}{\partial t} = D \frac{\partial^2 c(x,t)}{\partial x^2} + f(x,t)$$
- We can approximate the time derivative using Euler's forward rule and the spatial second derivative using central difference
- Put together, we get
  $$c(x, t+\Delta t) = c(x,t) + D\Delta t \frac{c(x+\Delta x, t) - 2c(x,t) + c(x-\Delta x, t)}{(\Delta x)^2}$$
- Simulating this, starting with an initial concentration gradient, final result is uniform concentration ($f(x,t) = 0$)



Open-circuit voltage

- While using PDEs directly in a BMS is (presently) unreasonable, some cell-level variables can be understood quite easily from them: OCP, capacity, SOC
- OCV is steady-state terminal voltage when cell in equilibrium
- Steady-state condition means both c_s and c_e are uniform
- OCV can be related to the *open-circuit potentials* of both electrodes $U_{ocv}^{cell}(z) = U_{ocp}^{p}(\theta^p) - U_{ocp}^{n}(\theta^n)$
- High cell voltages (for high energy density), require high positive-electrode potential and low negative-electrode potential (vs. Li/Li⁺)
- Positive and negative plotted versus $\theta^p = c_s^p / c_{s,\max}^p$ and $\theta^n = c_s^n / c_{s,\max}^n$ where $c_{s,\max}^r$ is amount of Li stored when electrode crystal lattice structure completely full





Cell total capacity and SOC

- In "ideal" case, we might think that cell uses capacity from $c_s = 0$ to $c_s = c_{s,\max}$
- Practical cells don't use entire range (to avoid rapid cell degradation or power depletion)
  - Use only from $x_{0\%}$ to $x_{100\%}$ in negative and $y_{0\%}$ to $y_{100\%}$ in positive electrode
  - In terms of physical cell-model parameter values,

    $Q^n = AFL^n \varepsilon_s^n c_{s,\max}^n |x_{100\%} - x_{0\%}| / 3600 \text{ Ah}$

    $Q^p = AFL^p \varepsilon_s^p c_{s,\max}^p |y_{100\%} - y_{0\%}| / 3600 \text{ Ah}$
  - These capacities are matched, by definition of compatible $x_{0\%}$, $x_{100\%}$, $y_{0\%}$, $y_{100\%}$
- Notice that cell total capacity is not a function of temperature, rate, and so forth

- Cell SOC varies linearly as electrode stoichiometry varies
- Therefore, we can compute cell-level state of charge z as either

$$z = \frac{c_{s,avg}^n / c_{s,\max}^n - x_{0\%}}{x_{100\%} - x_{0\%}} = \frac{c_{s,avg}^p / c_{s,\max}^p - y_{0\%}}{y_{100\%} - y_{0\%}}$$

Part 1.4

Parameter Identification for Physics-Based Cell Models

Parameter identification for PBMs

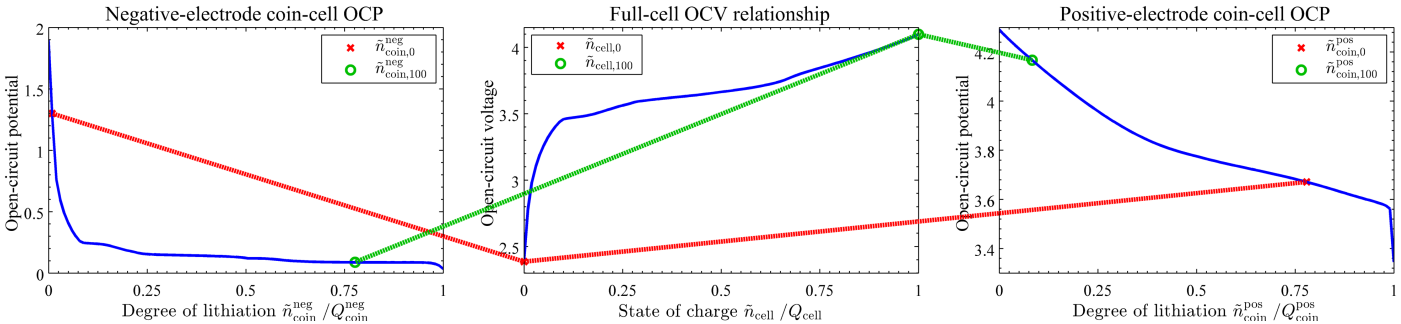
- We now consider parameter identification for PBMs
- For ECM, fit values of R_1, R_0, C_1 (etc.) so model predictions match measured current–voltage data as well as possible
  - A simple optimization since there are few values to find
- For PBM, at least 35 unique values must be measured, plus two OCP relationships
  - Not all are observable from current–voltage data
  - Traditionally, the process is done via cell teardown and costly electrochemical experiments
  - Dimensional parameters are relatively easy to measure via teardown; others are difficult to impossible to measure
- Our procedure: (1) reformulate model, (2) conduct lab tests designed to isolate specific parameters, (3) process test data

Negative electrode	Separator	Positive electrode
$\sigma_{\text{eff}}^{\text{neg}}$		$\sigma_{\text{eff}}^{\text{pos}}$
a_s^{neg}		a_s^{pos}
L^{neg}	L^{sep}	L^{pos}
A		
$\kappa_{\text{eff}}^{\text{neg}}$	$\kappa_{\text{eff}}^{\text{sep}}$	$\kappa_{\text{eff}}^{\text{pos}}$
D_s^{neg}		D_s^{pos}
R_s^{neg}		R_s^{pos}
$\varepsilon_e^{\text{neg}}$	$\varepsilon_e^{\text{sep}}$	$\varepsilon_e^{\text{pos}}$
$D_{e,\text{eff}}^{\text{neg}}$	$D_{e,\text{eff}}^{\text{sep}}$	$D_{e,\text{eff}}^{\text{pos}}$
t_+^0		
k_0^{neg}		k_0^{pos}
$c_{s,\max}^{\text{neg}}$		$c_{s,\max}^{\text{pos}}$
α^{neg}		α^{pos}
$R_{\text{film}}^{\text{neg}}$		$R_{\text{film}}^{\text{pos}}$
$c_{e,0}$		
θ_0^{neg}		θ_0^{pos}
$\theta_{100}^{\text{neg}}$		$\theta_{100}^{\text{pos}}$

Model reformulation and OCP determination

- We have previously reported a method to identify parameter values of a Doyle–Fuller–Newman (DFN) cell model, and have presented System ID results [1,2]
- Method first notices that some parameters always occur in groups, so only the group (not the individual parameter values) can be identified by input–output data: e.g, $\sigma_{\text{tot}}^{\text{reg}} = \sigma_{\text{eff}}^{\text{reg}} A/L^{\text{reg}}$
  - This reduced parameter count from 35 to 24
- Then, we find the OCP operational windows of each electrode by correlating electrode OCP and cell OCV relationships

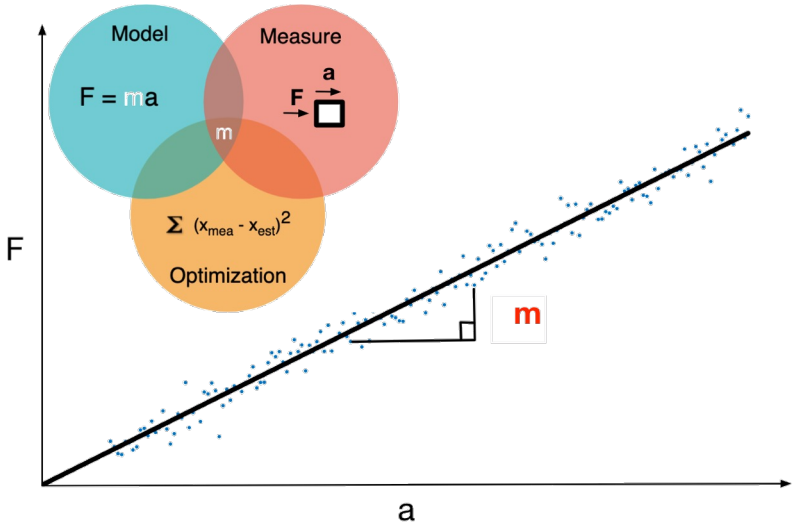
Negative electrode	Separator	Positive electrode
$\sigma_{\text{tot}}^{\text{neg}}$		$\sigma_{\text{tot}}^{\text{pos}}$
$\kappa_{\text{tot}}^{\text{neg}}$	$\kappa_{\text{tot}}^{\text{sep}}$	$\kappa_{\text{tot}}^{\text{pos}}$
$D_{s,\text{tot}}^{\text{neg}}$		$D_{s,\text{tot}}^{\text{pos}}$
$L_{e,\text{mod}}^{\text{neg}}$	$L_{e,\text{mod}}^{\text{sep}}$	$L_{e,\text{mod}}^{\text{pos}}$
$D_{e,\text{mod}}^{\text{neg}}$	$D_{e,\text{mod}}^{\text{sep}}$	$D_{e,\text{mod}}^{\text{pos}}$
t_+^0		
$k_{\text{step}}^{\text{neg}}$		$k_{\text{step}}^{\text{pos}}$
$n_{s,\text{max}}^{\text{neg}}$		$n_{s,\text{max}}^{\text{pos}}$
$R_{\text{film,tot}}^{\text{neg}}$		$R_{\text{film,tot}}^{\text{pos}}$
θ_0^{neg}		θ_0^{pos}
$\theta_{100}^{\text{neg}}$		$\theta_{100}^{\text{pos}}$

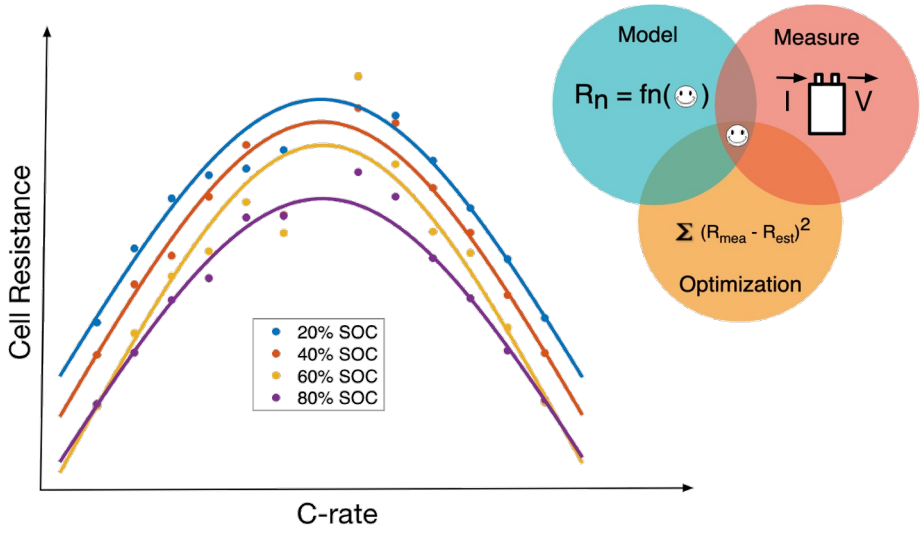


[1] Jobman, R., Trimboli, M.S., Plett, G.L., "Identification of lithium-ion physics-based model parameter values," *J. Energy Challenges & Mechanics*, 2(2), 45–55, 2015
[2] Jobman, R. *Identification of Lithium-Ion Cell Physics-Model Parameter Values*, PhD dissertation, UCCS, 2015, http://hdl.handle.net/10976/166641

Finding parameters of dynamic portion of model

- Process of system identification for dynamic portion of PBM is similar to that for ECM

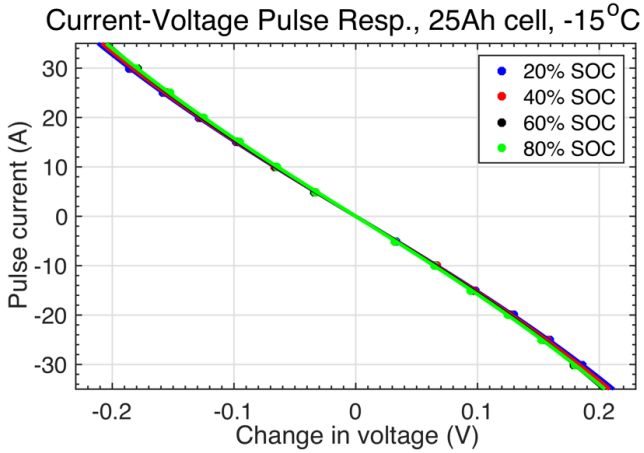




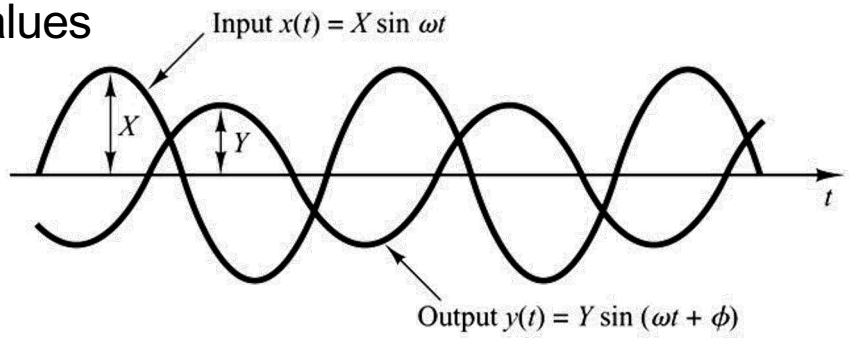
- However, the problem now is that we have many, many more parameter values to find
- Cleverly designed lab tests help by isolating responses from certain groups of parameters
  - Variety of input (e.g., different frequencies, magnitudes; SOC setpoints)
  - Necessary to be able to to formulate submodels for each test to aid optimizations

Pulse and EIS testing

- Pulse tests measure instantaneous resistance as a function of SOC, rate, and temperature
  - Removes diffusion parameters from consideration since concentrations do not change instantly
  - Optimizes model parameter values to match model resistance to measured resistance as well as possible
  - Resolves values for 15 parameters! Only 9 remain



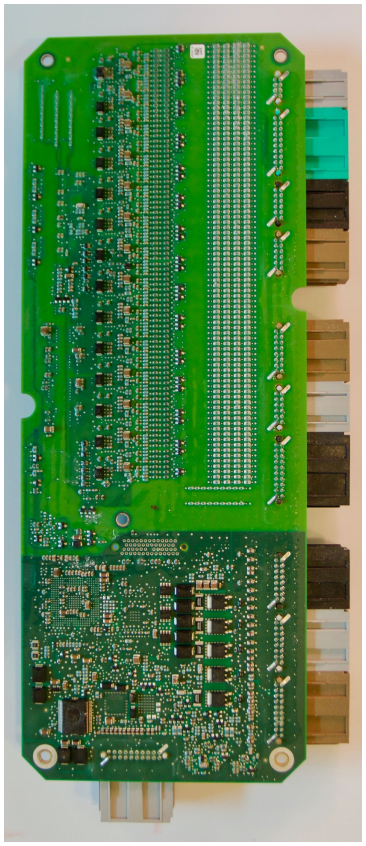
- Finally, EIS tests conducted over wide frequency range collect data to determine remaining parameter values
- Optimize model parameter values to match model frequency response to measured frequency response as well as possible



Part 2
Algorithms for Battery Management Systems

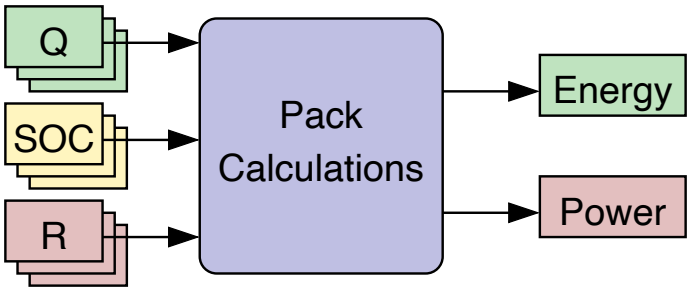
BMS Tasks

- A battery-management system (BMS) is required to monitor and control battery operation
- A BMS has the following priorities:
  - Protects safety of the operator of the host application; detects unsafe operating conditions and responds
  - Protects cells of battery from damage in abuse/failure cases
  - Prolongs service lifetime of battery (normal operating cases)
  - Maintains battery in a state in which it can fulfill its functional design requirements
  - Informs the host-application control computer how to make the best use of the pack right now (e.g., power limits), control charger, etc.
- There are both hardware and software elements in a BMS design
  - This lecture will focus on the software/algorithm requirements related to careful battery management, as well as hardware sensing requirements to enable these algorithms



BMS algorithm outputs

- Battery applications need to know two battery quantities:
  - How much energy is presently stored in the battery pack
  - How much power is available in the immediate future
- Knowing energy is most important for applications such as EV:
  - Tells me how far I can drive (or, how much runtime remains)
- Knowing power is most important for applications such as HEV:
  - Tells me whether I can accelerate or accept braking charge
- Neither can be measured directly
  - Energy can be calculated if all cell total capacities Q and states of charge are known
  - Power limits can be estimated if all cell resistances R and states of charge are known
- Neither SOC, Q, nor R can be measured directly: these must be estimated using more primitive measurements

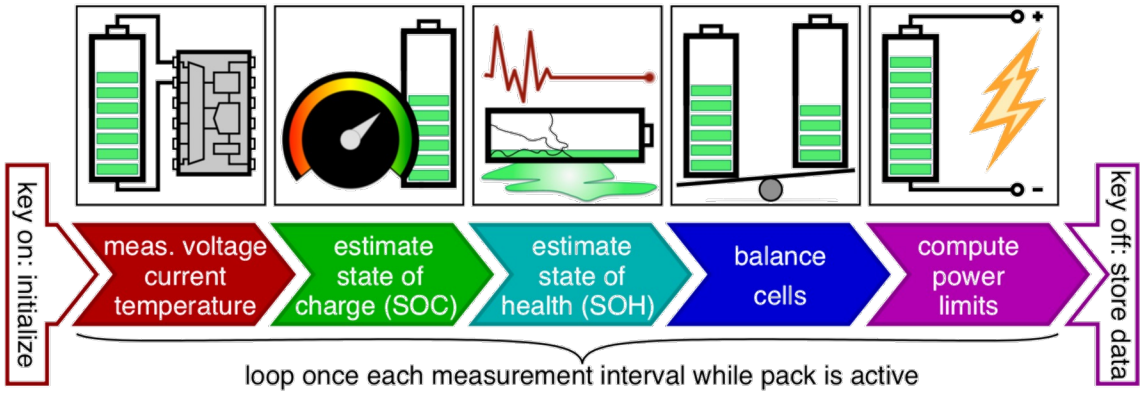


Topic 2.1

Estimating State of Charge

SOC estimation in the BMS algorithm control loop

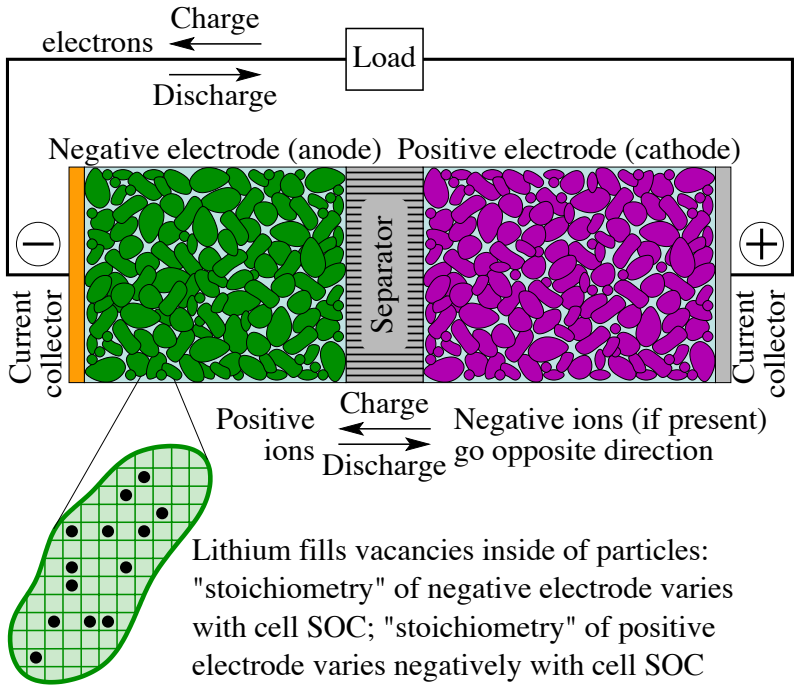
- Battery-cell SOC quantifies how much charge is stored that might be released to a load circuit to accomplish some task
- There is no practical sensor that can measure SOC; instead, its value must be estimated using more basic measurements of cell voltage, current, and temperature (for example)



- Knowledge of SOC is needed to calibrate many SOH estimates, and in the calculation of SOE and SOP themselves
- Knowing SOC is important to avoid overcharge and undercharge conditions, for charge control in general, and for balancing
- Accurate SOC estimates enhance: longevity, performance, reliability, density, economy

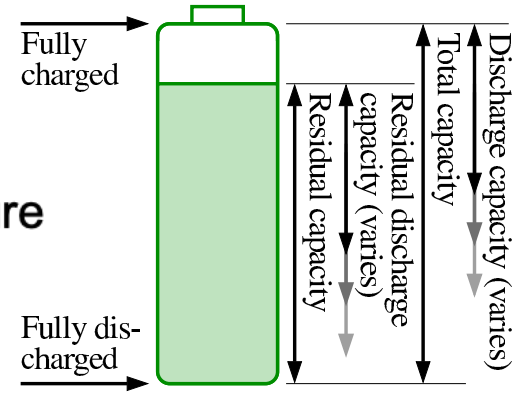
Physical significance of SOC

- SOC is a physical quantity that (in principle) could be measured directly, although no practical sensor exists that can do so
- In negative- and positive-electrode particles, there are a discrete number of sites that can hold lithium
- For longevity, we never fill all vacancies nor do we empty all sites; we use a predetermined range
- At one end of the range, we define cell SOC to be 0%; at the other end, we define cell SOC to be 100%
- SOC varies linearly between these extremes
- Note that it is physically possible to overcharge and undercharge: the definition of “0%” and “100%” are operational design limits, not physical limits



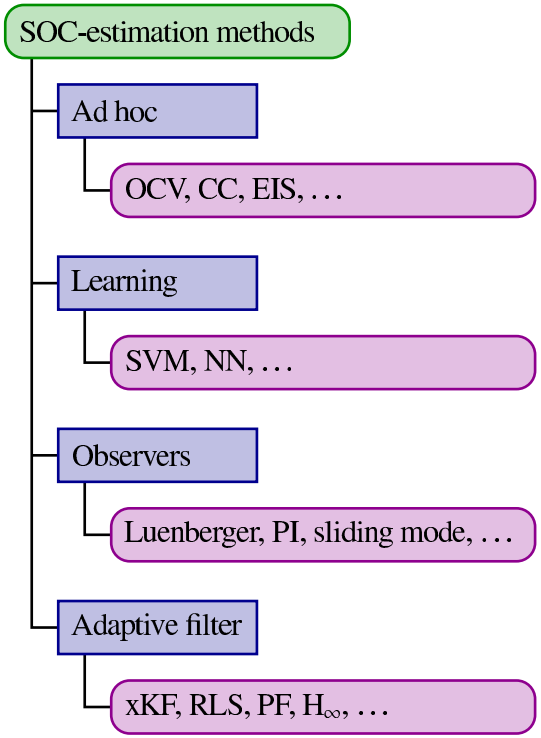
Definitions

- A cell is *fully charged* when its OCV is equal to $v_{max}(T)$
- A cell is *fully discharged* when its OCV is equal to $v_{min}(T)$
- ***Total capacity*** Q is quantity of charge removed bringing cell from fully charged to fully discharged state: not a fn of rate or temperature
- *Discharge capacity* $Q_{[rate]}$ is quantity of charge removed bringing cell *at a constant rate* from fully charged state until its loaded terminal voltage reaches $v_{min}(T)$: fn of both rate and temperature

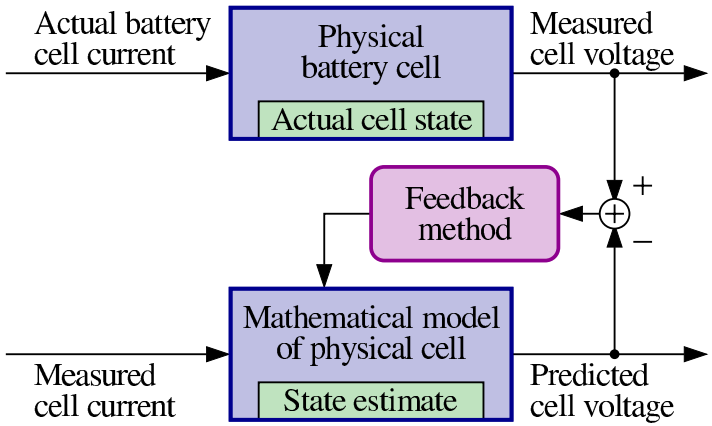


- *Nominal capacity* Q_{nom} is cell rating representing Q_{1C} but $Q_{nom} \neq Q_{1C}$ and $Q_{nom} \neq Q$
- ***Residual capacity*** is quantity of charge that would be removed if the cell were brought from its present state to a fully discharged state
- *Residual discharge capacity* is quantity of charge that would be removed if cell were brought from present state to point where loaded terminal voltage reaches $v_{min}(T)$
- (Physical) cell ***state-of-charge*** is the ratio of its ***residual capacity*** to its ***total capacity***
- (There exist "engineering SOC" definitions that are difficult to calibrate, less useful overall)

Taxonomy of SOC-estimation methods

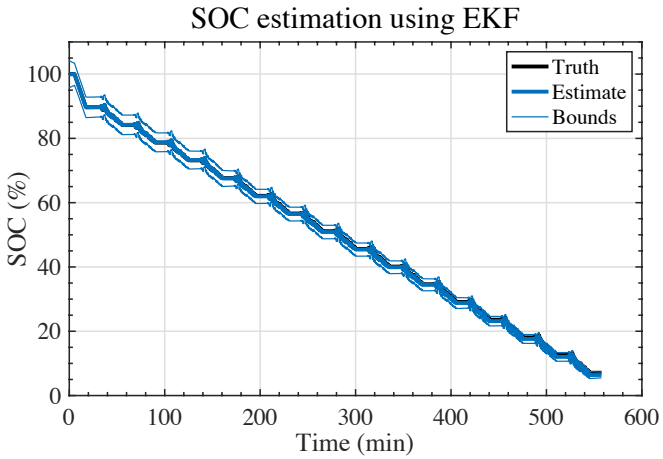


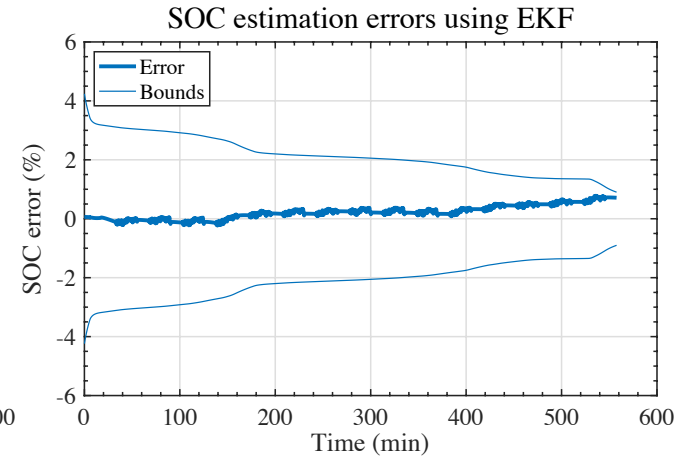
- SOC estimation is a very mature field; many approaches
- BMS-algorithm engineers naturally tend to implement methods that "make sense" to them, regardless of accuracy/complexity/ robustness…
- Note: there is a difference between *conceptual complexity* and *computational complexity* – in a product, the latter matters more
- My opinion is that model-based methods are best approach
  - "Don't estimate what you already know" … use your model!
  - Based on tried-and-true control-systems principles
  - "Observers" and "adaptive filters" fall into this category

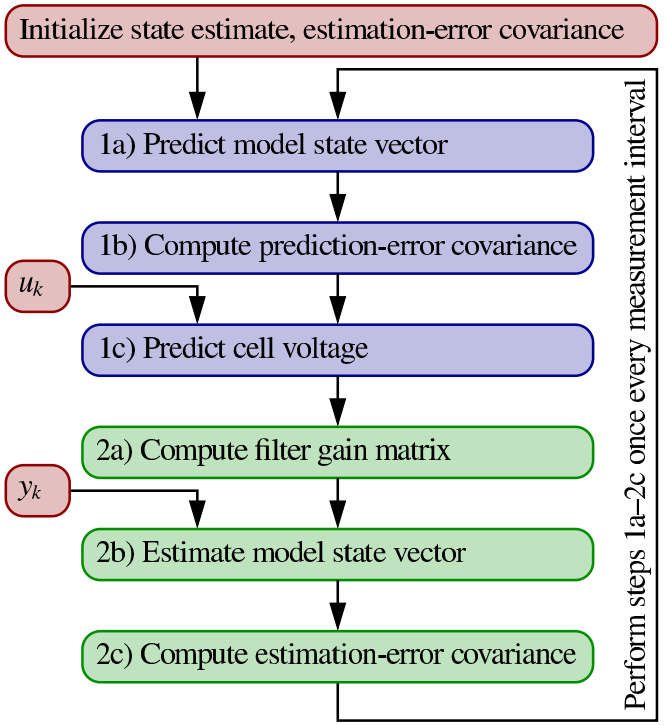


Kalman-filter approach to SOC estimation

- With some assumptions, KF is optimal: often work well even when assumptions violated
- Standard KF uses linear models; lithium-ion cells are nonlinear so must use nonlinear variant; e.g., extended KF, sigma-point KF (incl. UKF, CKF)
- Filter predicts state and voltage; then updates prediction based on measured voltage and time-varying gain matrix
- Important feature of xKF: confidence bounds on estimate!
- Example using EKF below:

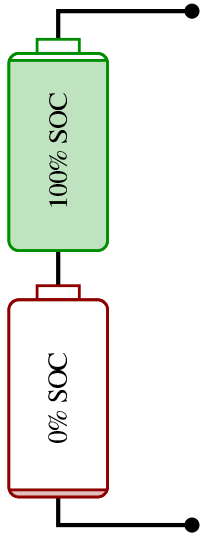






Estimating "battery-pack SOC"?

- "Battery-pack SOC" is not a physical quantity, so attempting to estimate a value for it is an ill-posed problem (solution not well defined, not unique)
  - Should battery-pack SOC be 0%? 100%? 50%?
  - Even if a pack is assumed always to be balanced, what is usually wanted is a "fuel gauge" which is computed by SOE, not by SOC
- SOC estimates for every cell in a battery pack are required for SOH estimates, exact calculation of battery-pack SOE and SOP/SOF
- Cells connected in parallel electrically average their behavior, so we need to compute only a single SOC value for parallel cells
- For every cell group connected in series, we need an independent SOC estimate
- Efficient "bar-delta" and "cell mean model + cell difference model" (CMM+CDM) approaches exist, which are computationally not much more complex than computing a single SOC estimate for a single cell

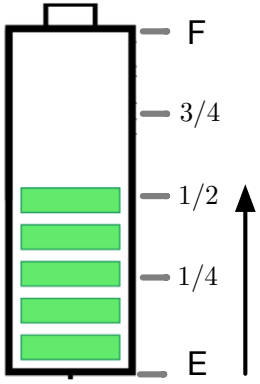


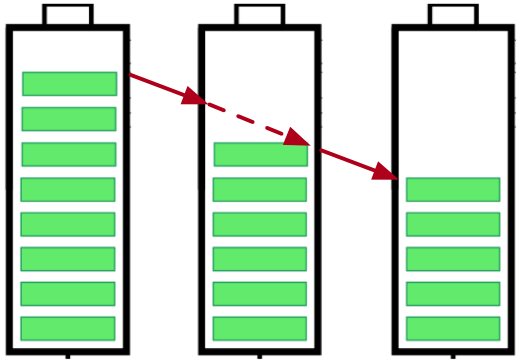
Topic 2.2

Estimating State of Power

Energy and Power

- **Energy** is the ability of the battery to do work…
- Normally measured in Wh or KWh, it indicates a quantity of charge
- Available energy equates to a fuel gage… full or empty?





- **Power** indicates the manner in which energy is removed (or added) to the battery →

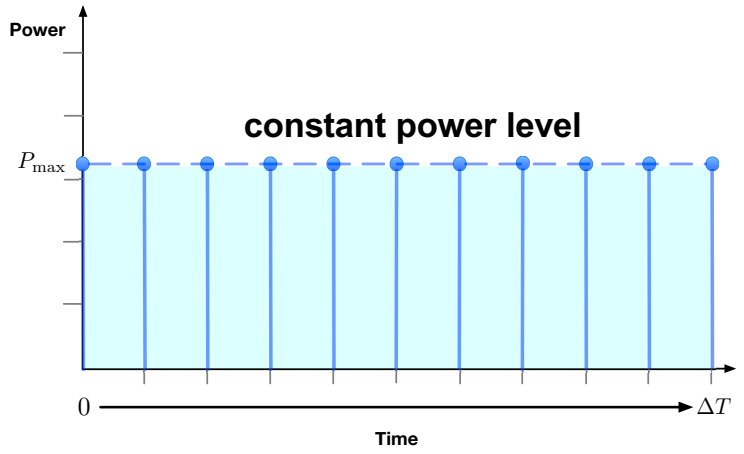
Power = time-rate-of-change of Energy

- Relates to the *movement of charge* into and out of the cell; e.g, *high-power* cells can move charge at high current rates

$$P(t) = V(t) \times I(t)$$

State of Power: Defined

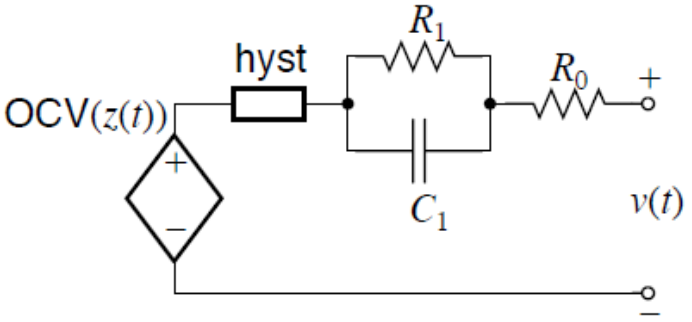
- State of Power (SOP) is commonly defined to mean *how much power* – on charge or discharge – can be sustained over a specified time into the future
- The term takes on a variety of forms in the literature – some examples..
  - *Power Limits*
  - *State of Available Power*
  - *Peak Power*
- Generally, SOP is used in a predictive sense:
  - We wish to supply an upcoming load demand (e.g., accelerate, climb a hill, or supply charge from regen braking) and must inform the vehicle controller of what it can safely expect from the battery



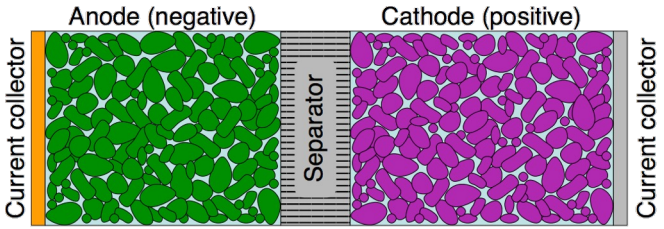
Battery's maximum sustained power places limits on vehicle performance

State of Power: Estimation Methods

- **Equivalent-Circuit Model Methods**
  - **Model-based** approach -- relies on simplified battery dynamics represented by common circuit elements
  - Generally, produces good estimates over a wide range of operating conditions, but requires increased computational effort compared to CM
  - Currently viewed as the mainstream technique

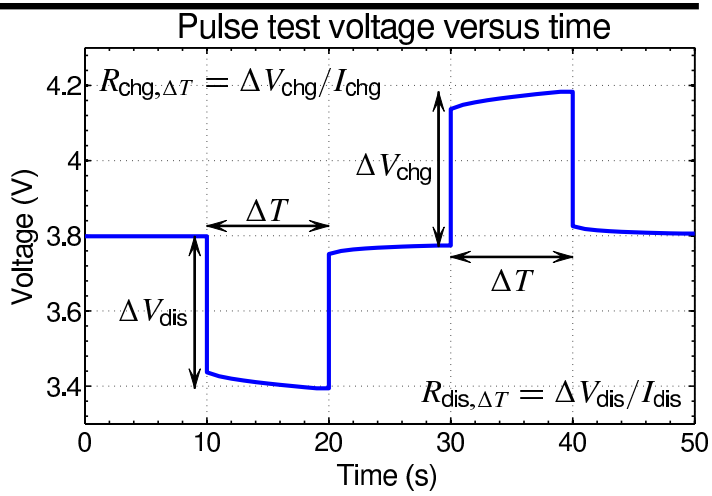


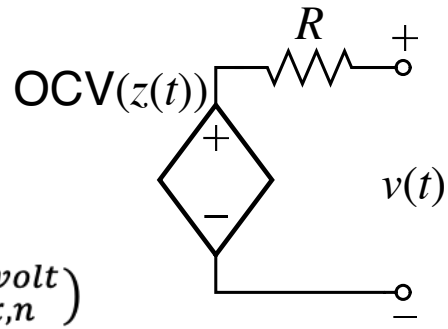
- **Physics-Based Model Methods**
  - **Model-based** approach based on math models derived from first-principles of electrochemistry
  - Many advantages owing to internal state information available from modeled electrochemical variables
  - Most complex computationally, can produce accurate estimates throughout wide range of operating conditions



Voltage-based *discharge* limits, simple cell model

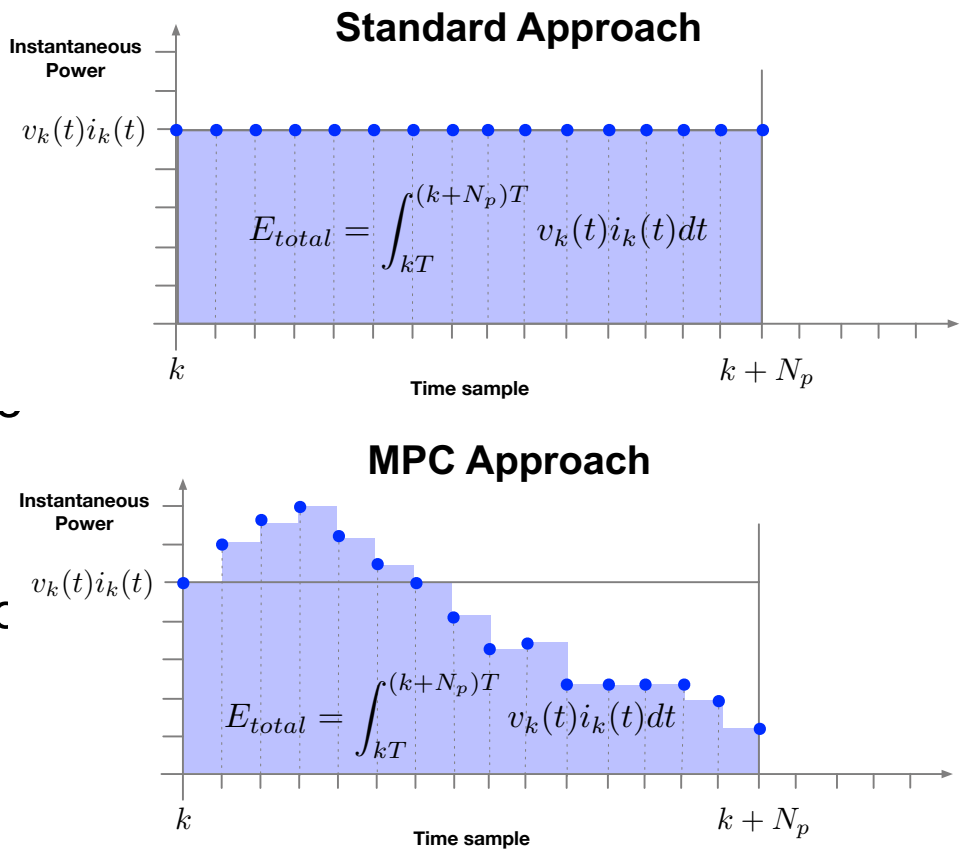
- "Hybrid Pulse Power Characterization" (HPPC) method by Partnership for New Generation Vehicles (PNGV)
- Conduct simple lab experiment, tabulating effective ΔT s cell pulse resistances at different SOCs, temperatures
- Assume a simplified cell model $v(t) = \mathrm{OCV}\big(z(t)\big) - i(t)R$ or $i(t) = \Big(\mathrm{OCV}\big(z(t)\big) - v(t)\Big)/R$
- To compute power limit, assume we are concerned only with keeping terminal voltage between v_{min} and v_{max}
- For discharge power, set $R = R_{dis,\Delta T}$ and clamp $v(t) = v_{min}$
- Then, calculate maximum discharge current as constrained by voltage as $i_{max,n}^{dis,volt} = \big(\mathrm{OCV}\big(z_n(t)\big) - v_{min}\big)/R_{dis,\Delta T}$
- Pack discharge power is then calculated as $P_{max}^{dis} = N_s N_p v_{min} \min_n \big(i_{max,n}^{dis,volt}\big)$



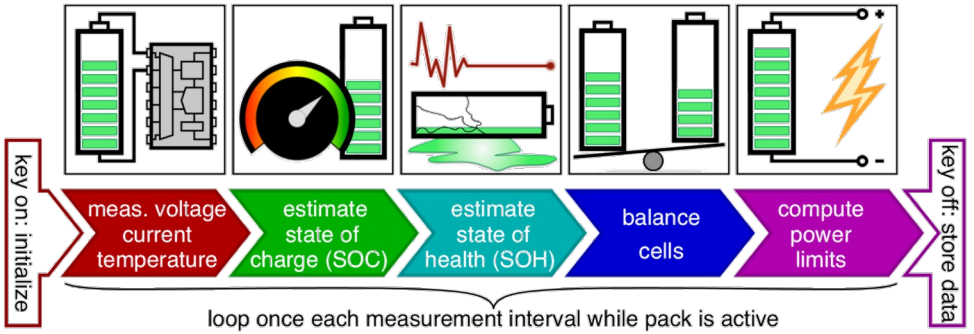


Power Limit Estimation: A New MPC Approach

- In this adaptation, we'll use MPC to construct an accurate estimate of available (charge/discharge) power over a finite time horizon by --
  - executing a constrained MPC algorithm at each sample point to predict an optimal future power profile
  - numerically integrating power to compute total energy
  - averaging over a finite time horizon to estimate max sustainable power
- ***Note:*** MPC is not used to <u>control</u> the battery, but rather to <u>inform</u> the BMS



Summary: Main Points



- BMS can be developed either with **ECM**- or **PBM**-based models for control
  - Present state-of-the-art uses ECMs, but PBMs unlock possibility of extending life and improving battery-pack performance
- ECMs represent cell behavior using analogs built from common circuit elements – resulting in computationally *simple* structures
- PBMs use first-principles mathematical equations of electrochemistry – and can be highly complicated to implement
- BMS control algorithms are designed to estimate: SOC, SOH, SOE, SOP
  - Battery-cell SOC quantifies how much charge is stored that might be released to a load circuit to accomplish some task
  - SOP indicates maximum power level that can be sourced/supplied from/to a battery over a fixed time

For further study

- Three volumes on BMS topics available from Artech House.
- ECMs and PBMs are taught in Volume I.
- BMS algorithms for SOC, SOH, SOE, SOF estimation using circuit models are discussed in Volume II.
- Physics-based parameter estimation, improved impedance models and ROM generation, physics-based state estimation, health estimation, and optimal power-limits calculations are discussed in Volume III.

- Can also find full semester-long graduate course PDF notes plus lecture videos on ECMs and PBMs at http://mocha-java.uccs.edu/ECE5710/
- Can find full semester-long graduate course PDF notes plus lecture videos on ECM-based BMS algorithms at http://mocha-java.uccs.edu/ECE5720/

For further study (mostly from the UCCS research team)

- **ECMs**
  - Hu X, Li S, Peng H. A comparative study of equivalent circuit models for Li-ion batteries. *Journal of Power Sources*. 2012, 198:359-67.
  - Jackey, R., Plett, G.L., and Klein, M., "Parameterization of a Battery Simulation Model Using Numerical Optimization Methods," *Proc. SAE World Congress 2009*, Detroit, MI (April 2009), 9 pages.
- **PBMs**
  - Doyle M, Fuller TF, Newman J. Modeling of galvanostatic charge and discharge of the lithium/polymer/insertion cell. *Journal of the Electrochemical Society*. 1993, 140(6):1526-33.
  - Newman J, Thomas-Alyea K.E.. *Electrochemical Systems*. John Wiley & Sons, 2012.
  - Chu, Z., Plett, G.L., Trimboli, M.S., Ouyang, M., "A control-oriented electrochemical model for lithium-ion battery, Part I: Lumped-parameter reduced-order model with constant phase element," *Journal of Energy Storage*, 25, 2019, 100828.
  - Jobman, R., Trimboli, M.S., Plett, G.L., "Identification of lithium-ion physics-based model parameter values," *Journal of Energy Challenges and Mechanics*, 2(2), pp. 45–55.
- **ROMs**
  - Rodríguez, A., Plett, G.L., Trimboli, M.S., "Comparing four model-order reduction techniques, applied to lithium-ion battery-cell internal electrochemical transfer functions," *eTransportation*, Vol. 1, 2019, 100009.
  - Rodríguez, A., Plett, G.L., Trimboli, M.S., "Improved transfer functions modeling linearized lithium-ion battery-cell internal electrochemical variables," *Journal of Energy Storage*, Vol. 20, 2018, pp. 560–575.

For further study (mostly from the UCCS research team)

- **ROMs (continued)**
  - Lee, J.L., Aldrich, L., Stetzel, K., Plett, G.L., "Extended operating range for reduced-order model of lithium-ion cells," *Journal of Power Sources*, 255, 2014, pp. 85–100.
  - Lee, J.L., Chemistruck, A., Plett, G.L., "One-dimensional physics-based reduced-order model of lithium-ion dynamics," *Journal of Power Sources*, 220, 2012, pp. 430–448.
  - Lee, J.L., Chemistruck, A., Plett, G.L., "Discrete-Time Realization of Transcendental Impedance Functions, with Application to Modeling Spherical Solid Diffusion," *Journal of Power Sources*, 206, 2012, pp. 367–377.
  - Speltino C, Di Domenico D, Fiengo G, Stefanopoulou A. Comparison of reduced order lithium-ion battery models for control applications. *Proceedings of the 48h IEEE Conference on Decision and Control (CDC) held jointly with 2009 28th Chinese Control Conference,* 2009, pp. 3276-3281
  - Smith K.A., Rahn C.D., Wang C-Y. Control oriented 1D electrochemical model of lithium ion battery. *Energy Conversion and Management*. 2007 Sep 1;48(9):2565-78.
- **Degradation**
  - Plett, G.L., "Reduced-order multi-modal model of SEI layer growth for management and control of lithium-ion batteries," in IEEE Conference on Control Technology and Applications 2017, Kohala Coast, Hawai'i (August 2017).
  - Barré A, Deguilhem B, Grolleau S, Gérard M, Suard F, Riu D. A review on lithium-ion battery ageing mechanisms and estimations for automotive applications. *Journal of Power Sources*. 2013, 241:680-9.
  - Plett, G.L., "Algebraic solution for modeling SEI layer growth," *ECS Electrochemistry Letters*, 2(7), 2013, pp. A63–A65.

For further study (mostly from the UCCS research team)

- **Degradation (continued)**
  - Perkins, R.D., Randall, A.V., Zhang, X., Plett, G.L., “Controls Oriented Reduced Order Modeling of Lithium Deposition on Overcharge,” *Journal of Power Sources*, 209, 2012, pp. 318-325.
  - Randall, A.V., Perkins, R.D., Zhang, X., Plett, G.L., “Controls Oriented Reduced Order Modeling of SEI Layer Growth,” Journal of Power Sources, Vol. 209, July 2012, pp. 282-288.
  - Park, J., Seo, J.H., Plett, G.L., Lu, W., Sastry, A.M., “Numerical Simulation of the Effect of the Dissolution of LiMn2O4 Particles on Li-Ion Battery Performance,” *Electrochemical and Solid State Letters*, 14(2), 2010, pp. A14–A18.
  - Seo, J.H., Park, J., Plett, G.L., Sastry, A.M., “Gas-evolution Induced Volume Fraction Changes and Their Effect on the Performance Degradation of Li-ion Batteries,” Electrochemical and Solid State Letters, 13(9), 2010, pp. A135–A137.
  - Safari M, Morcrette M, Teyssot A, Delacourt C. Multimodal physics-based aging model for life prediction of Li-ion batteries. Journal of The Electrochemical Society. 2009 Mar 1;156(3):A145-53.
  - Vetter J, Novák P, Wagner MR, Veit C, Möller KC, Besenhard JO, Winter M, Wohlfahrt-Mehrens M, Vogler C, Hammouche A. Ageing mechanisms in lithium-ion batteries. Journal of power sources. 2005 Sep 9;147(1-2):269-81.
  - Broussely M, Biensan P, Bonhomme F, Blanchard P, Herreyre S, Nechev K, Staniewicz RJ. Main aging mechanisms in Li ion batteries. Journal of power sources. 2005 Aug 26;146(1-2):90-6.
  - Arora P, Doyle M, White R.E.. Mathematical modeling of the lithium deposition overcharge reaction in lithium-ion batteries using carbon-based negative electrodes. *Journal of The Electrochemical Society*. 1999,146(10):3543-53.

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