Battery Modeling: Trade-offs between Accuracy and Complexity

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Smart Grid
Renewable generation to reduce carbon footprint
Pervasive sensing, communication, control
Storage to decouple supply and demand
Storage: A Hot Area

Global investment in energy storage technologies to reach $122 Billion by 2021

Source: Pike Research
Tesla/Panasonic and GM/LG Chem battery costs were already (in 2016) down to the lowest projections for 2020!
Why Storage?

Storage *decouples* supply and demand. Allows

Reliability

for large scale renewable integration

Flexibility

for energy management
Applications

- Congestion, upgrade deferral
- Smoothing/Firming
- Market Participation
- Demand management
- Frequency Regulation

Diagram showing a flow of energy from a generating plant through transmission lines, network transformer, distribution lines, and finally to a home. The diagram also highlights the importance of demand management and frequency regulation.
Battery Models

Electrochemical Models:
- Describes internal states of the battery by simulating chemical processes
- Useful for understanding and designing batteries

Equivalent Circuit Models:
- Resistance-capacitance components to model voltage non-linearities
- Partial-differential equations
- Typically useful for “small” simulations of energy systems

“Simplified Mathematical” Models:
- Black-box approach, model inputs and outputs
- Low-order polynomial functions
- Useful for large-scale simulation, optimization of energy systems
Tractable Models For Optimization

Accurate
- Required degree of accuracy depends on the application

Tractable and low computational complexity
- Explicitly described by polynomials. Linear is easiest to work with.

Calibrated using spec
- Battery specifications sheet is readily available, avoid experiment-based parameter derivation which is cumbersome and does not scale

Uses power as input
- Power is conserved, avoid having to explicitly model voltage/current transformations

Integrates BMS (battery management system) functionality
- Model the cells as well as the software that protects them from misuse.
Our approach

Start with a model that meets 4/5 requirements

- Accurate, spec-calibrated, power-based, integrated BMS, but is not explicit and based on polynomials

Explore different ways to approximate the complex parts of the PI model

- Approximate using polynomials of degree 0 (constants) through 4 (quartics)
- Get a sense of what is lost with each approximation by comparing with the PI model
Our Contributions

- Derive explicit models from the PI model
- Explore the effects of model accuracy with respect to the battery application
- Calibrate and validate the benchmark used by almost everyone

Note: All of this work is validated with an extensive measurement campaign
- Two Lithium-ion technologies
- Two cells per technology
- Charge/discharge test profiles exploring full capabilities of each cell
- Test profile resembling realistic usage
Disclaimer

We do not model:

- State of health (degradation)
- Battery lifetime
- Temperature effects
A Storage Model Based on First Principle

The storage has some **capacity** $B$ in Wh. At time $t$, it is charged with power $P(t) > 0$ or discharged with power $P(t) < 0$. Its content is $b(t)$

$P(t) > 0$  \hspace{5cm} P(t) < 0$

The **ideal** behavior is:

$$0 \leq b(t+\delta) = b(t) + P(t) \delta \leq B$$

where $\delta$ is the time-slot duration

However, it is important to consider **imperfections**, such as:

- charging/discharging speed limits
- energy conversion/inversion efficiency
- capacity limits
**The benchmark:** one input $P(k)$, one state variable $b(k)$

$$b(k) = b(k - 1) + \Delta_E(k)$$

$$\Delta_E(k) = \begin{cases} 
\eta_c P(k) \delta & : P(k) \geq 0 \\
\eta_d P(k) \delta & : P(k) < 0
\end{cases}$$

$$u_d \leq P(k) \leq u_c$$

$$a_1 \leq b(k) \leq a_2$$

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**Main differences:**
- voltage and current are internal variables,
- the inefficiencies and the capacity limits are no more constant
- the (dis)charging limits are on current
- Introduction of the empirical function $z=M(x,y)$

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**The PI model:** one input $P(k)$, one state variable $b(k)$, two internal variables $I(k)$ and $V(k)$

$$b(k) = b(k - 1) + \Delta_E(k)$$

$$\Delta_E(k) = \begin{cases} 
\eta_c(I(k),V(k)) P(k) \delta & : P(k) \geq 0 \\
\eta_d(I(k),V(k)) P(k) \delta & : P(k) < 0
\end{cases}$$

$$\eta_c(I(k),V(k)) = 1 - \frac{I(k)R_{ic}}{V(k)} : I(k) \geq 0$$

$$\eta_d(I(k),V(k)) = 1 - \frac{I(k)R_{id}}{V(k)} : I(k) < 0$$

$$V(k) = M(b(k), I(k))$$

$$I(k) = \frac{P(k)}{V(k)}$$

$$\alpha_d \leq I(k) \leq \alpha_c$$

$$a_1(I(k)) \leq b(k) \leq a_2(I(k))$$
Two Main Issues

- Calibrating these models, i.e., selecting the parameters out of the spec sheet.
- Validating them: is the benchmark good enough?
The Function $M(.)$

$M$ surface represents viable combinations of cell voltage, energy content, and applied current.

For $P(k)>0$, we need to find the intersection between the surface defined by $M(.)$ and the surface defined by:

$$b(k) = b(k-1) + P(k) - I^2(k)R_{ic}$$

$$V(k) = M(b(k), I(k))$$
1. Voltage Function Approximation

In the PI model, the M function is an interpolation of points obtained from the spec. We can approximate it as a bivariate polynomial.

**Linear approximation**

**Cubic approximation**
2. Energy Limit Functions

\[ a_1(I(k)) \leq b(k) \leq a_2(I(k)) \]

\( a_1 \) and \( a_2 \) are functions of the current (approximately linear)
3. Efficiency Functions

We approximate the efficiency functions using constants or lines.

Constant approximations look bad, but that’s what people have been doing! And not as carefully as shown here!
## Four models

V/E/\(\eta\) notation: Voltage, energy limit, and efficiency approximation  
C: constant, L: linear, Q: quadratic (in terms of model variables)

<table>
<thead>
<tr>
<th>Model</th>
<th>Voltage</th>
<th>Approximations</th>
<th>Efficiency</th>
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</thead>
<tbody>
<tr>
<td></td>
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<td>Voltage Content Limits</td>
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<tr>
<td>C/C/C</td>
<td>(V = \begin{cases} \ V_{nom,d} &amp; : P &lt; 0 \ \ V_{nom,c} &amp; : P \geq 0 \end{cases})</td>
<td>(a_1(P) = u_1(P/V_{nom,d}) + v_1) \quad (\tilde{\eta}_d) \quad (\tilde{\eta}_c)</td>
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<td>(a_1(P) = u_1(P/V_{nom,c}) + v_1) \quad (\eta_d(P) = 1 - PR_{id}/V_{nom,d}^2) \quad (\eta_c(P) = 1 - PR_{ic}/V_{nom,c}^2)</td>
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<td>L/L/Q</td>
<td>(V = x_{00} + x_{10}I + x_{01}b)</td>
<td>(a_1(I) = u_1I + v_1) \quad (\eta_d(I,V) = 1 - IR_{id}/V)</td>
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<td>(a_2(I) = u_2I + v_2) \quad (\eta_c(I,V) = 1 - IR_{ic}/V)</td>
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C/C/C is equivalent to the benchmark
Four Models: Complexity

Consider an optimization problem where b and P are variables.

Complexity of each model w.r.t. the variables
- C/C/C: Linear (hence its popularity)
- C/L/C: Linear
- C/L/L: Quadratic (efficiency is a function of the power)
- L/L/Q: Cubic (efficiency is a function of power and voltage)
Evaluation

**Metric**: Energy

- Compute the mean absolute energy error (MAEE) when cycling the battery at constant current
- Ground truth: PI model.
- Battery chemistries: Lithium Titanate and Lithium Ferrous Phosphate.
Evaluation
Evaluation: Lithium-Titanate

Models perform in order of the degree of their complexity.
Evaluation on Applications

- How do we convince people to adopt our models?
- Accuracy metrics aren’t always convincing…
- Let’s see how model results differ for two applications
  - **Solar farm**: participating in electricity market in the form of constant hourly production
    - Key variable: The amount of energy that the farm committed to providing, but did not deliver (unmet load)
  - **Regulation**: ancillary service, focus on discharging
    - Key variable: Maximum power that we can guarantee to provide.
Solar Farm

C/L/L and L/L/Q results are almost identical

Minimum # of cells to get 25% unmet load:
- PI: 50
- **C/C/C**: 77
- C/L/C: 56
- **C/L/L**: 48
- L/L/Q: 49
Regulation

This is the maximum power that we could guarantee to provide for the length of the contract, if the battery starts at 50% capacity.

All models perform quite well, except for C/C/C, hence the winner is C/L/C.
What Did We Learn?

- Not trivial to calibrate even the benchmark
- C/L/C > C/C/C while remaining linear
- Understanding the approximations made in simpler models is crucial.

What Is Next?

- Experiments are under-way to validate our models for different Lithium-ion chemistries, as well as other battery technologies
  - Lead-Acid,
  - Redox-Flow
  - Sodium-Nickel-Chloride
- How to take into account temperature? state of health?
What next?