Battery Modeling: Trade-offs between Accuracy and Complexity

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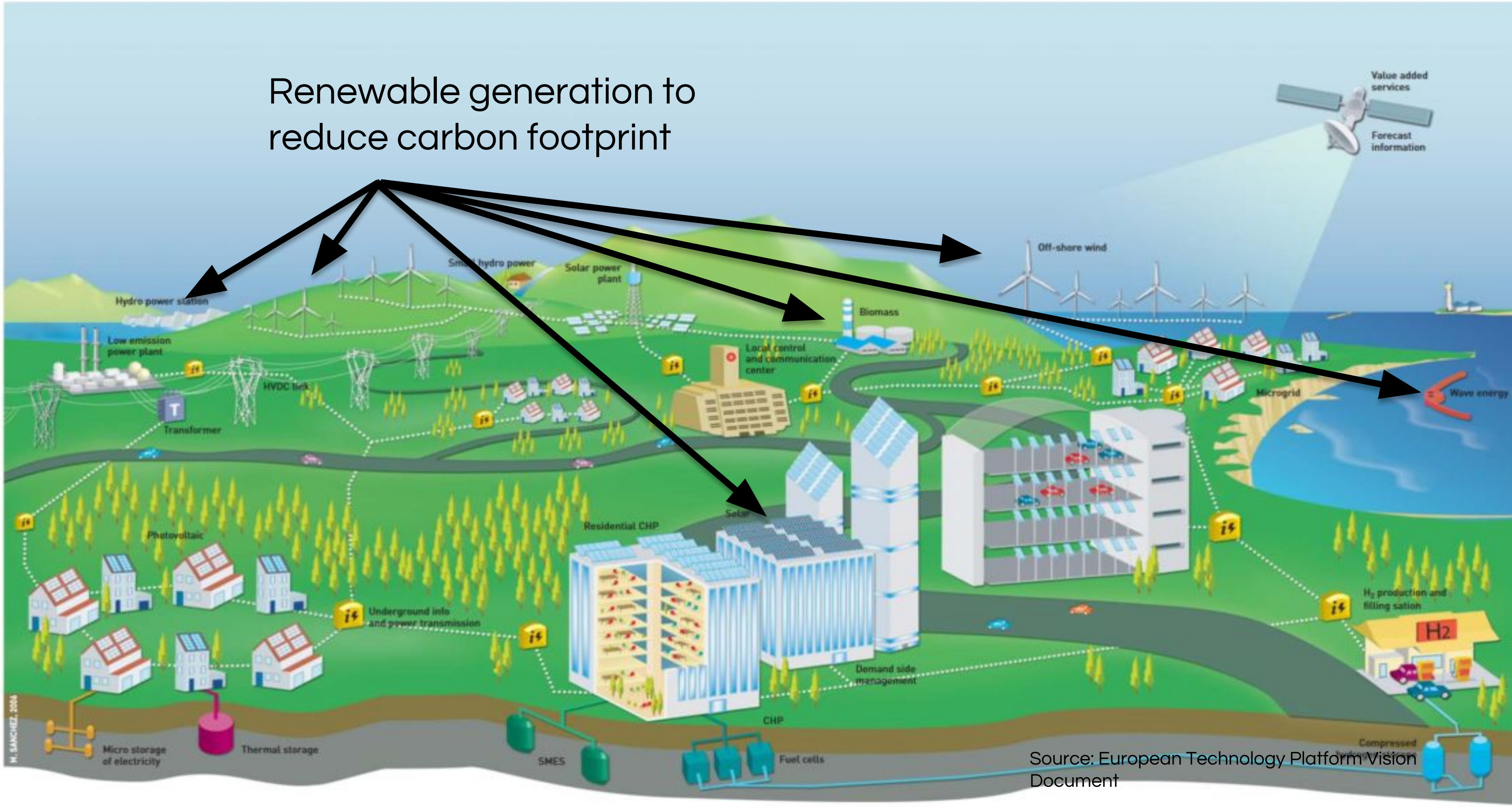
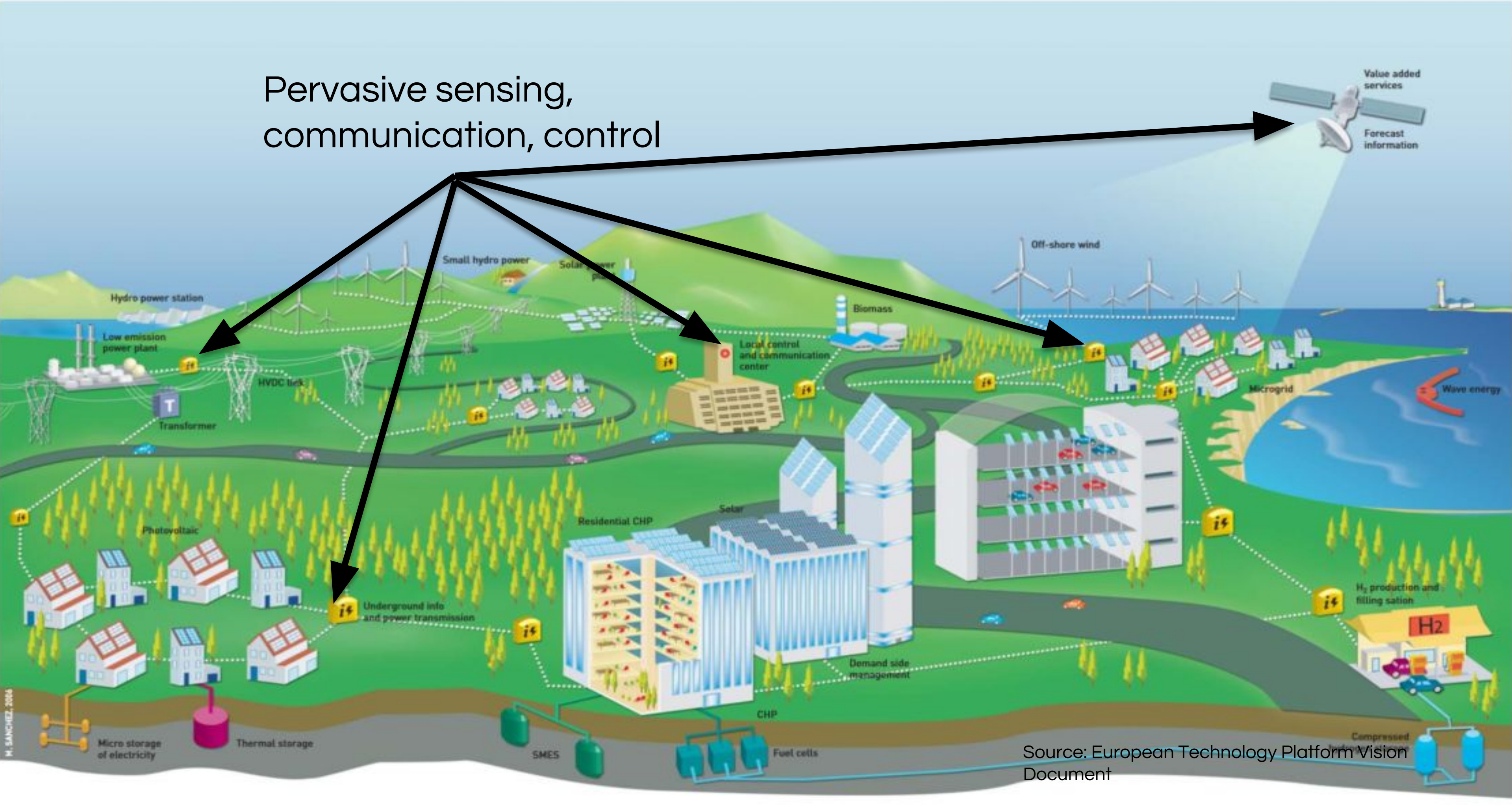
Smart Grid


Value added services
Forecast information
Off-shore wind
Small hydro power
Solar power plant
Hydro power station
Biomass
Low emission power plant
Local control and communication center
HVDC link
Transformer
Microgrid
Wave energy
Photovoltaic
Residential CHP
Solar
Underground info and power transmission
H₂ production and filling sation
H2
Demand side management
CHP
Micro storage of electricity
Thermal storage
SMES
Fuel cells
Compressed hydrogen storage
M. SANCHEZ, 2006



Renewable generation to reduce carbon footprint

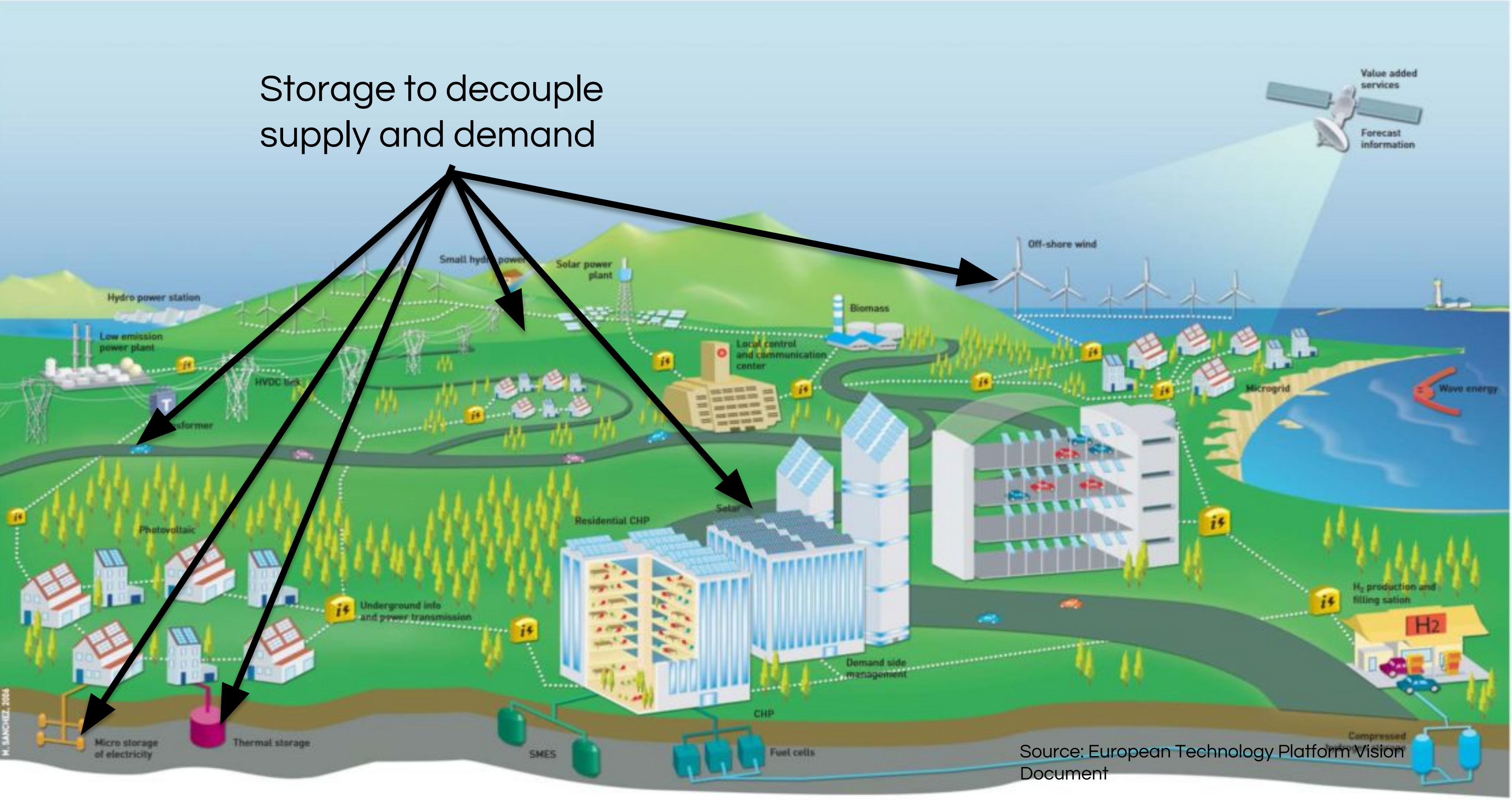
Source: European Technology Platform Vision Document



Pervasive sensing, communication, control

Source: European Technology Platform Vision Document

Storage to decouple supply and demand



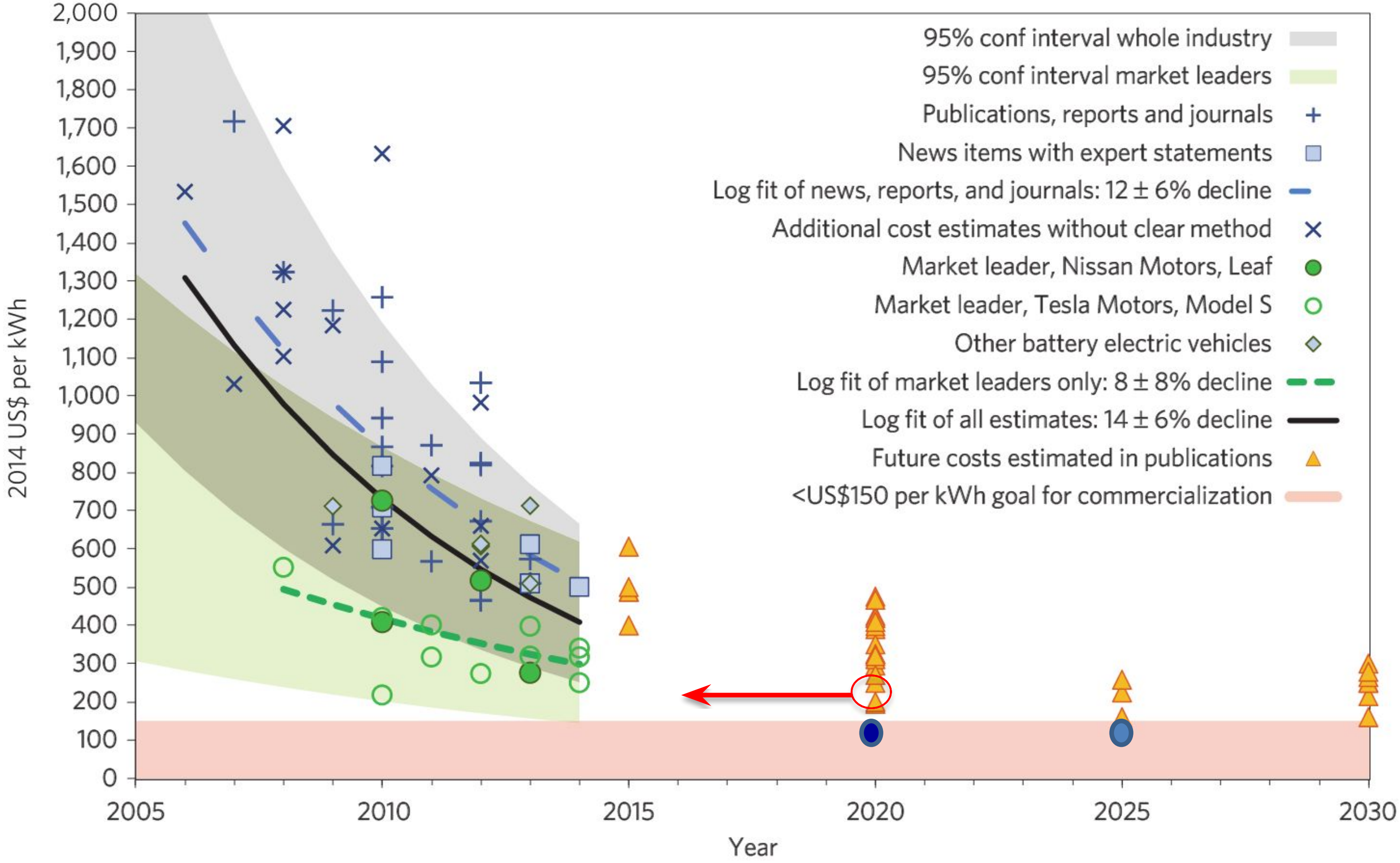
Source: European Technology Platform Vision Document

Storage: A Hot Area

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

Source: Pike Research

Battery Costs: Current and Projections



Change: 2014

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

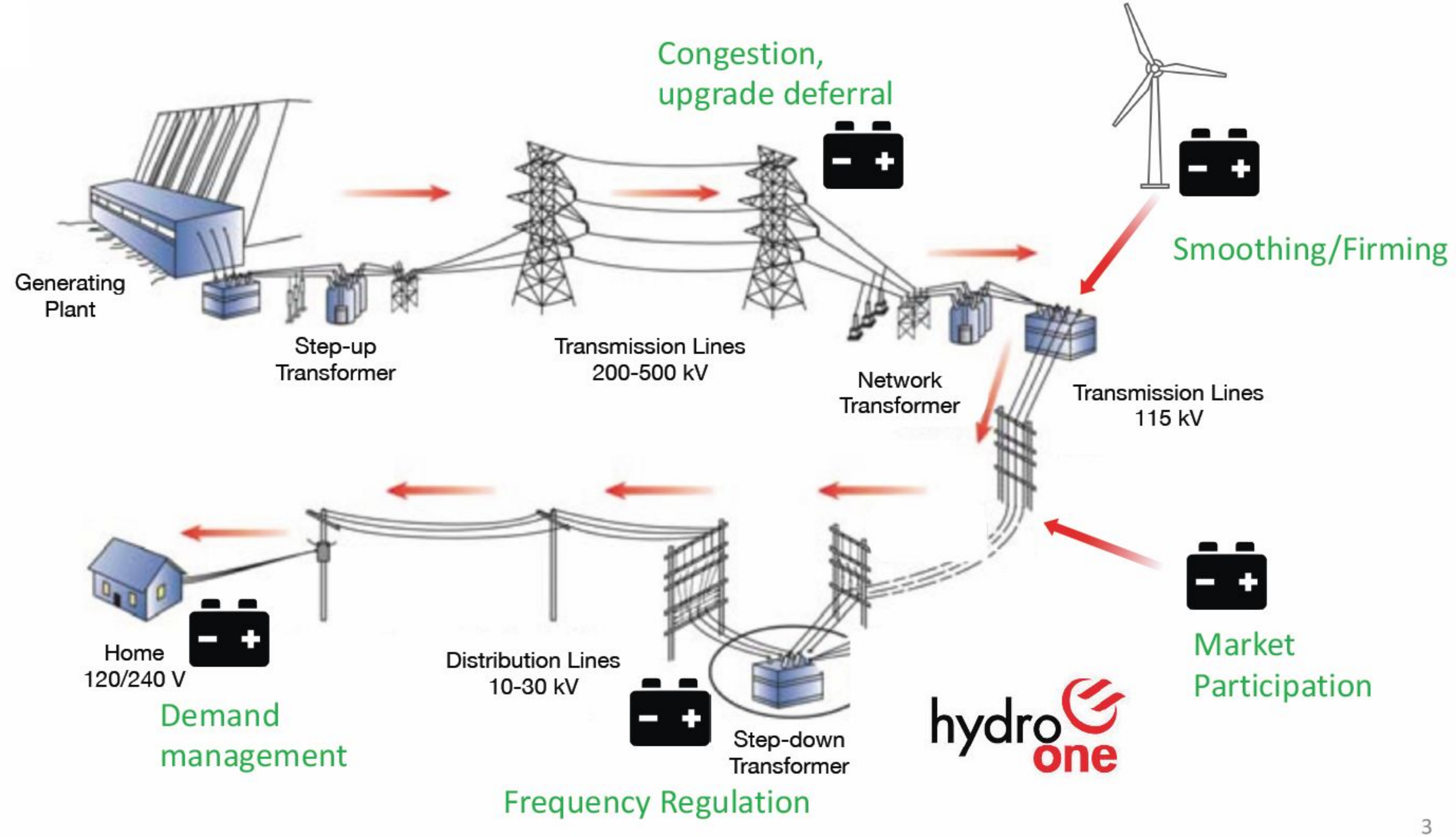
Reliability

for large scale
renewable integration

Flexibility

for energy management

Applications



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
- Power-based Integrated (PI) model *(F. Kazhamiaka, S. Keshav, C. Rosenberg, and K-H. Pettinger, "Simple Spec-Based Modelling of Lithium-Ion Batteries", accepted to IEEE Transactions on Energy Conversion, April 2018.)*

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

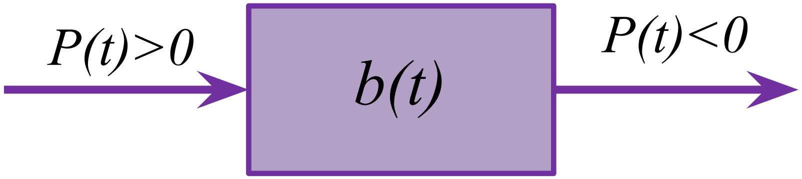
Disclaimer

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 $b(t)$



The **ideal** behavior is:

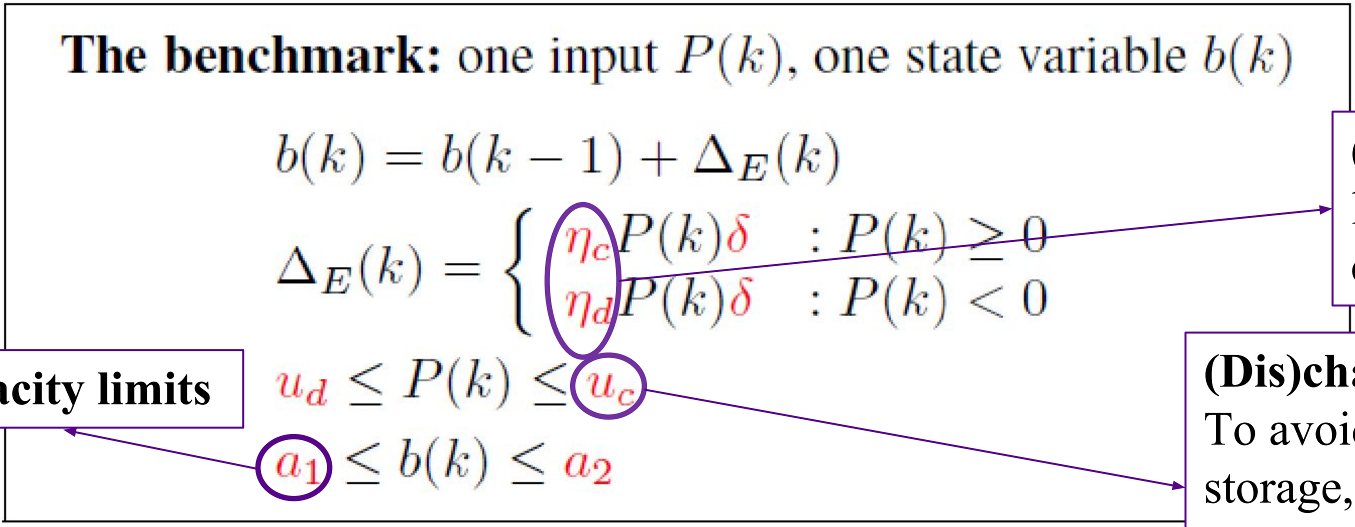
$$0 \leq b(t+\delta) = b(t) + P(t)\,\delta \leq B$$

where δ is the time-slot duration

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

- charging/discharging speed limits
- energy conversion/inversion efficiency
- capacity limits

Red and blue are for system parameters



The benchmark: one input $P(k)$, one state variable $b(k)$

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

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

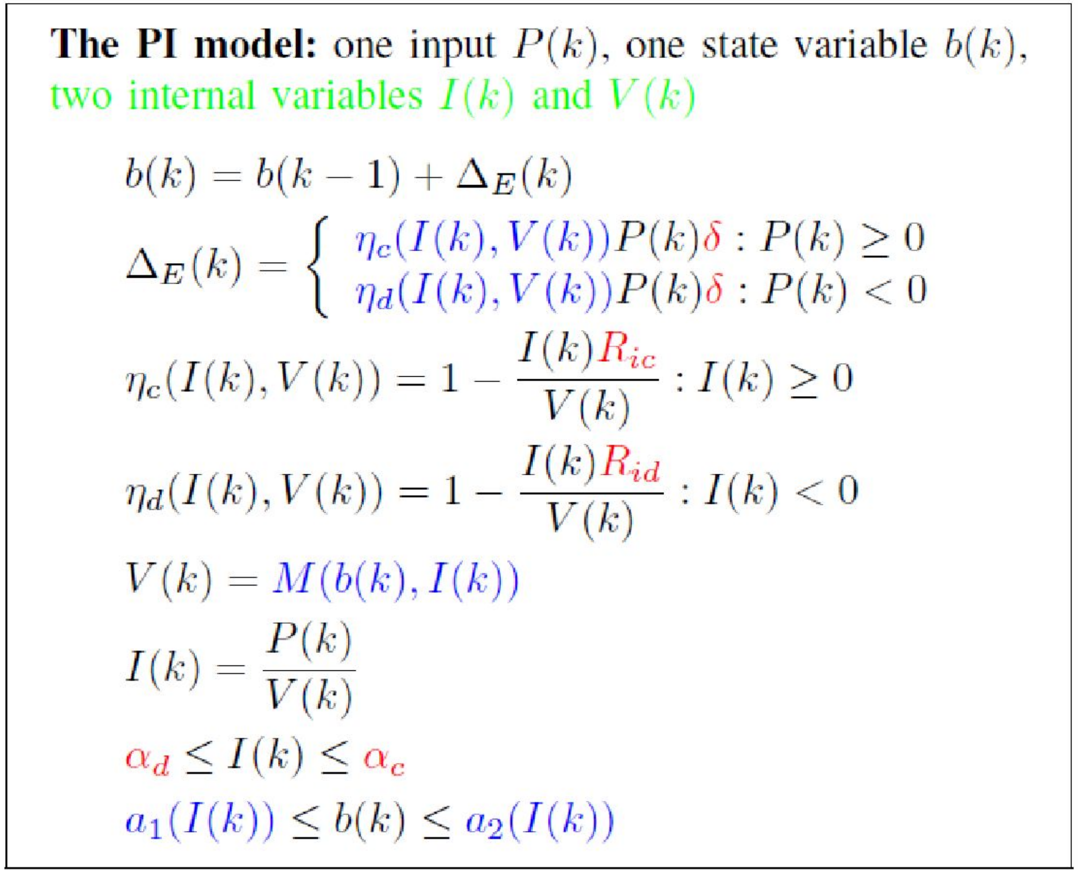
$$u_d \leq P(k) \leq u_c$$

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

(In) efficiency: losses in energy conversion

Capacity limits

(Dis)charging limits: To avoid damaging storage, the BMS might prevent charging or discharging too quickly



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

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

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

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

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

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

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

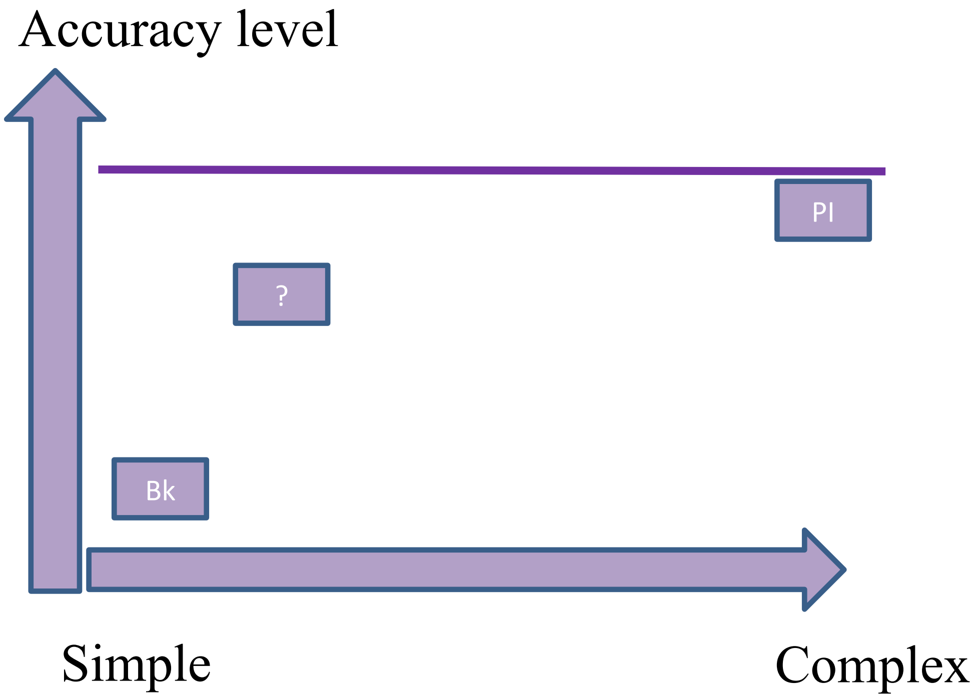
$$\alpha_d \leq I(k) \leq \alpha_c$$

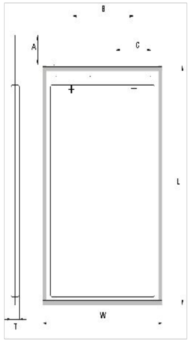
$$a_1(I(k)) \leq b(k) \leq a_2(I(k))$$

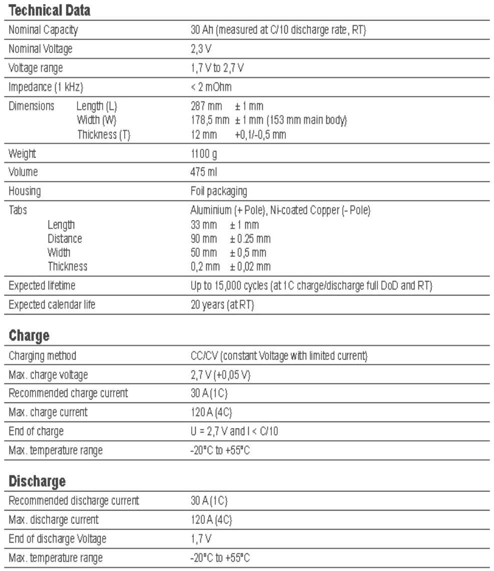
Main differences:
- voltage and current are internal variables,
- the inefficiencies and the capacity limits are no more constant
- the (dis)charging limits are on current
- Introduction of the empirical function *z=M(x,y)*

Two Main Issues

- Calibrating these models, i.e., selecting the parameters out of the spec sheet.
- Validating them: is the benchmark good enough?







Technical Data

Nominal Capacity	30 Ah (measured at C/10 discharge rate, RT)
Nominal Voltage	2,3 V
Voltage range	1,7 V to 2,7 V
Impedance (1 kHz)	< 2 mOhm
Dimensions Length (L) Width (W) Thickness (T)	287 mm ± 1 mm 178,5 mm ± 1 mm (153 mm main body) 12 mm +0,1/-0,5 mm
Weight	1100 g
Volume	475 ml
Housing	Foil packaging
Tabs Length Distance Width Thickness	Aluminium (+ Pole), Ni-coated Copper (- Pole) 33 mm ± 1 mm 90 mm ± 0.25 mm 50 mm ± 0,5 mm 0,2 mm ± 0,02 mm
Expected lifetime	Up to 15,000 cycles (at 1C charge/discharge full DoD and RT)
Expected calendar life	20 years (at RT)

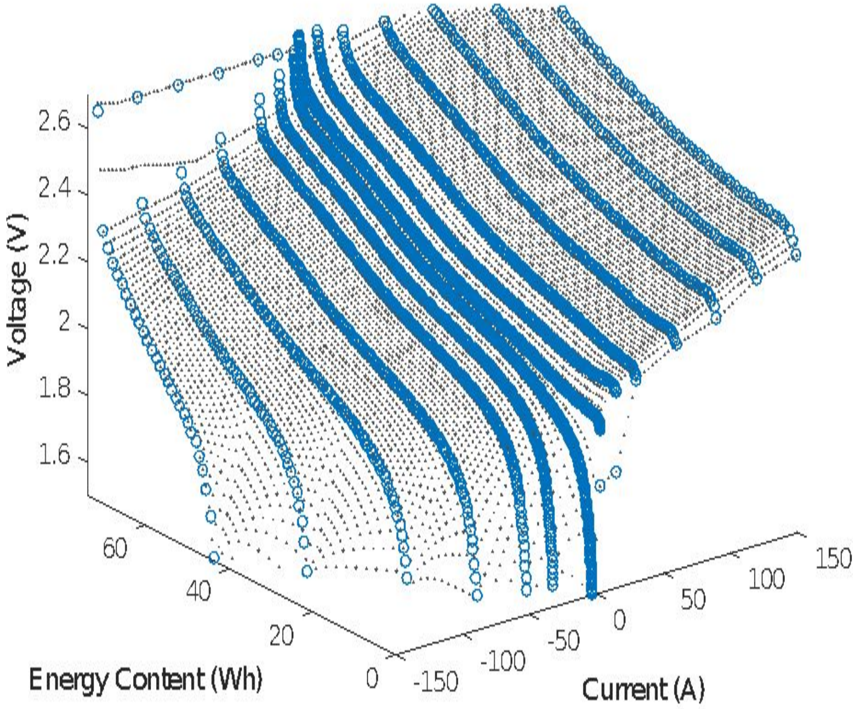
Charge

Charging method	CC/CV (constant Voltage with limited current)
Max. charge voltage	2,7 V (+0,05 V)
Recommended charge current	30 A (1C)
Max. charge current	120 A (4C)
End of charge	U = 2,7 V and I < C/10
Max. temperature range	-20°C to +55°C

Discharge

Recommended discharge current	30 A (1C)
Max. discharge current	120 A (4C)
End of discharge Voltage	1,7 V
Max. temperature range	-20°C to +55°C

The Function M(.)



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

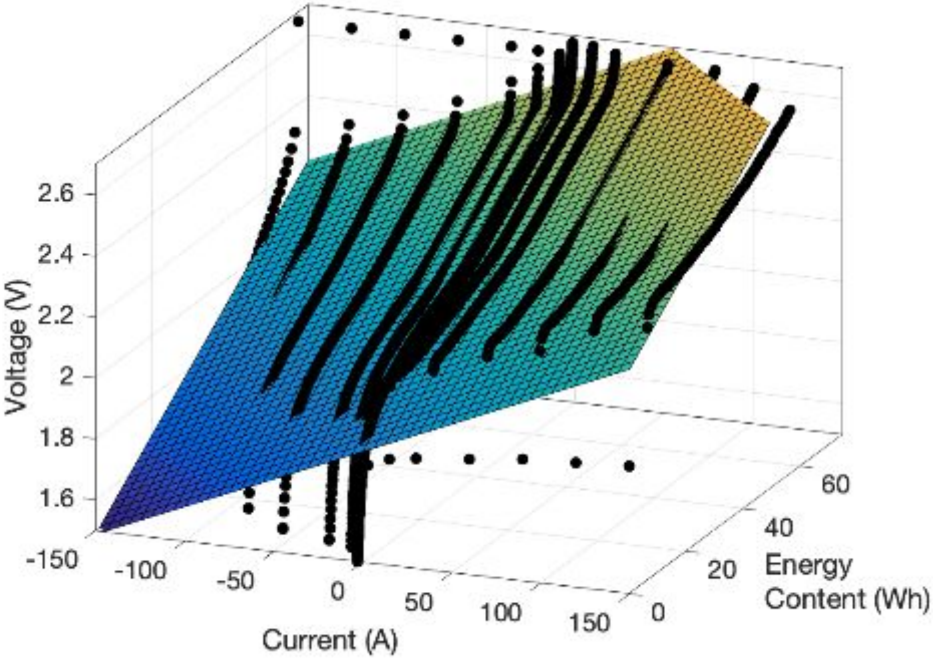
For $P(k) > 0$, we need to find the intersection between the surface defined by M(.) and the surface defined by:

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

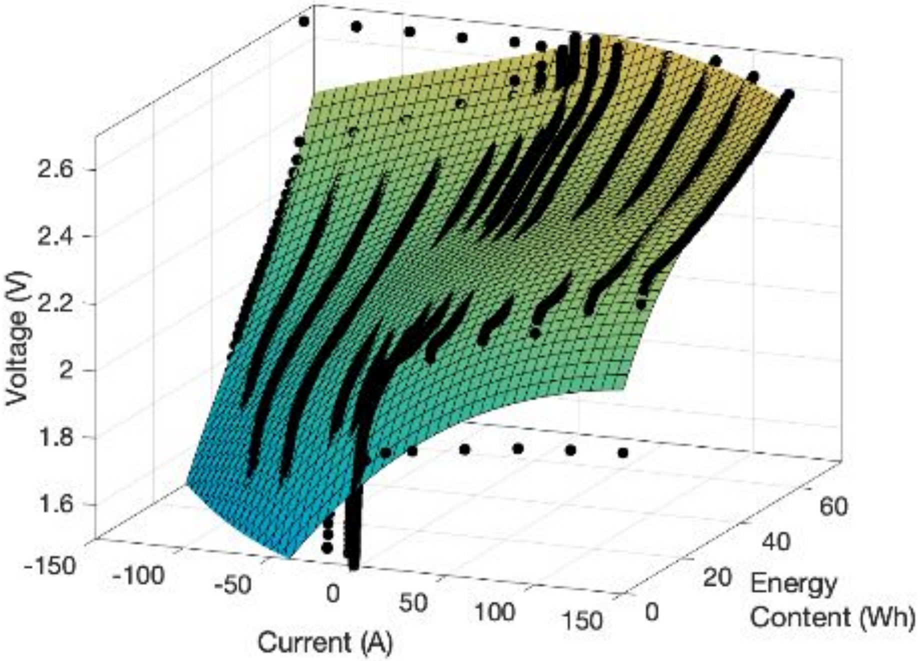
$$V(k) = M(b(k), I(k))$$

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

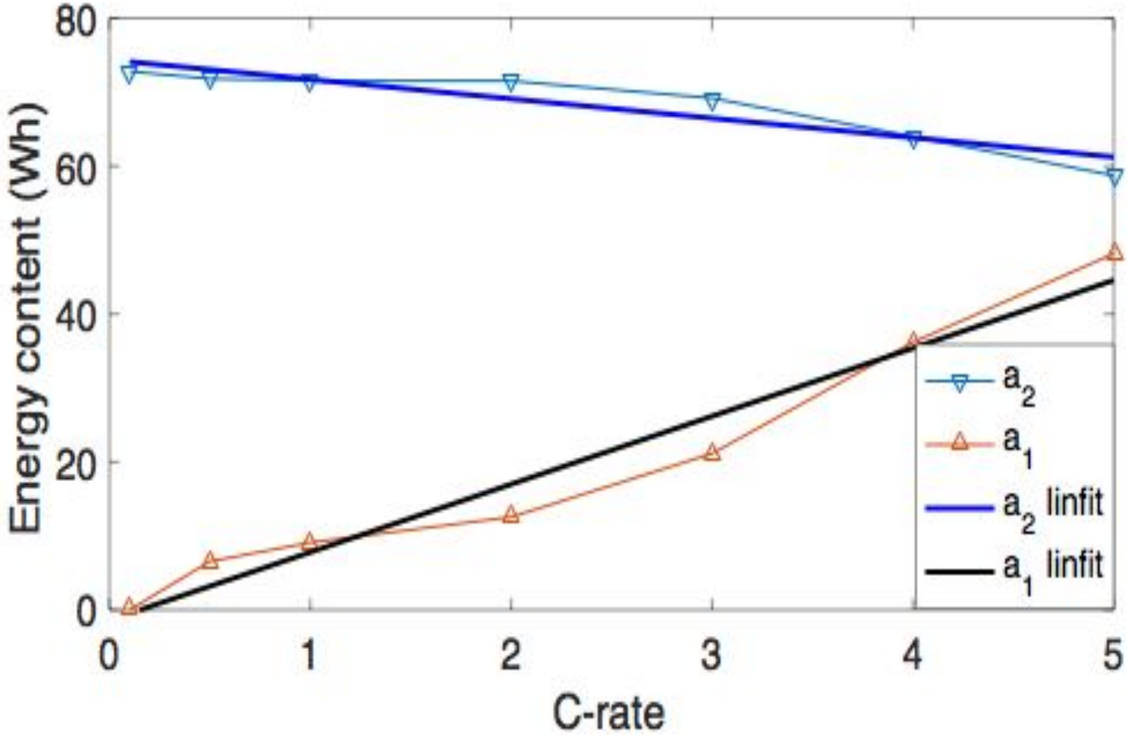


Cubic approximation

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)



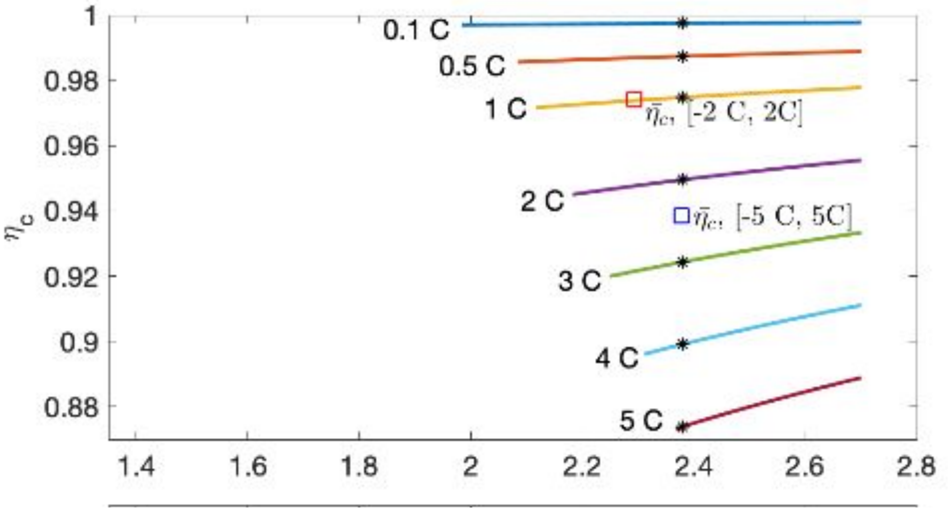
3. Efficiency Functions

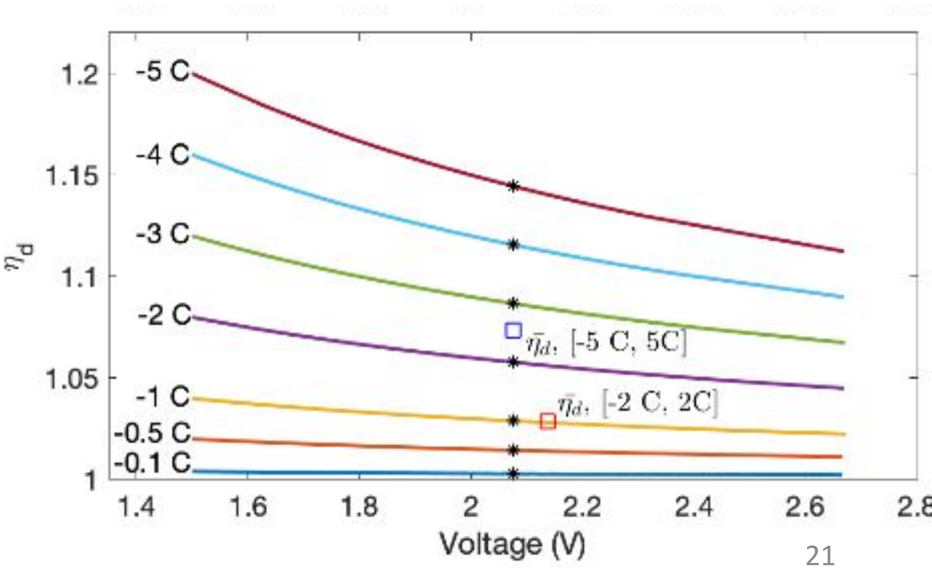
$$\eta_c(I(k),V(k)) = 1 - \frac{I(k)R_{ic}}{V(k)} : I(k) \geq 0$$

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

We approximate the efficiency functions using constants or lines.

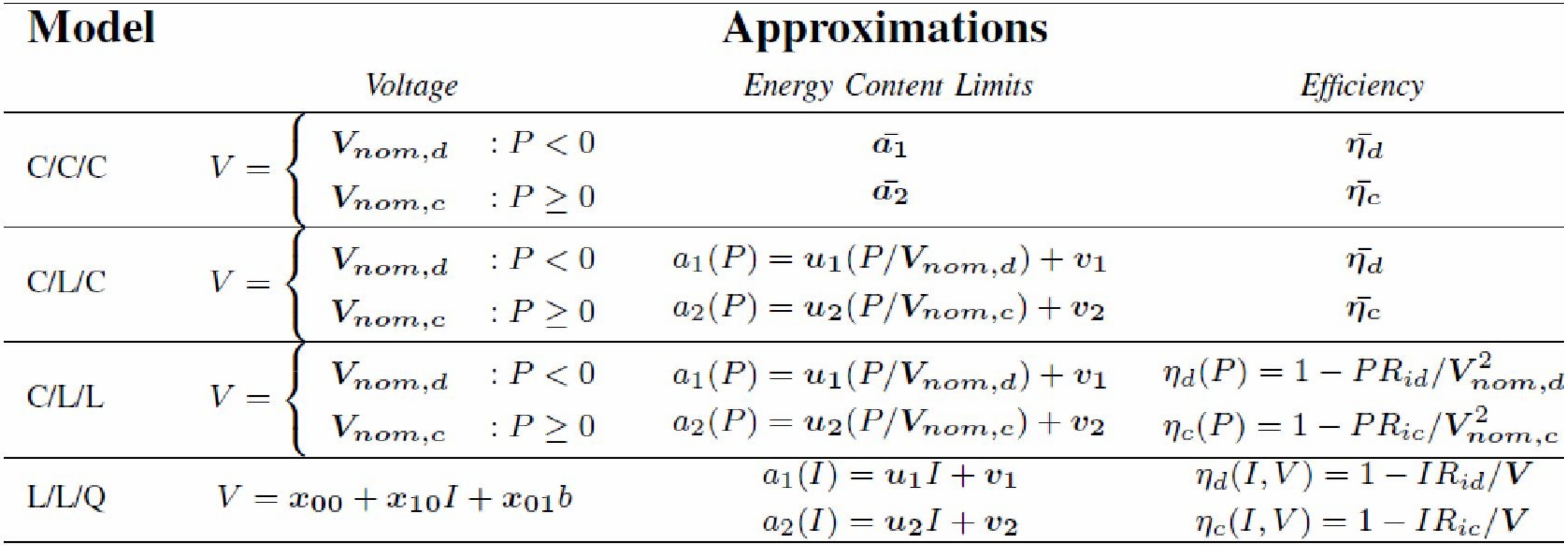
Constant approximations look bad, but that's what people have been doing! And not as carefully as shown here!





Four models

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



Model	**Approximations**		
	Voltage	*Energy Content Limits*	*Efficiency*
C/C/C	$V = \begin{cases} V_{nom,d} & : P < 0 \\ V_{nom,c} & : P \geq 0 \end{cases}$	$\bar{a}_1$ $\bar{a}_2$	$\bar{\eta}_d$ $\bar{\eta}_c$
C/L/C	$V = \begin{cases} V_{nom,d} & : P < 0 \\ V_{nom,c} & : P \geq 0 \end{cases}$	$a_1(P) = u_1(P/V_{nom,d}) + v_1$ $a_2(P) = u_2(P/V_{nom,c}) + v_2$	$\bar{\eta}_d$ $\bar{\eta}_c$
C/L/L	$V = \begin{cases} V_{nom,d} & : P < 0 \\ V_{nom,c} & : P \geq 0 \end{cases}$	$a_1(P) = u_1(P/V_{nom,d}) + v_1$ $a_2(P) = u_2(P/V_{nom,c}) + v_2$	$\eta_d(P) = 1 - PR_{id}/V^2_{nom,d}$ $\eta_c(P) = 1 - PR_{ic}/V^2_{nom,c}$
L/L/Q	$V = x_{00} + x_{10}I + x_{01}b$	$a_1(I) = u_1 I + v_1$ $a_2(I) = u_2 I + v_2$	$\eta_d(I,V) = 1 - IR_{id}/V$ $\eta_c(I,V) = 1 - IR_{ic}/V$

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

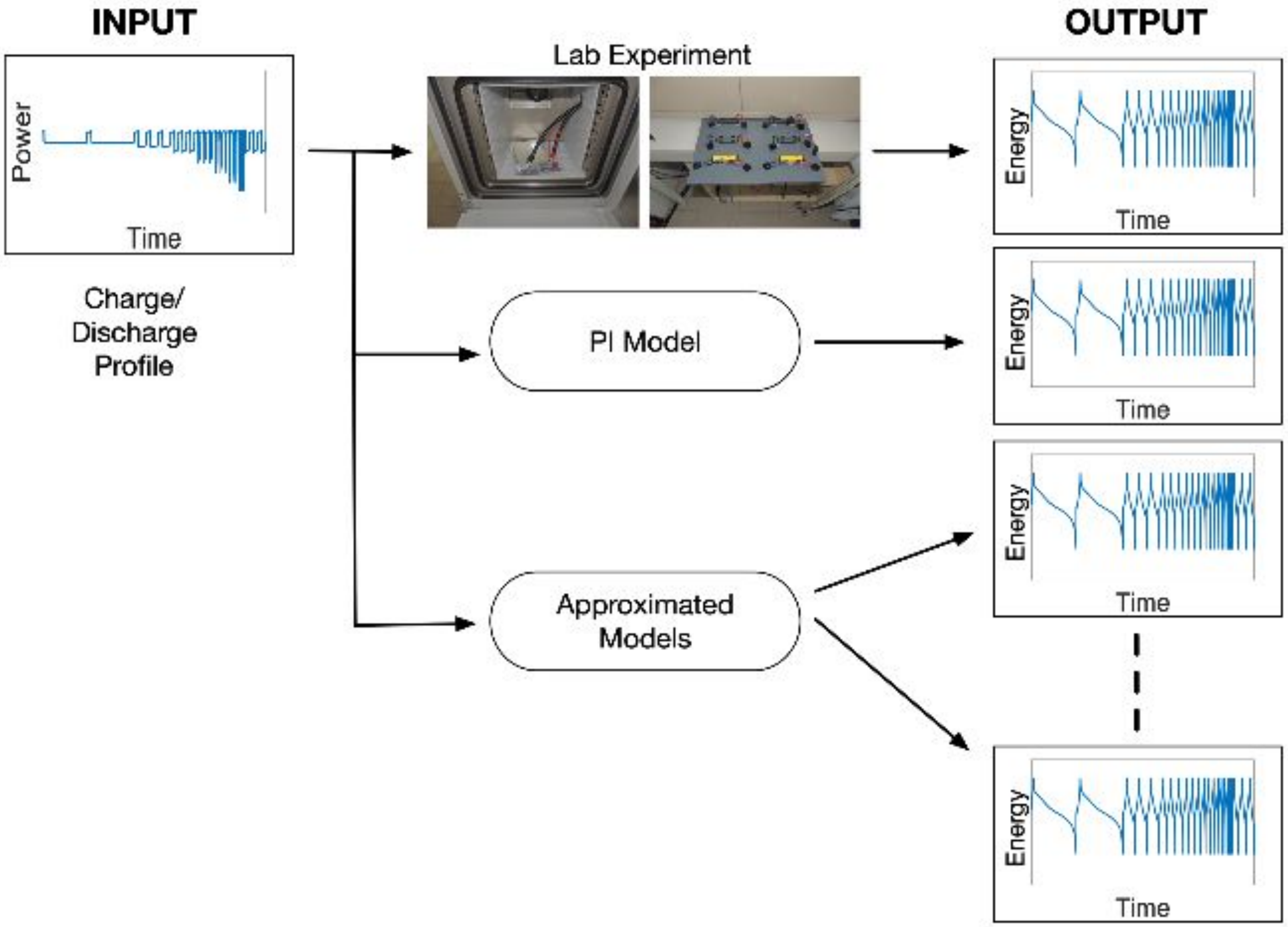
- C/C/C: Linear (hence its popularity)
- C/L/C: Linear ★
- C/L/L: Quadratic (efficiency is a function of the power)
- L/L/Q: Cubic (efficiency is a function of power and voltage)

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



INPUT

Charge/
Discharge
Profile

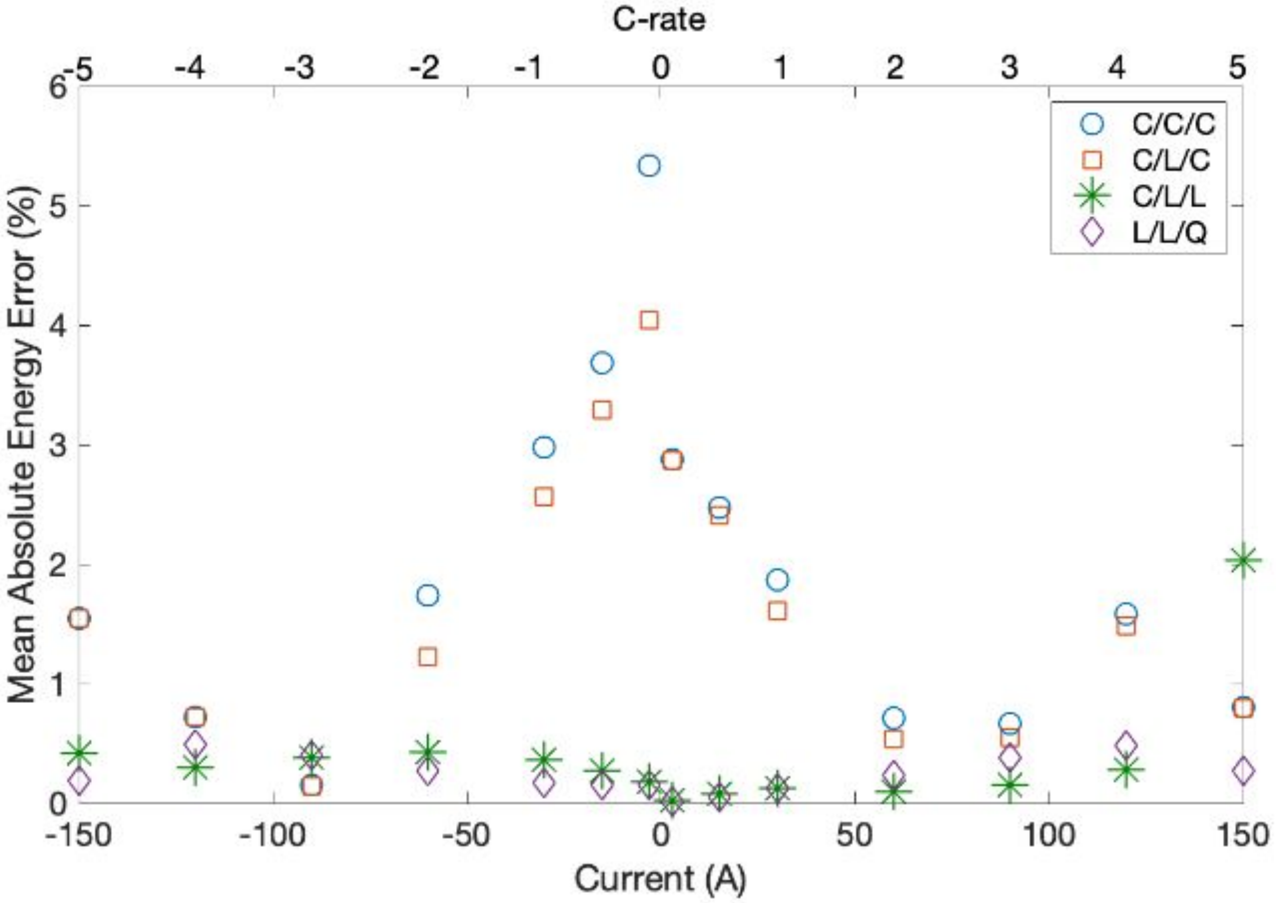
Lab Experiment

PI Model

Approximated
Models

OUTPUT

Evaluation: Lithium-Titanate

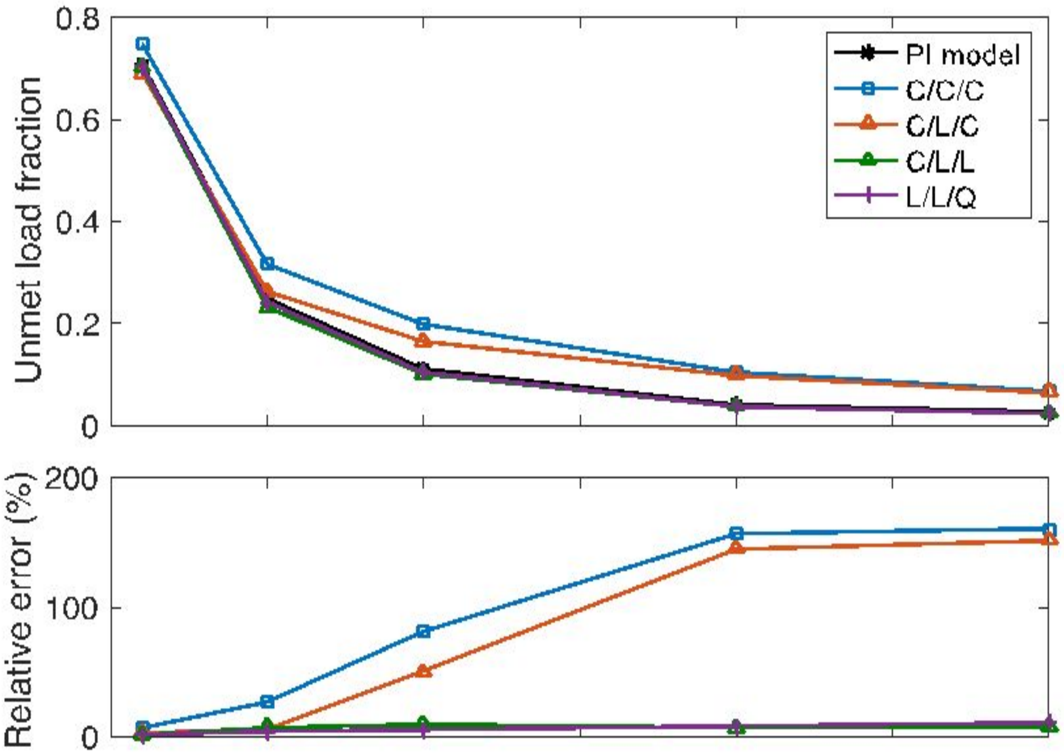


Models perform in order of the degree of their complexity.

Evaluation on Applications

- How do we convince people to adopt our models?
- Accuracy metrics aren’t always convincing…
- Lets 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

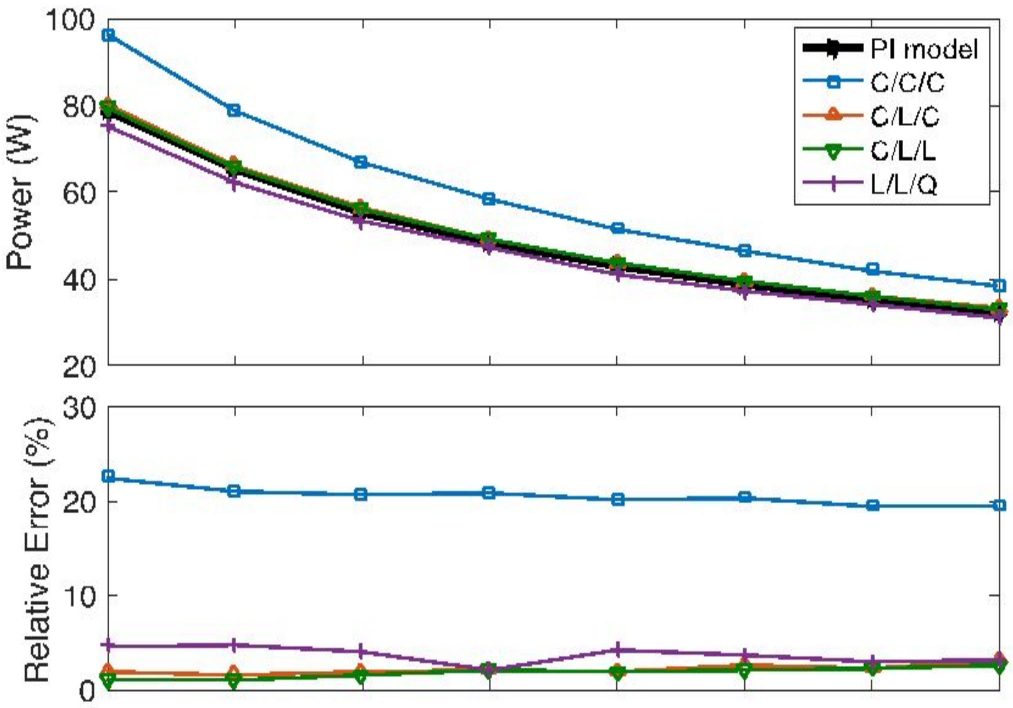


C/L/L and L/L/Q results are almost identical

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?