Predicting the onset of rapid degradation using data-driven approaches

Using automated feature generation and selection then Gaussian processes to map accelerating Li-ion battery degradation.

Samuel Greenbank and Dr. David Howey

NASA Battery Workshop 2020

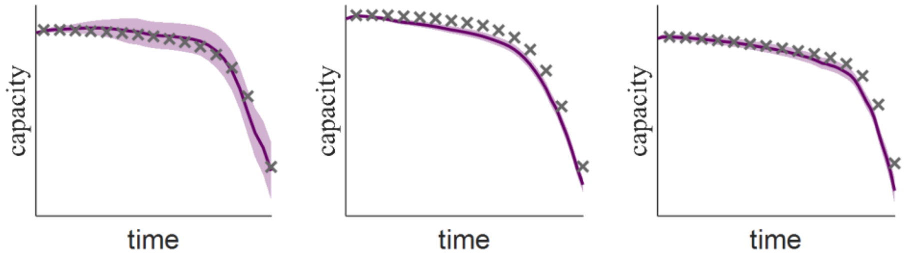
Battery Intelligence Lab

UNIVERSITY OF OXFORD

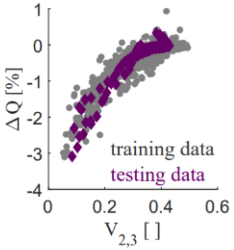
Battery Intelligence Lab

The background of my group and this work

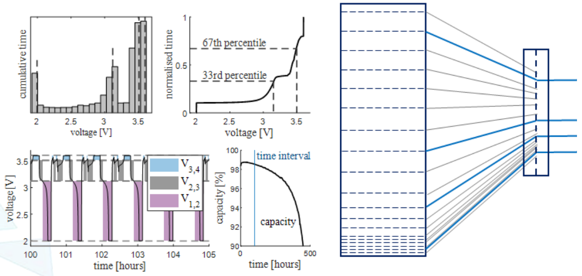
< 1



2 > Initial presentation of results



Detailed look at the automated techniques used



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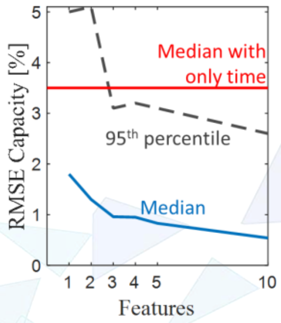
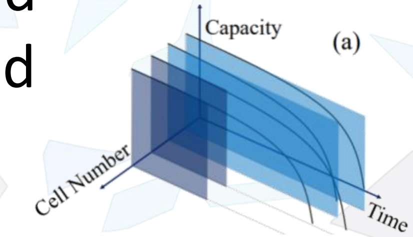
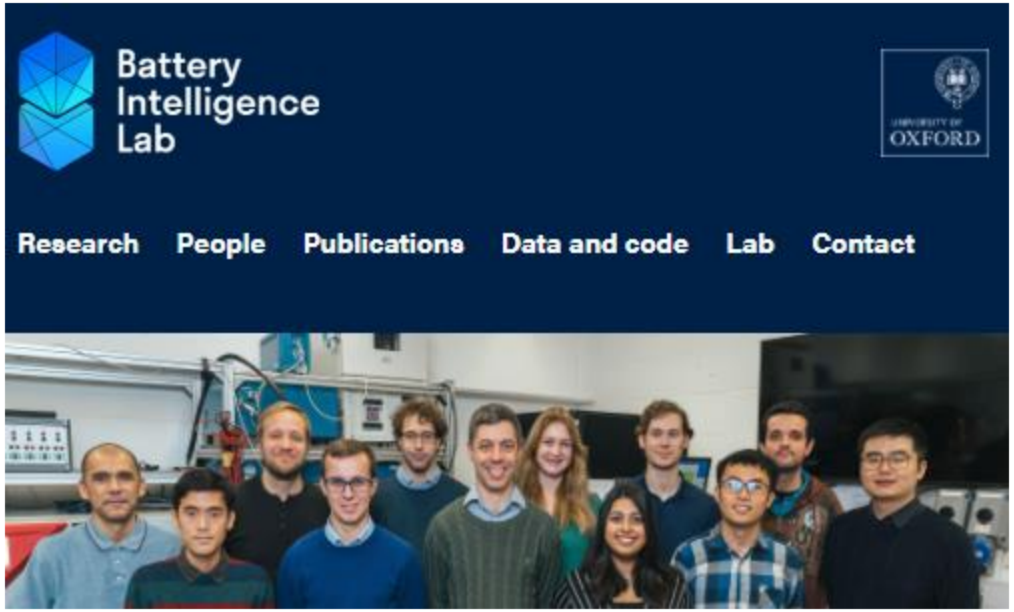


4 > Extended look at the performance of the automated approaches used





PhD focus: data-driven approaches for battery health

Journal of Power Sources 357 (2017) 209–219

Contents lists available at ScienceDirect

ELSEVIER

Journal of Power Sources

journal homepage: www.elsevier.com/locate/jpowsour

Gaussian process regression for forecasting battery state of health

Robert R. Richardson, Michael A. Osborne, David A. Howey*

Department of Engineering Science, University of Oxford, Oxford, UK

Journal of Energy Storage 23 (2019) 320–328

Contents lists available at ScienceDirect

ELSEVIER

Journal of Energy Storage

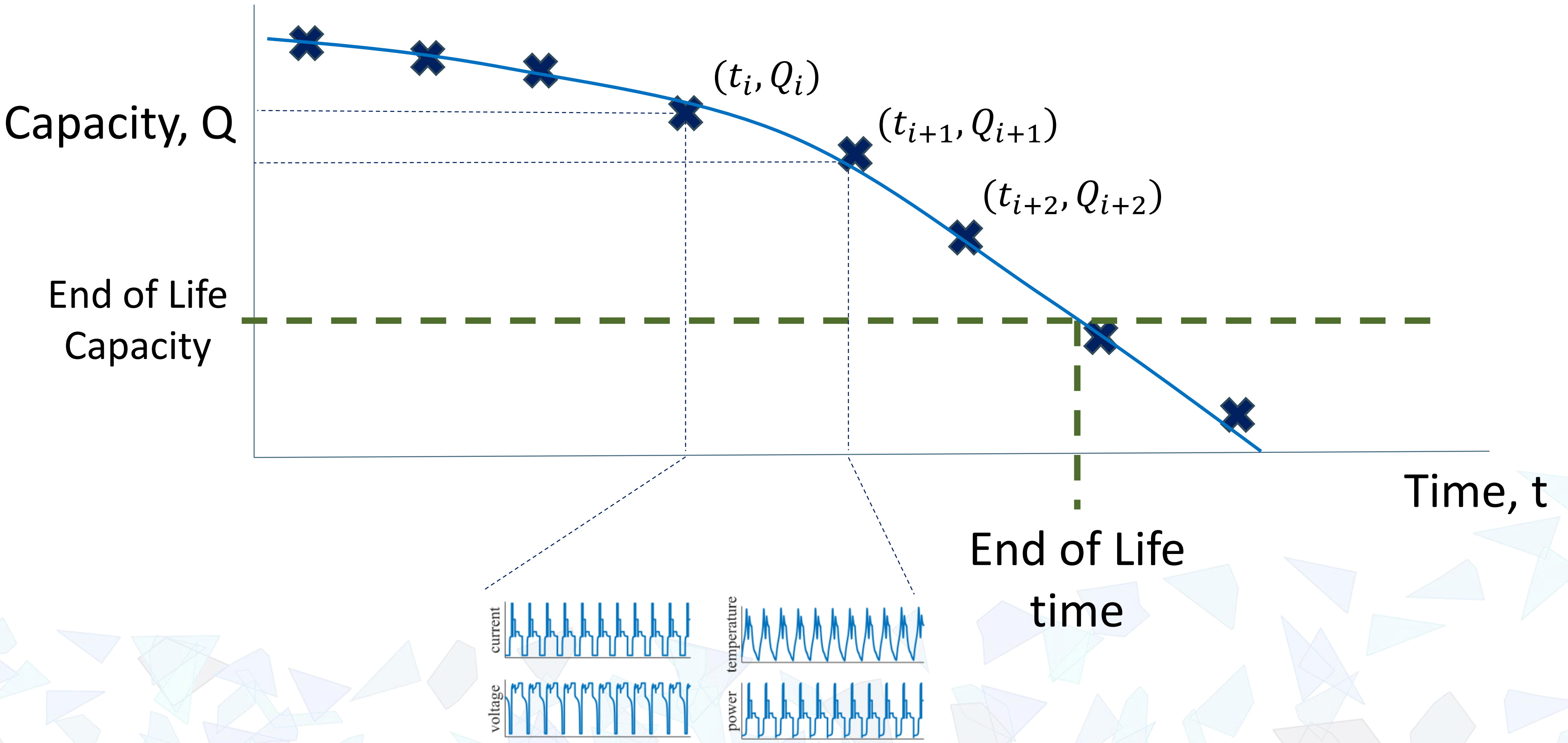
journal homepage: www.elsevier.com/locate/est

Battery health prediction under generalized conditions using a Gaussian process transition model

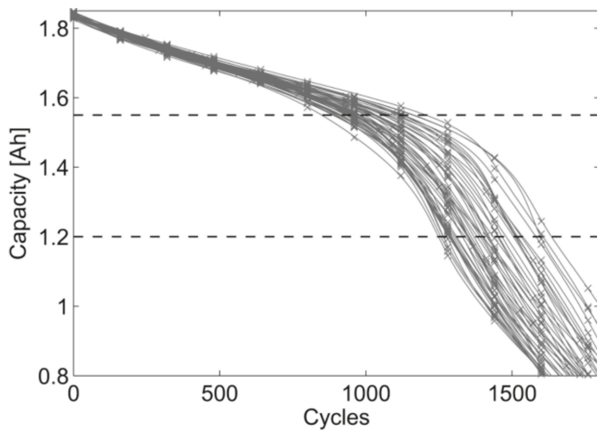
Robert R. Richardson, Michael A. Osborne, David A. Howey*

Department of Engineering Science, University of Oxford, Parks Road, Oxford, OX1 3PJ, United Kingdom

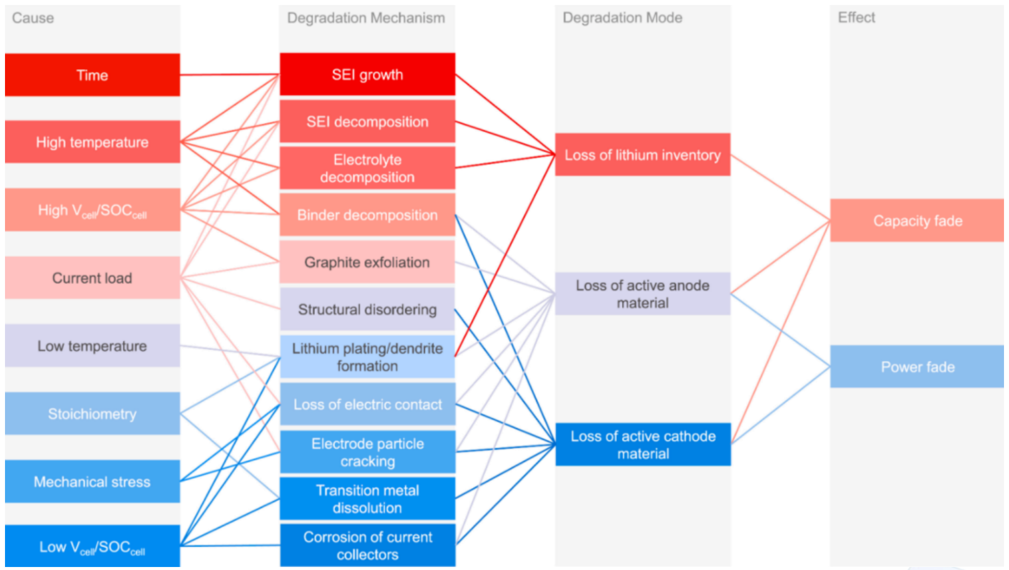
State of health, capacity and end of life



Muddle, couple, toil and trouble



Baumhöfer et al., "Production caused variation in capacity aging trend and correlation to initial cell performance," *Journal of Power Sources*, **247**, 332-338, 2014.



Birkl et al., "Degradation diagnostics for lithium ion cells," *Journal of Power Sources*, **341**, 373-386, 2017.

Particle filters

Neural Networks

Gaussian Process regression

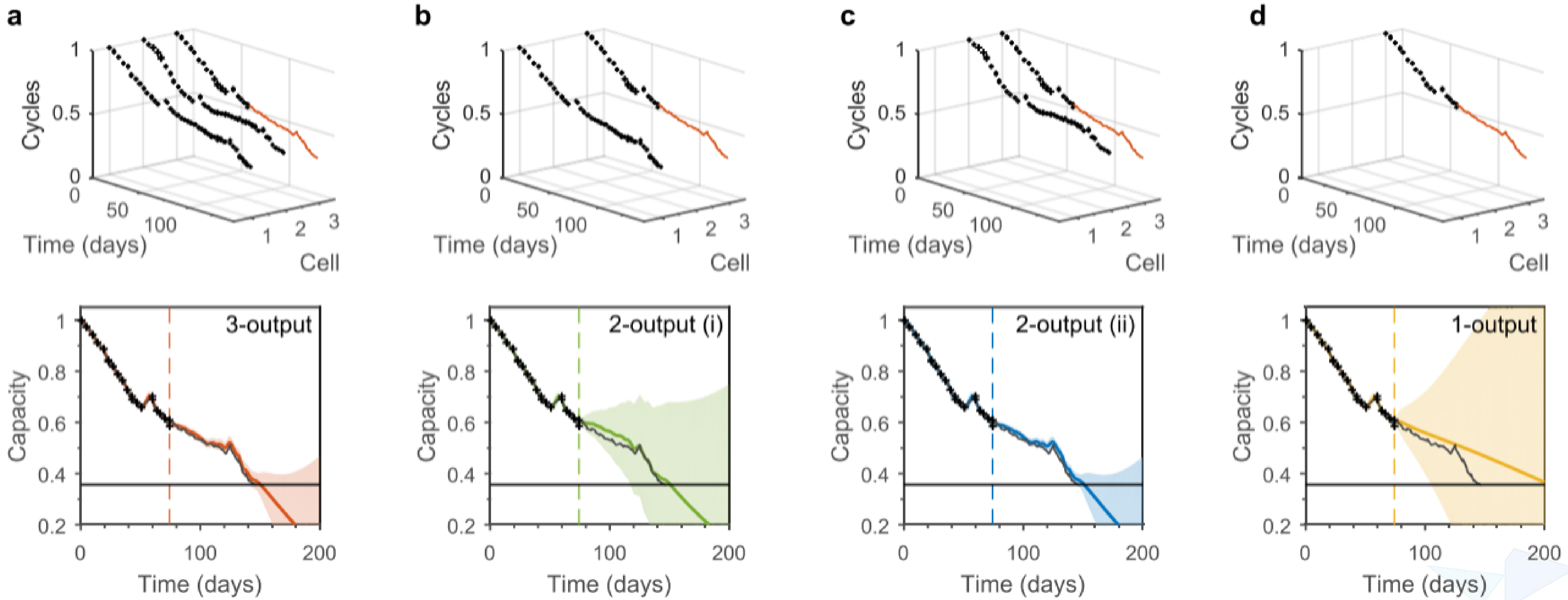
Relevance Vector Machines

Data-driven approaches have a problem.

As part of designing a given model of battery degradation, an engineer must make a decision over what shall be the input. In question form, that is "What causes the Li-ion battery to behave in that way?" However humans are prone to bias, and our understanding of battery degradation is insufficiently comprehensive to confidently map between use and capacity over an entire cell life. For data-driven techniques, this is especially critical. The performance of a given model will effectively be decided by the choice of inputs, a choice which we are very likely to get wrong. If that probable wrong decision is made, then the results will be poor. The results will be especially poor the further you push your test set from any training data.

or…

Garbage in ➔ Garbage out



$$(a) \approx (c)+(b)$$
$$\approx (c)$$
$$> (b)$$
$$>> (d)$$

So how to forecast the “knee”?

Energy and AI 1 (2020) 100006

Contents lists available at ScienceDirect

Energy and AI

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ELSEVIER

Identification and machine learning prediction of knee-point and knee-onset in capacity degradation curves of lithium-ion cells

Paula Fermín-Cueto[a], Euan McTurk[b], Michael Allerhand[a], Encarni Medina-Lopez[c], Miguel F. Anjos[a], Joel Sylvester[b], Gonçalo dos Reis[a,d,*]

energies

MDPI

Article

Algorithm to Determine the Knee Point on Capacity Fade Curves of Lithium-Ion Cells

Weiping Diao *, Saurabh Saxena, Bongtae Han and Michael Pecht

Journal of Power Sources 360 (2017) 28–40

Contents lists available at ScienceDirect

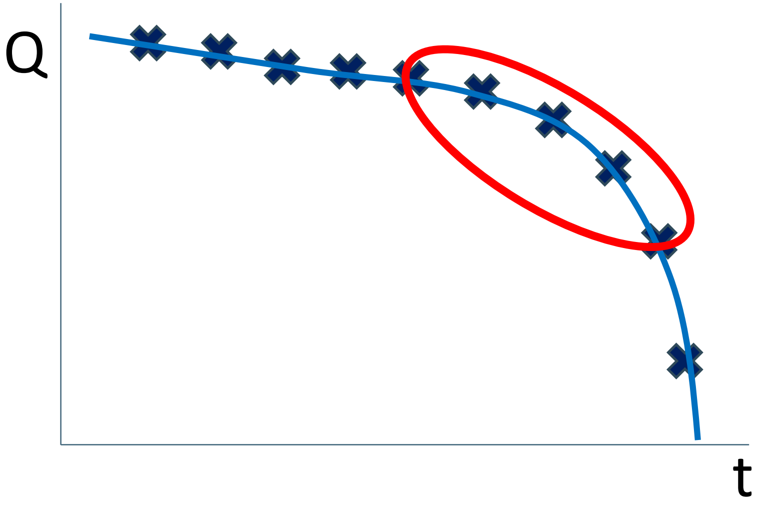
Journal of Power Sources

journal homepage: www.elsevier.com/locate/jpowsour

ELSEVIER

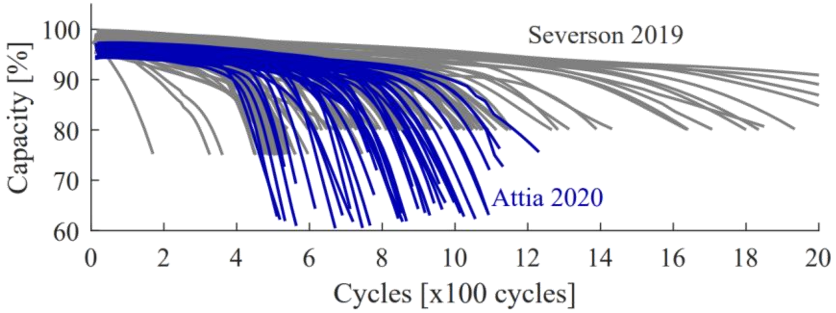
Modeling of lithium plating induced aging of lithium-ion batteries: Transition from linear to nonlinear aging

Xiao-Guang Yang[a,*], Yongjun Leng[a], Guangsheng Zhang[a], Shanhai Ge[b], Chao-Yang Wang[a,b,**]



(t_{knee}, Q_{knee}) ???

Good results were achieved by prioritising work on the inputs



nature energy
ARTICLES
https://doi.org/10.1038/s41560-019-0356-8

Data-driven prediction of battery cycle life before capacity degradation

Kristen A. Severson[1,5], Peter M. Attia[2,5], Norman Jin[2], Nicholas Perkins[2], Benben Jiang[1], Zi Yang[2], Michael H. Chen[2], Muratahan Aykol[3], Patrick K. Herring[3], Dimitrios Fraggedakis[1], Martin Z. Bazant[1], Stephen J. Harris[2,4], William C. Chueh[2]* and Richard D. Braatz[1]*

Article

Closed-loop optimization of fast-charging protocols for batteries with machine learning

https://doi.org/10.1038/s41586-020-1994-5
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Peter M. Attia[1,7], Aditya Grover[2,7], Norman Jin[1], Kristen A. Severson[3], Todor M. Markov[2], Yang-Hung Liao[1], Michael H. Chen[1], Bryan Cheong[1,2], Nicholas Perkins[1], Zi Yang[1], Patrick K. Herring[4], Muratahan Aykol[4], Stephen J. Harris[1,5], Richard D. Braatz[3], Stefano Ermon[2] & William C. Chueh[1,6]

Median results

Root mean square error of capacity:	0.83%
End of Life time prediction error:	1.3%
Time of knee point prediction error:	2.6%

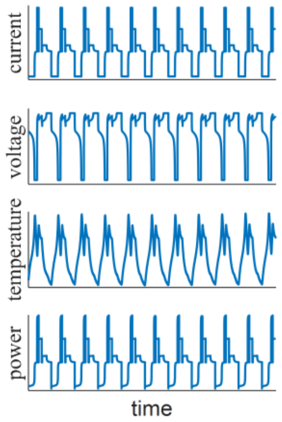
Battery Intelligence Lab
University of Oxford

Severson 2019: Severson et al., *"Data-driven … degradation,"* Nature Energy, vol. 4, pp. 383--391, 2019.
Attia 2020: Attia et al., *"Closed-loop … learning,"* Nature, vol. 578, pp. 397--402, 2020.

Automating feature generation and selection

How to produce a set of model inputs that reflect the range of use in a data set but are sensitive the variability of battery degradation.

We propose to automate the process prior to modelling.



Raw use data

Find model inputs

Data-driven degradation model

Severson 2019: Severson et al., *“Data-driven … degradation,''*
Nature Energy, vol. 4, pp. 383--391, 2019.

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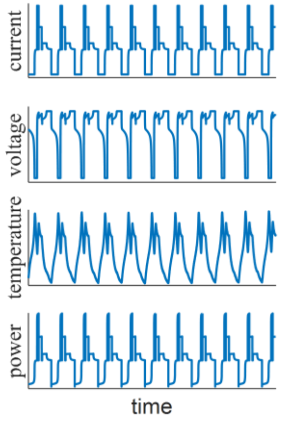
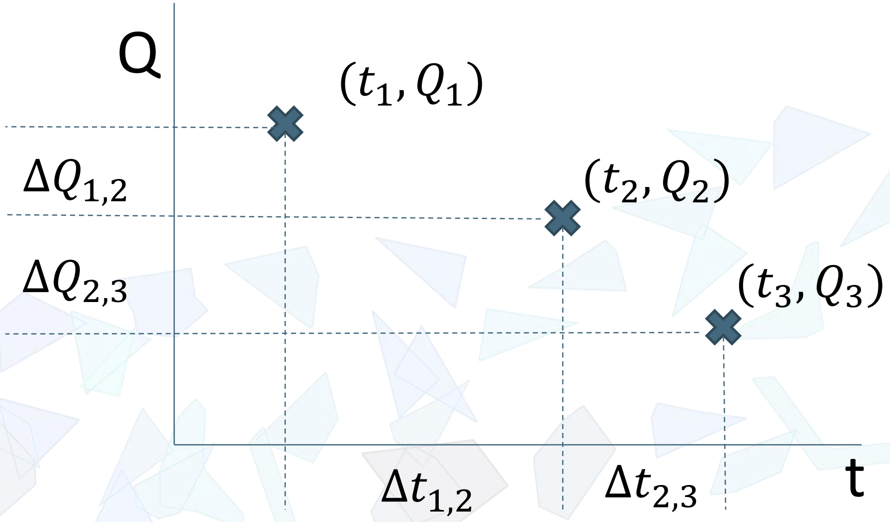


Raw use data

→ Find model inputs → Capacity transition model



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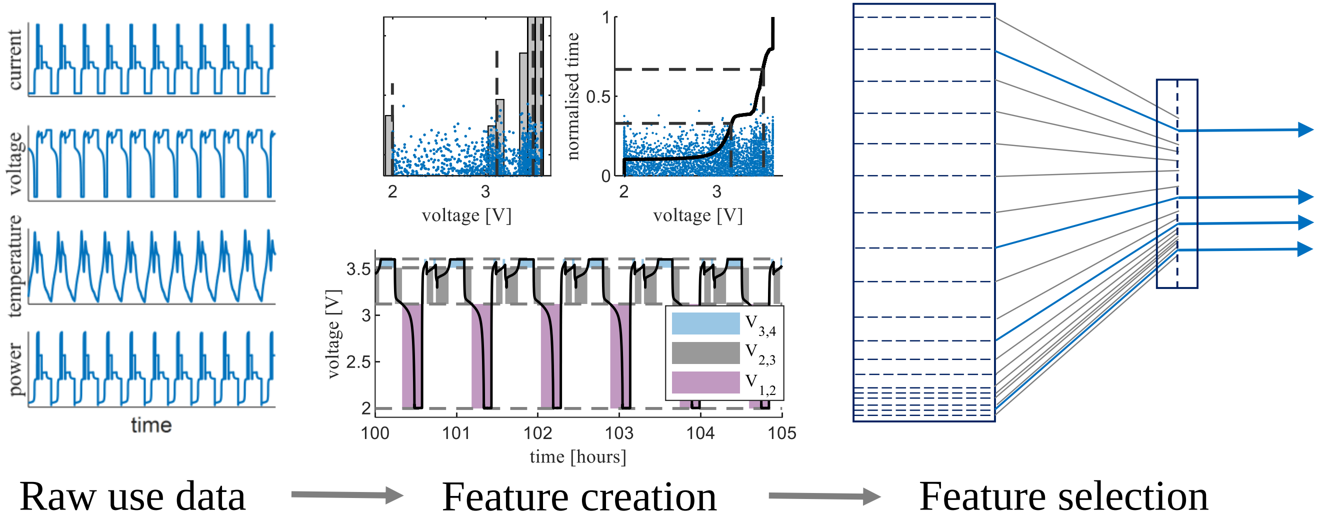
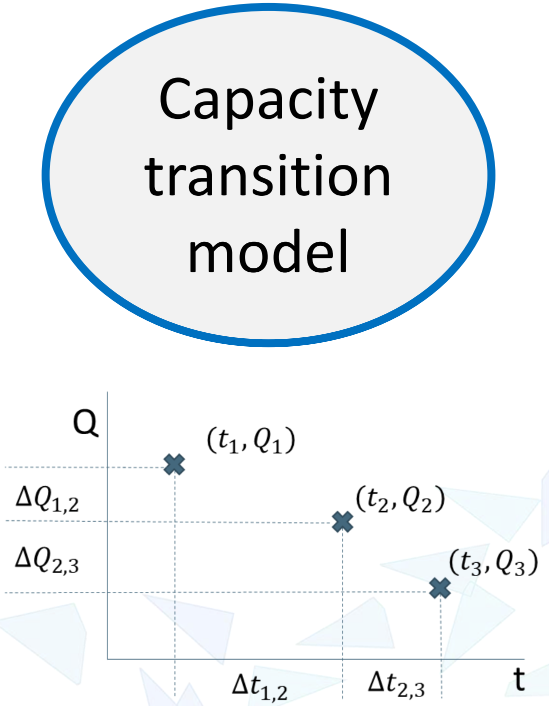
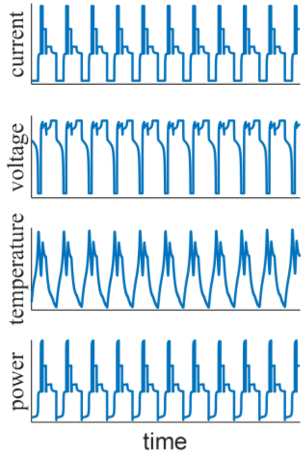
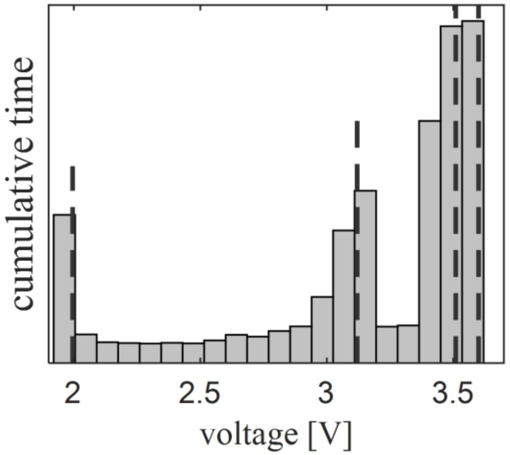


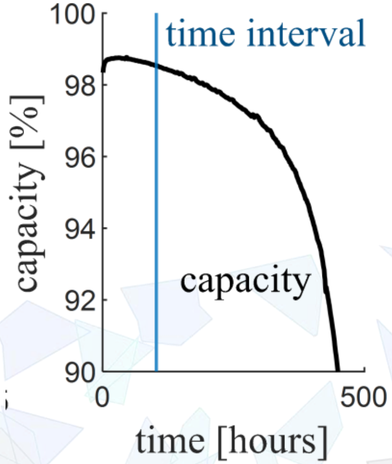


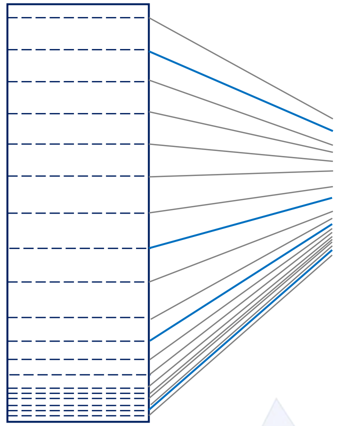
Severson 2019: Severson et al., *"Data-driven … degradation,"*
Nature Energy, vol. 4, pp. 383--391, 2019.

Model inputs (features) are calculated based on time spent in different regions.









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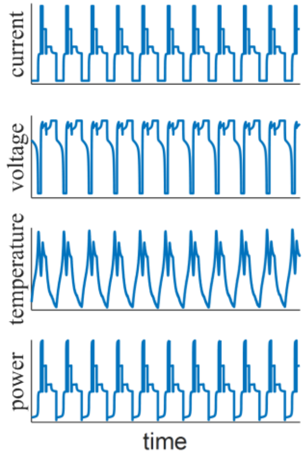

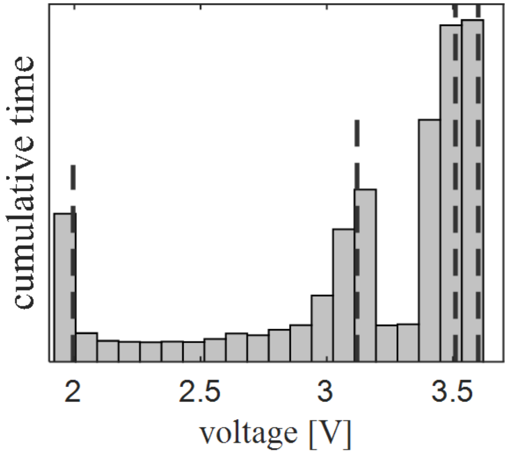

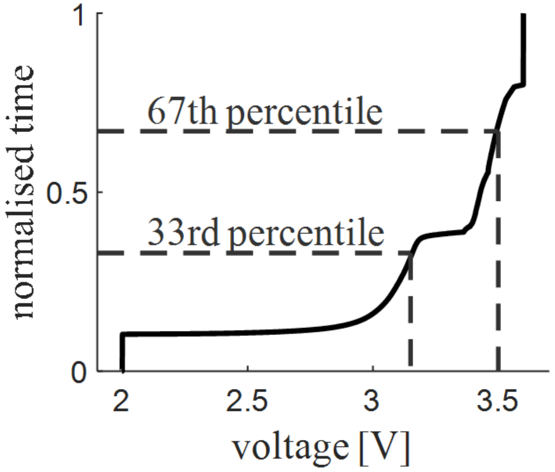

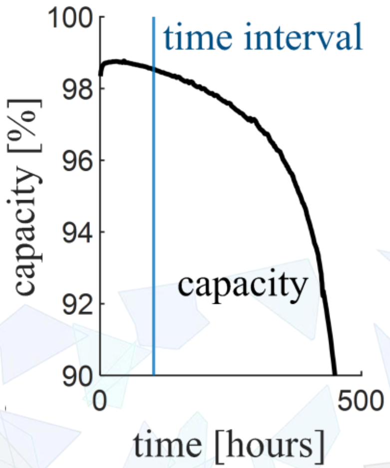

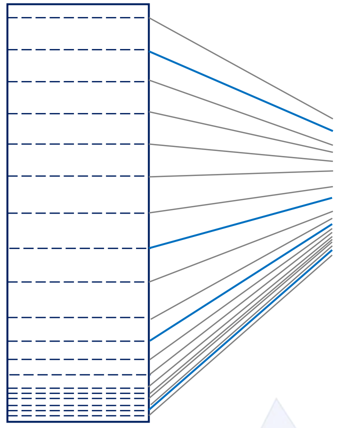

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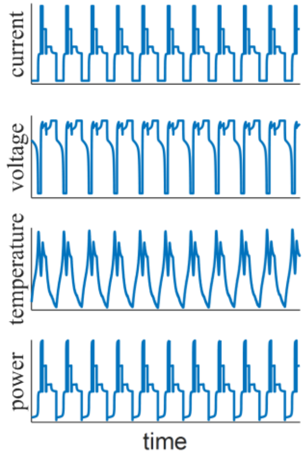
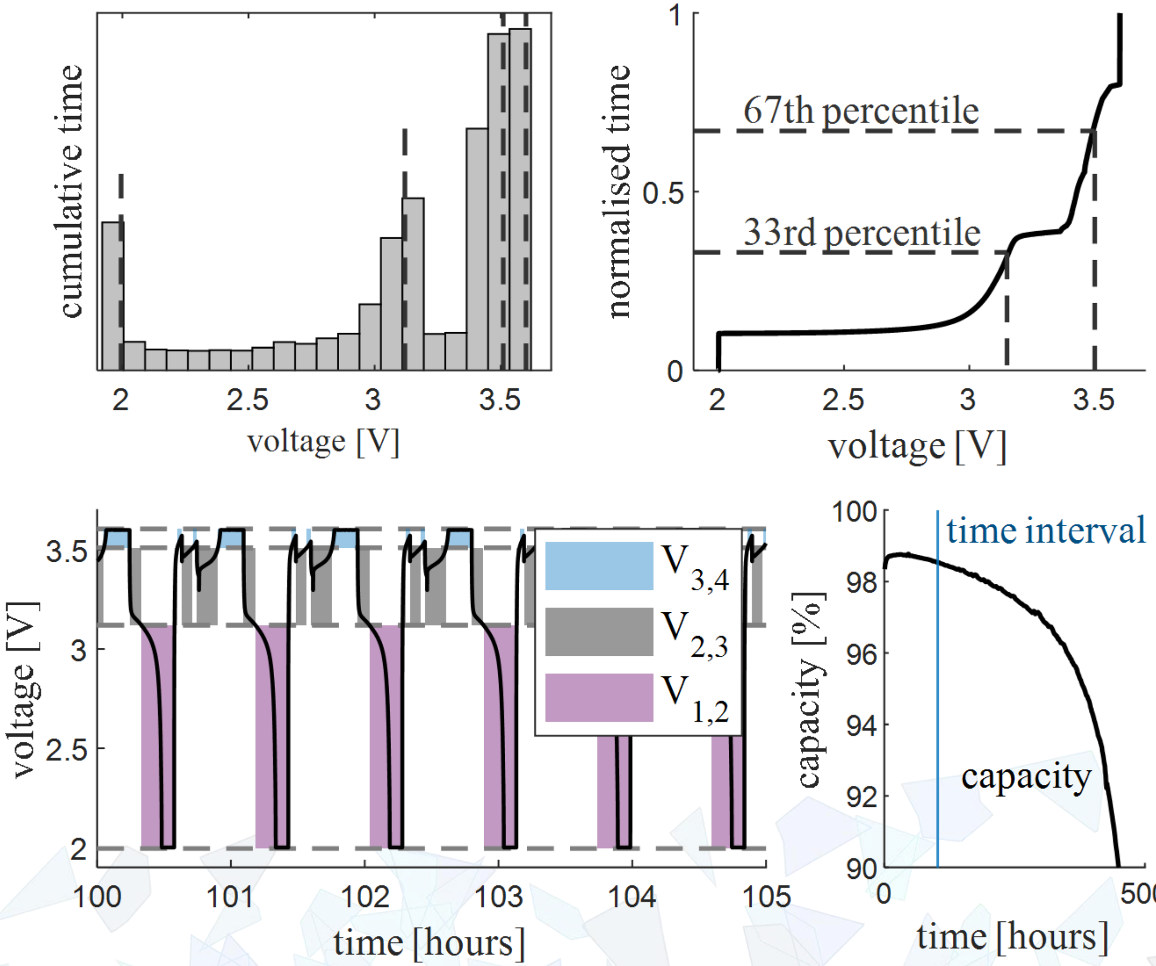
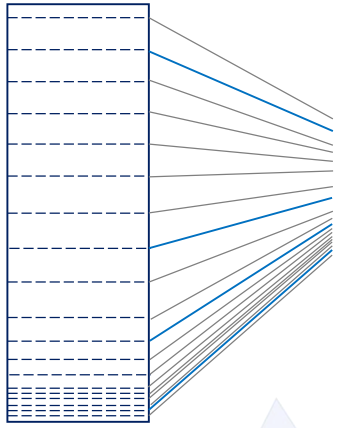




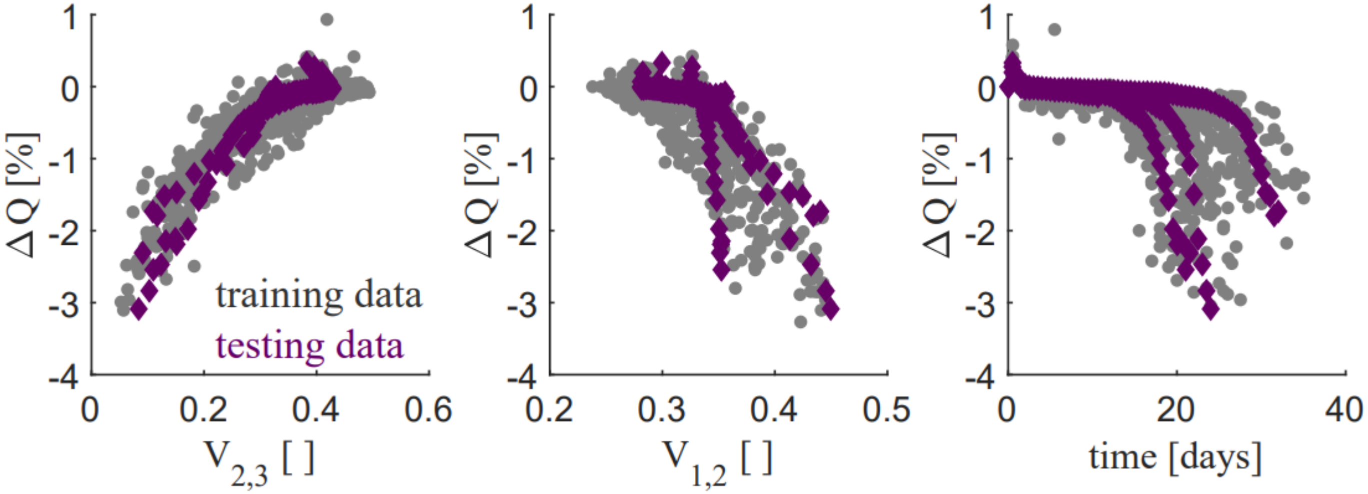


Severson 2019: Severson et al., *"Data-driven … degradation,"*
Nature Energy, vol. 4, pp. 383--391, 2019.

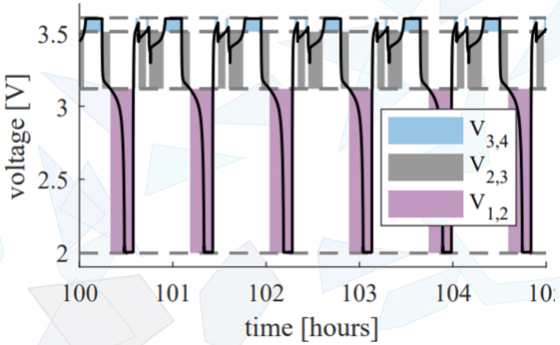
Pearson's rank produces a reliable set of inputs.

	time	$V_{2,3}$	$T_{1,4}$	$V_{1,2}$	$I_{2,3}$	$P_{2,4}$	ΔQ
time	1	0.59	0.09	0.58	0.17	0.28	0.69
$V_{2,3}$	0.59	1	0.04	0.88	0.44	0.16	0.85
$T_{1,4}$	0.09	0.04	1	0.12	0.38	0.43	0.12
$V_{1,2}$	0.58	0.88	0.12	1	0.18	0.01	0.79
$I_{2,3}$	0.17	0.44	0.38	0.18	1	0.86	0.11
$P_{2,4}$	0.28	0.16	0.43	0.01	0.86	1	0.09

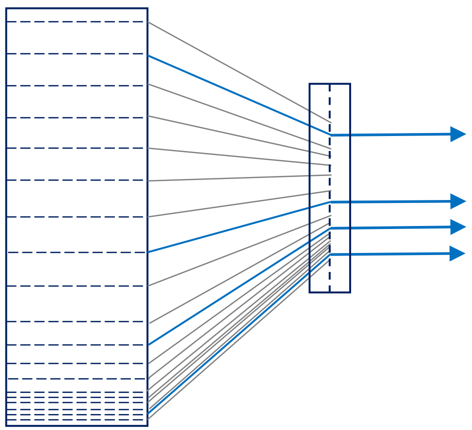
Correlation matrix

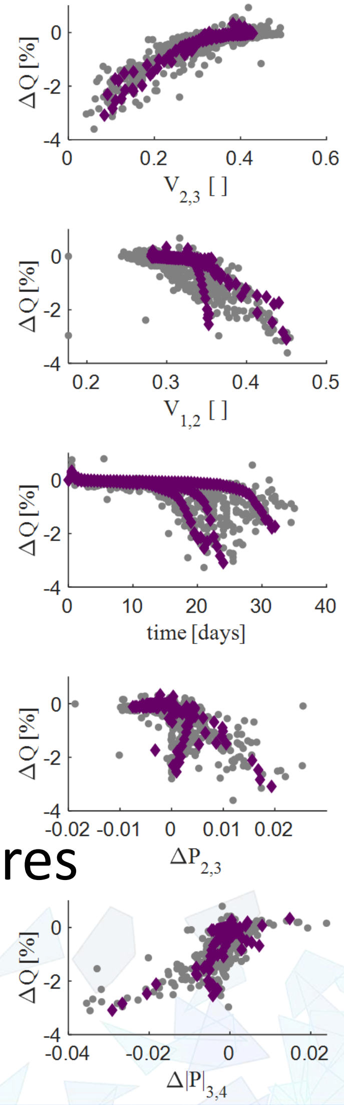


Selected features



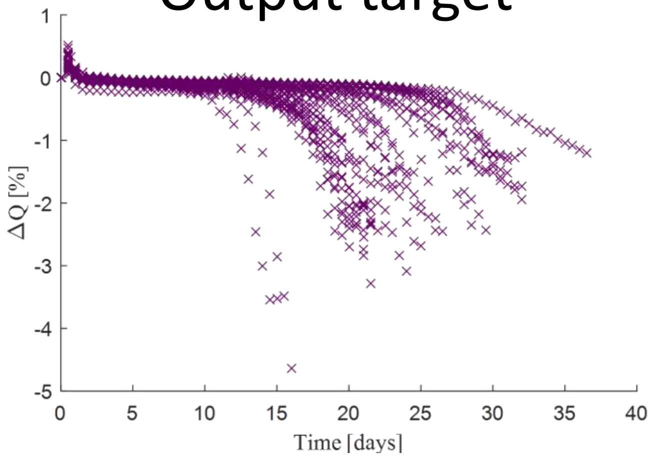
5 varied features can then be passed to the degradation model





Input features

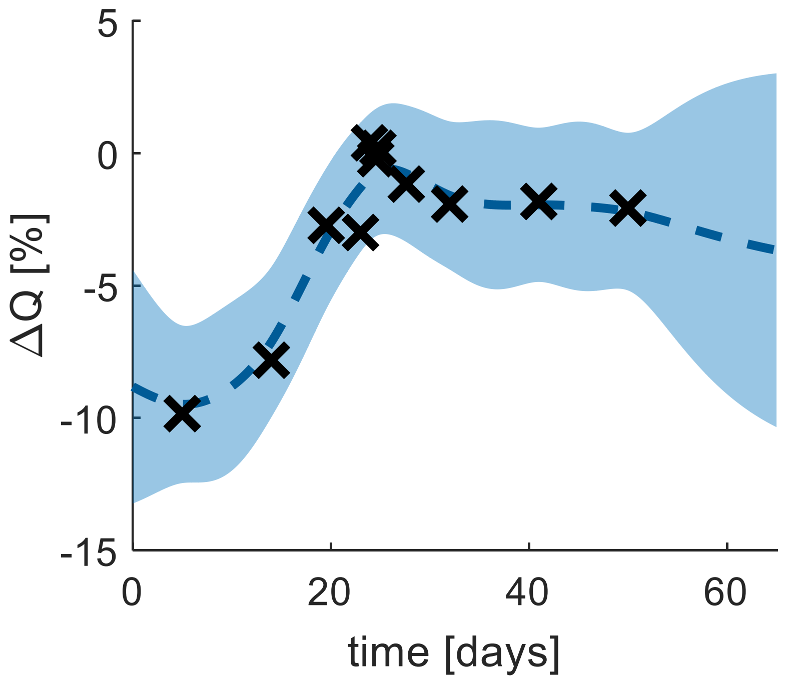
Output target



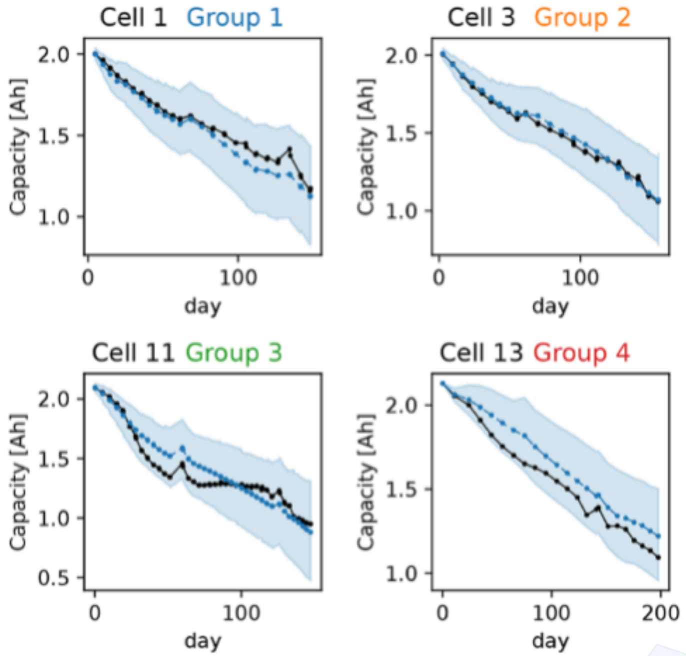
Data-driven degradation model

Gaussian processes are known to be effective for batteries.

Data-driven degradation model

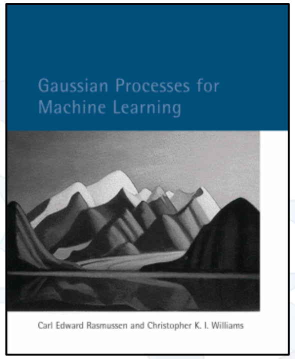


Transition model



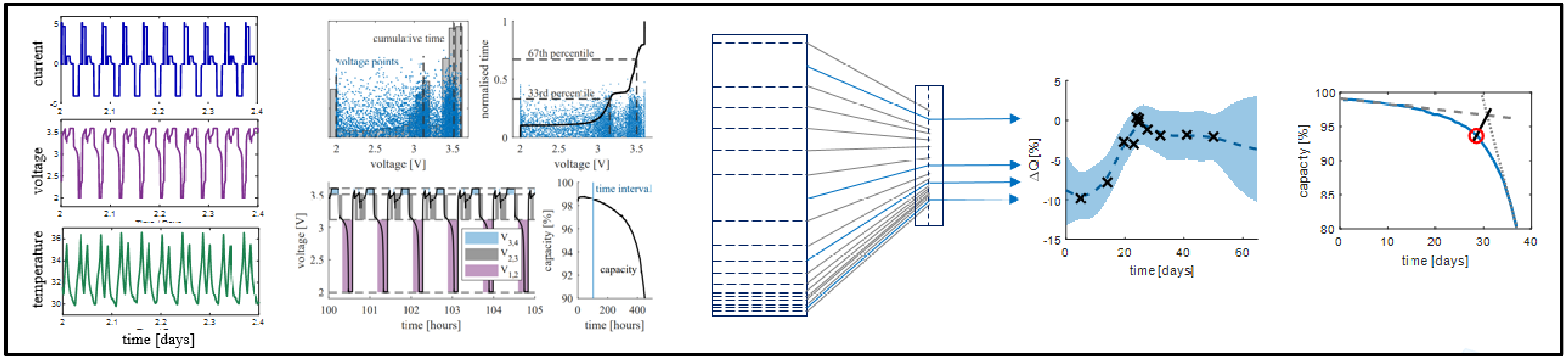
Richardson et al., *"Battery … model"*, Journal of Energy Storage, **vol. 23**, pp. 320-328, 2019

Capacity forecast



Gaussian processes for machine learning, Rasmussen and Williams, 2006.

Testing

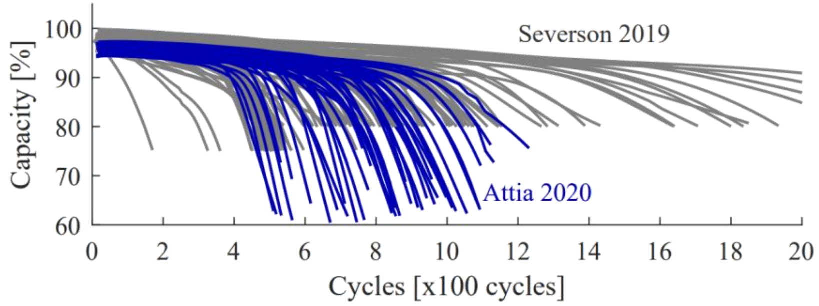


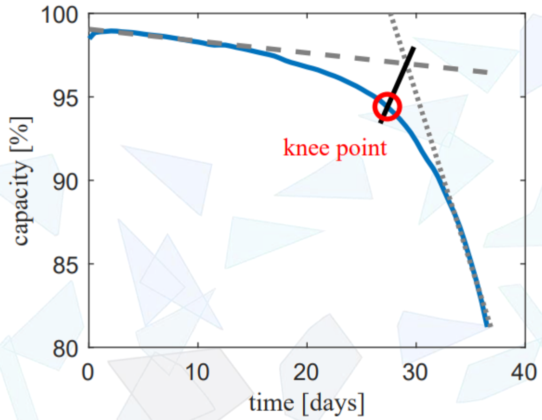
100 training cells
30 test cells
Repeat 20 times

600 trials

Raw variables: current, voltage, temperature, absolute current, power, absolute power
Percentiles: 1st, 33rd, 67th, 99th

147 cells in total from Severson 2019 and Attia 2020





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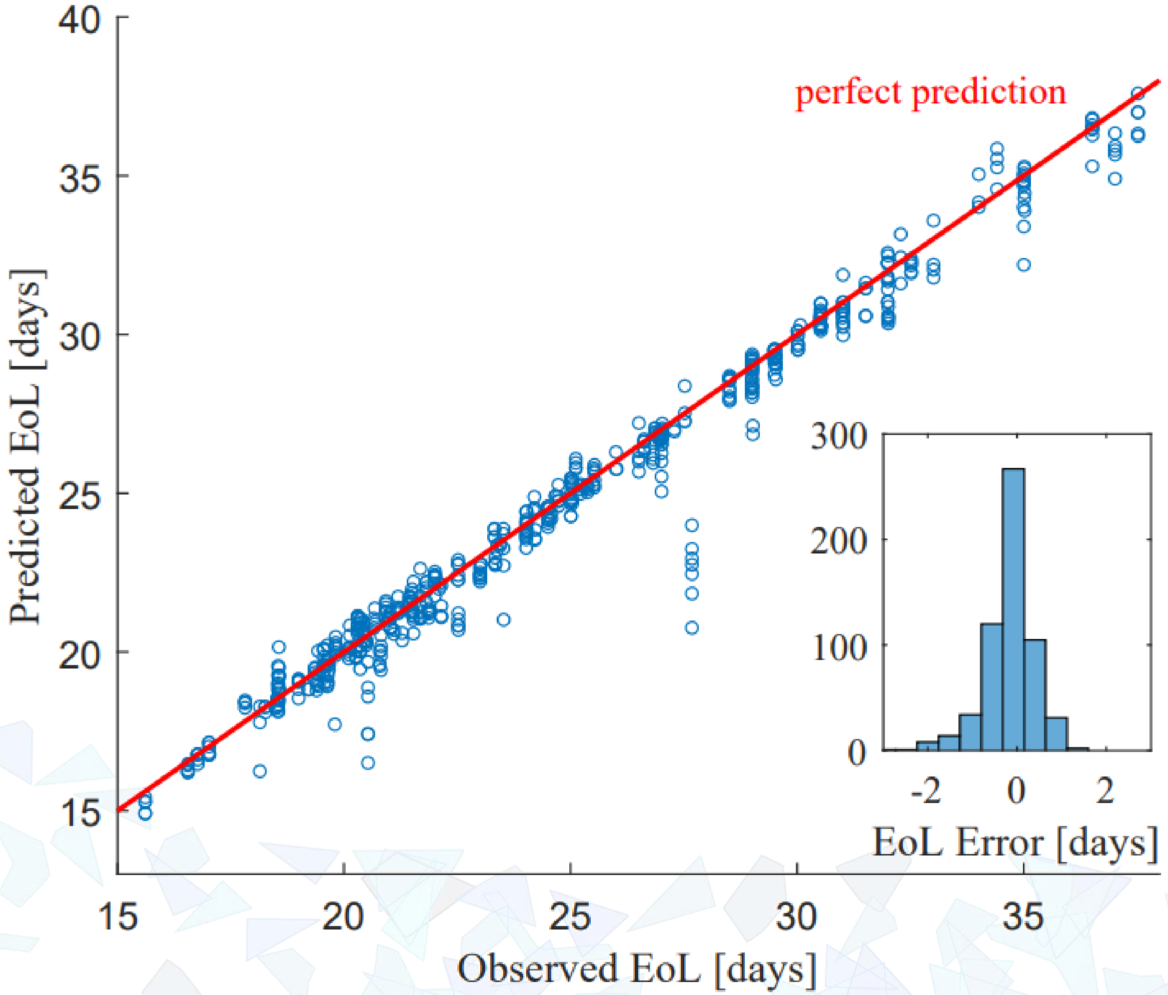
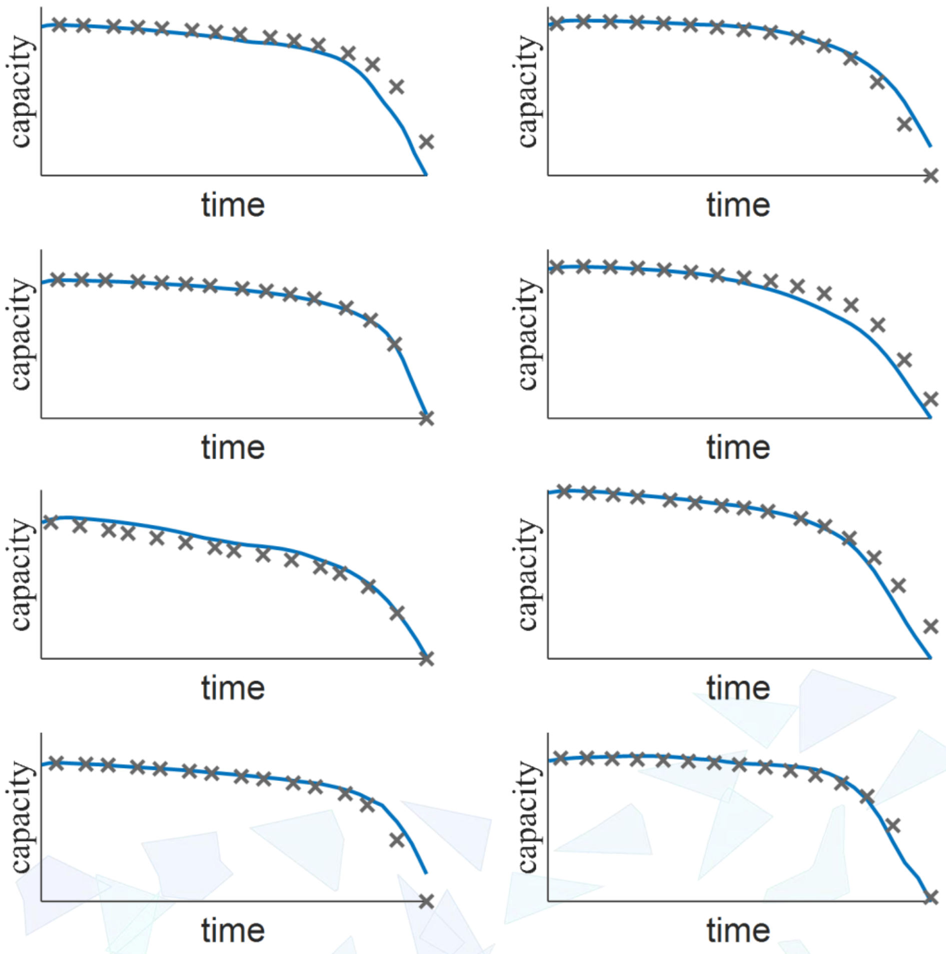
Attia 2020: Attia et al., *“Closed-loop … learning,"* Nature, vol. 578, pp. 397--402, 2020.

End of life scatter

Measured capacity

Predicted capacity





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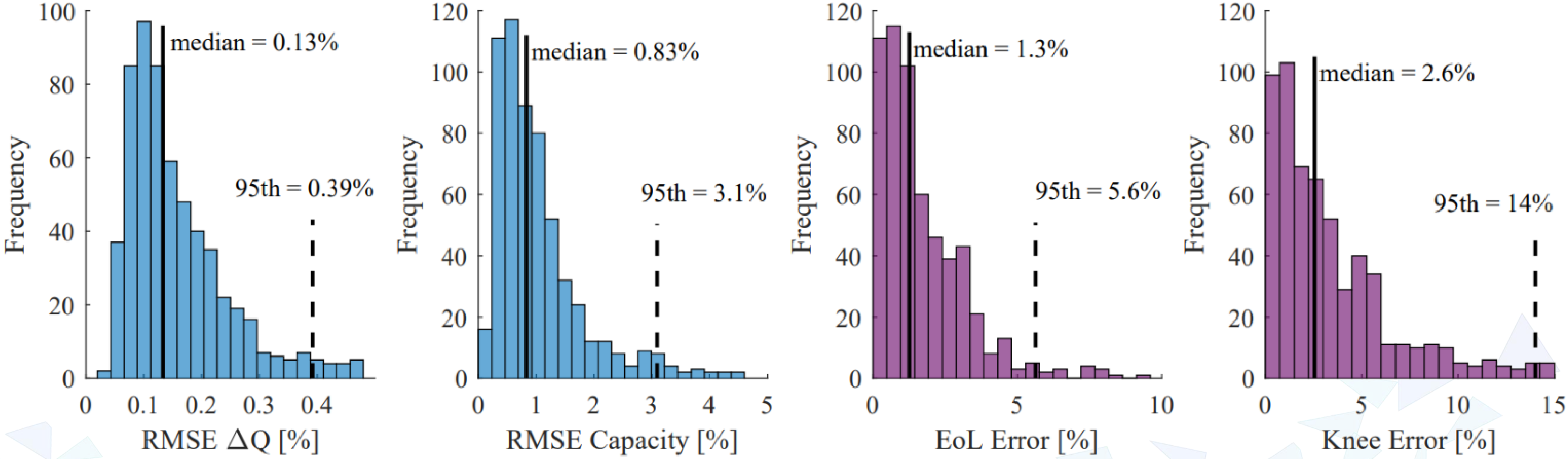
Attia 2020: Attia et al., *"Closed-loop … learning,"* Nature, vol. 578, pp. 397--402, 2020.

We see tight profiles and consistent knee forecasts.



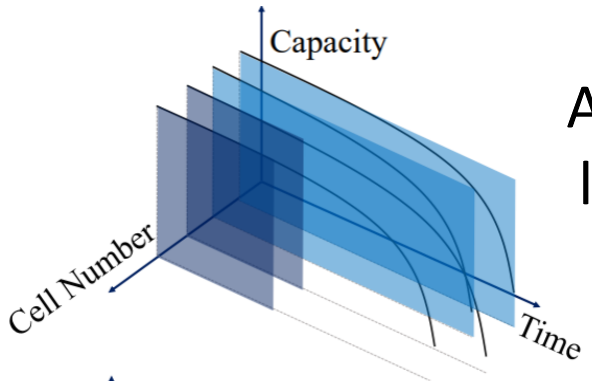
Model performance

Capacity accuracy

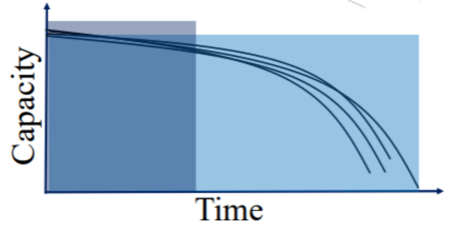
Lifetime estimation
(Mean = 2.0%)

Knee point forecasts

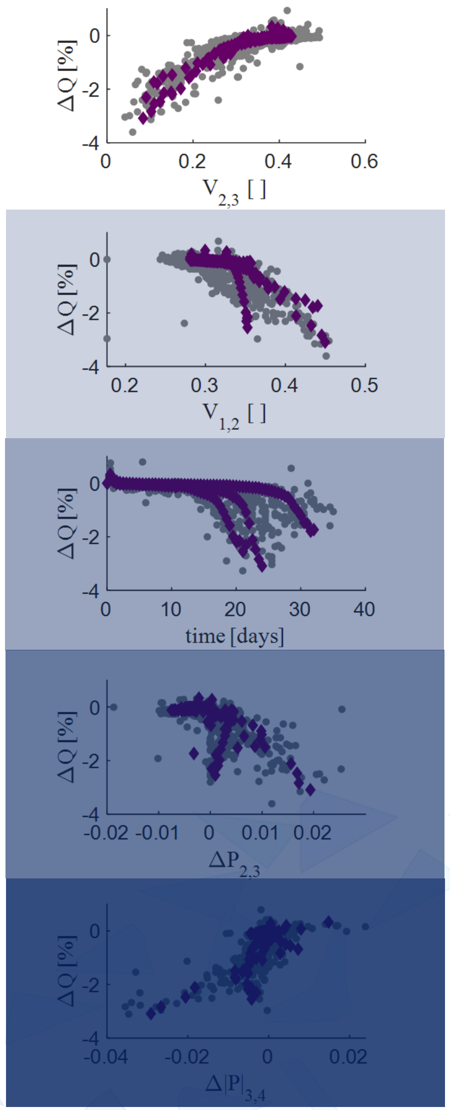
Severson 2019: Severson et al., *"Data-driven … degradation,"* Nature Energy, vol. 4, pp. 383--391, 2019.
Attia 2020: Attia et al., *"Closed-loop … learning,"* Nature, vol. 578, pp. 397--402, 2020.



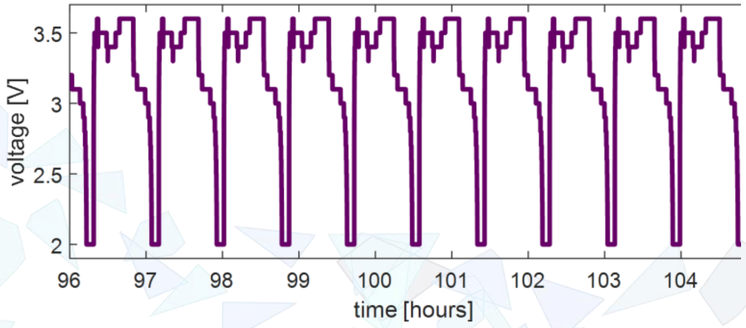
Availability of late-life data



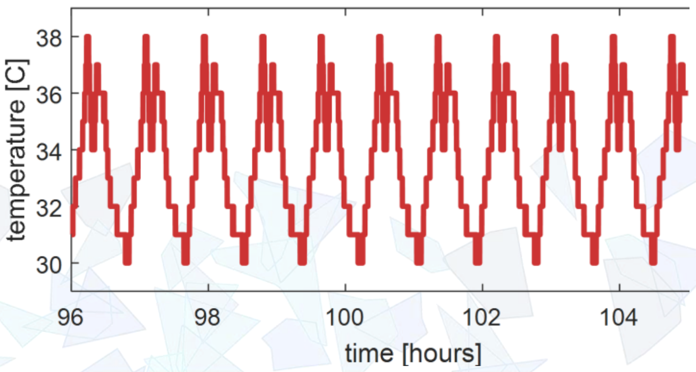
Number of features



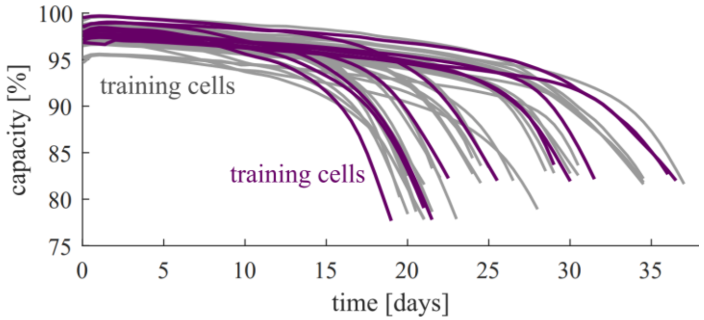
How to test further?

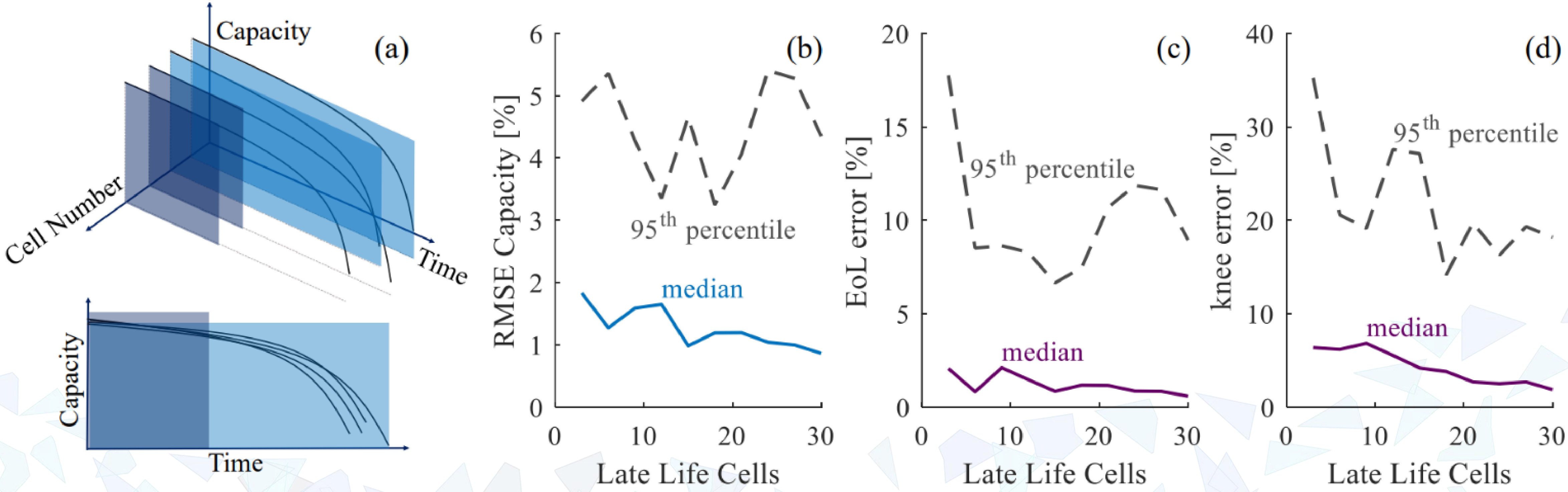


Precision of input



Whole process coped with reduced late-life data





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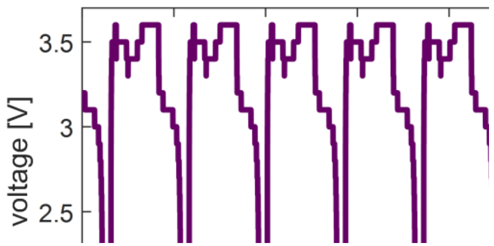
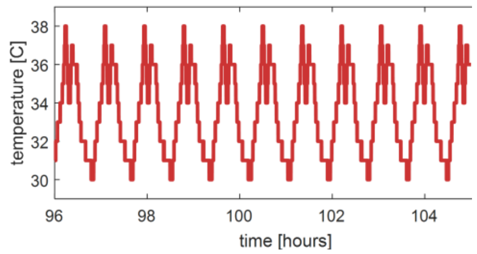
Attia 2020: Attia et al., *"Closed-loop … learning,"* Nature, vol. 578, pp. 397--402, 2020.

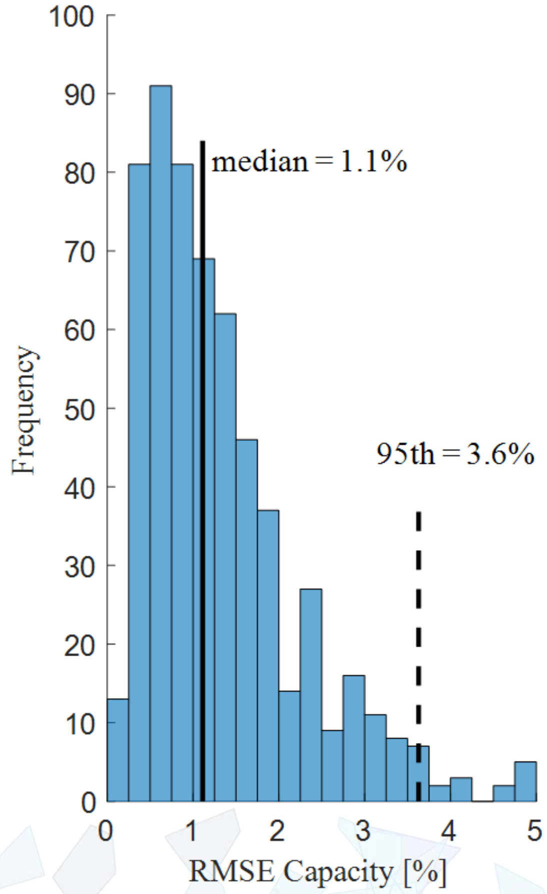
50 training cells, but rounded raw data

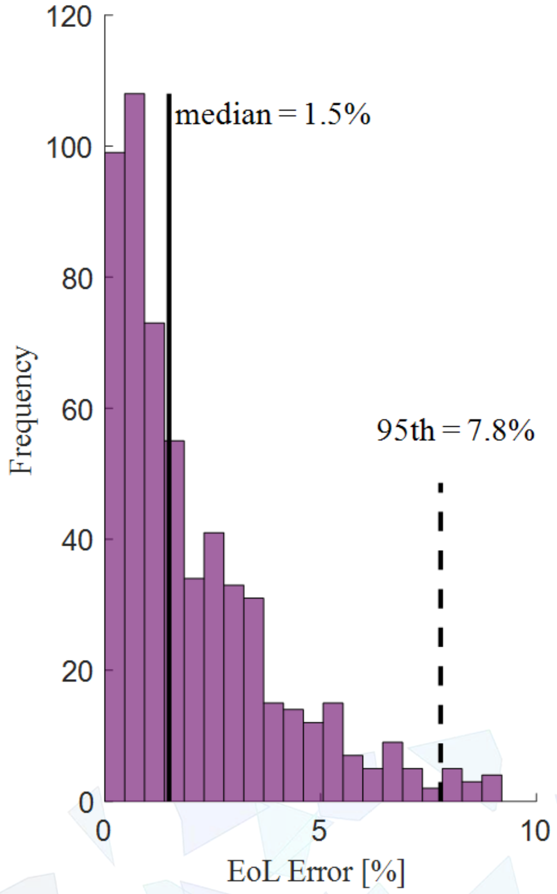


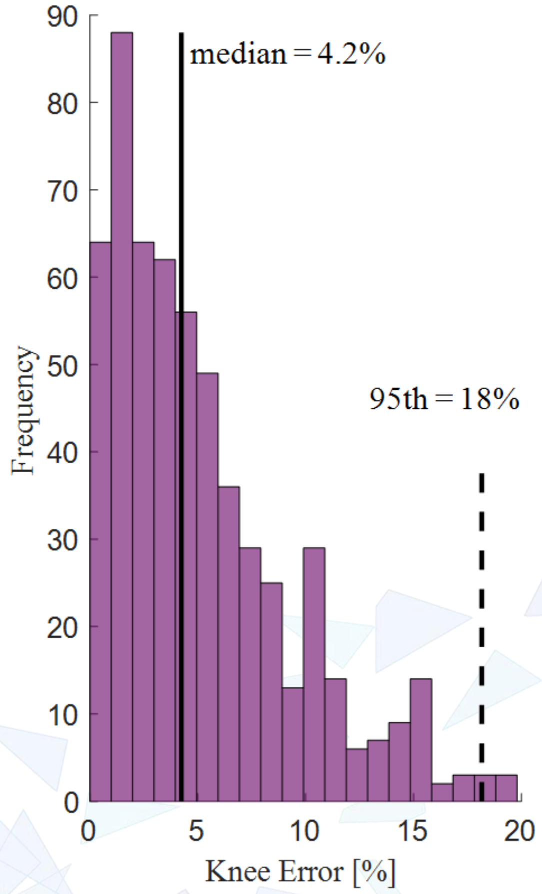


Rounding current and temperature to integers and voltage to 2 s.f.

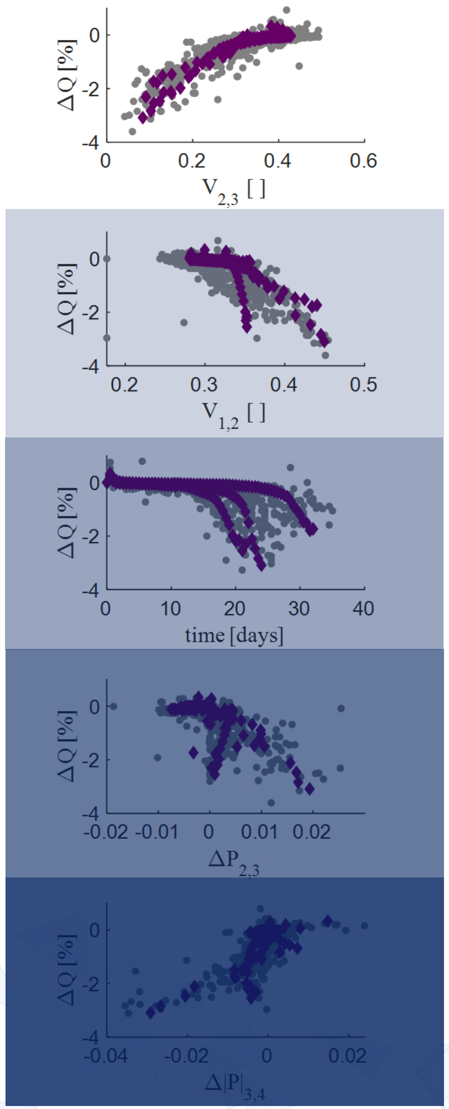
Still fairly successful for EoL estimation, but higher degradation rates were poorly predicted.



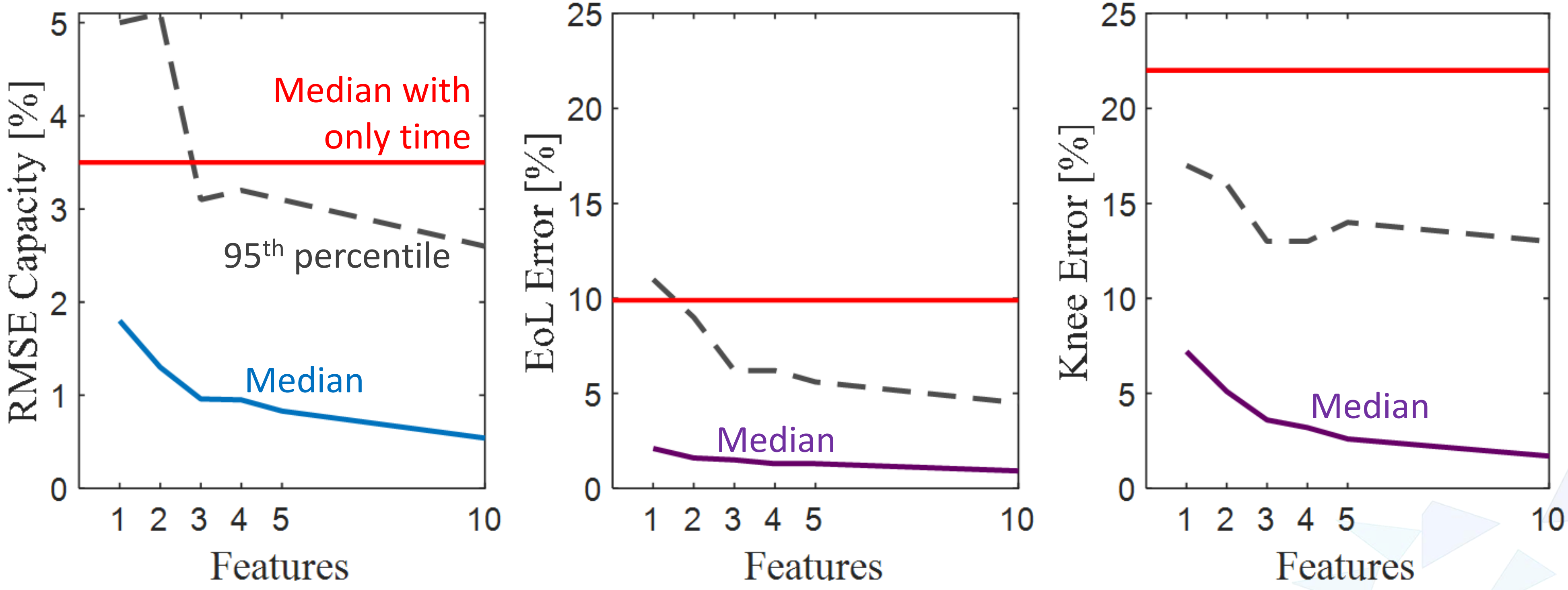




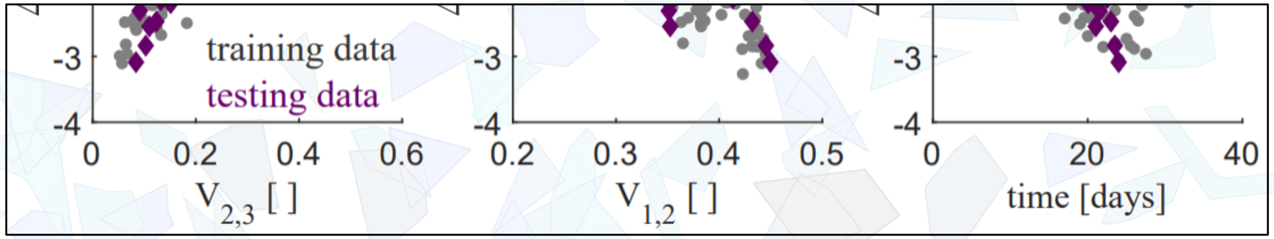
Severson 2019: Severson et al., *"Data-driven … degradation,"* Nature Energy, vol. 4, pp. 383--391, 2019.
Attia 2020: Attia et al., *"Closed-loop … learning,"* Nature, vol. 578, pp. 397--402, 2020.



Automated approach is quite robust to reducing features.

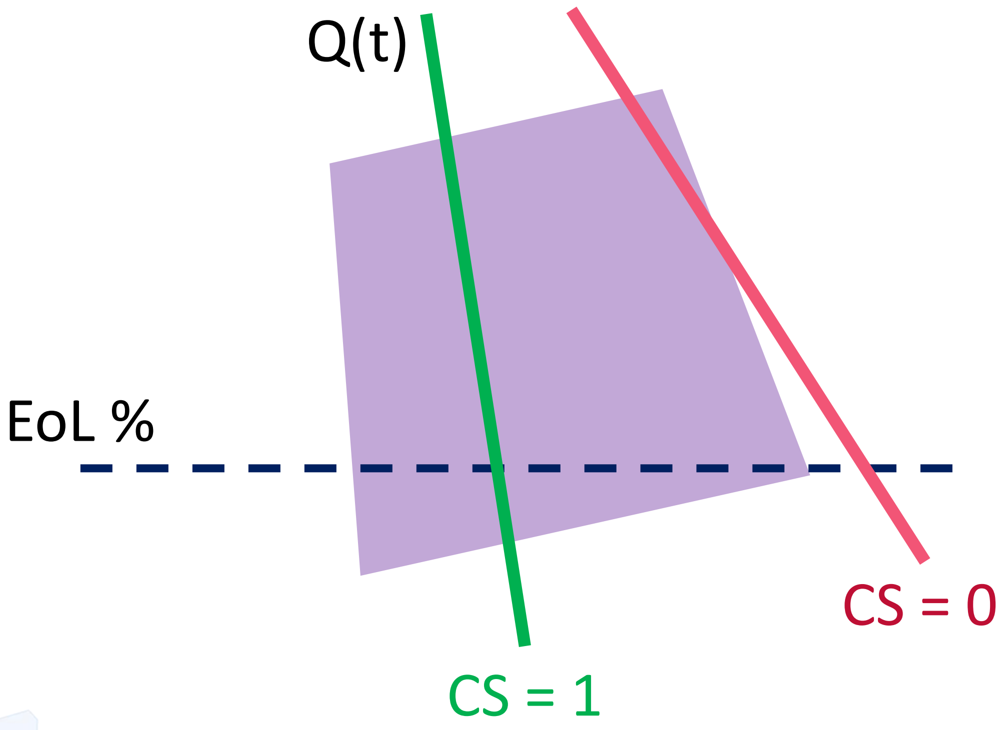


Most common selection of three inputs:

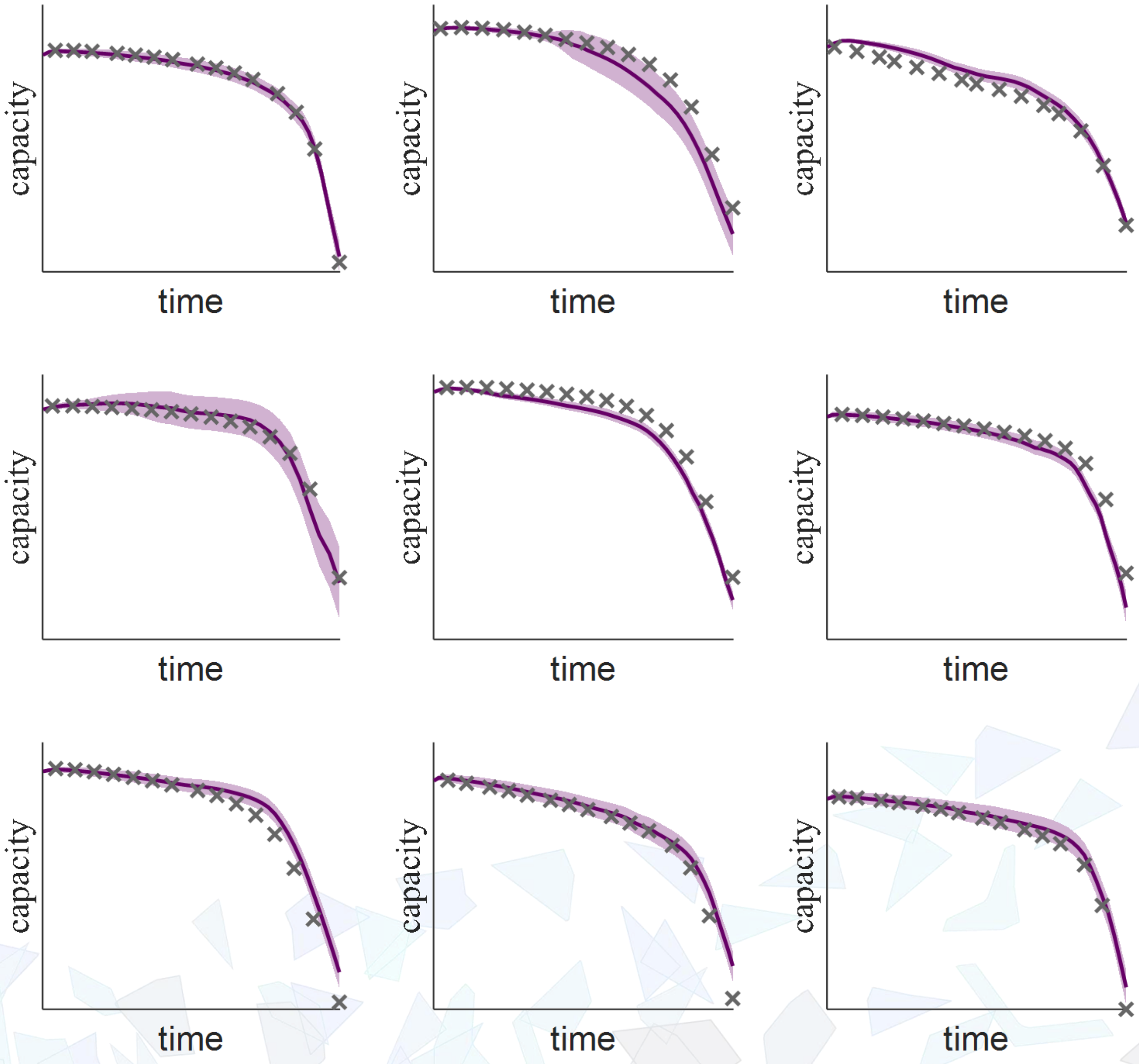


Severson 2019: Severson et al., *"Data-driven … degradation,"* Nature Energy, vol. 4, pp. 383--391, 2019.
Attia 2020: Attia et al., *"Closed-loop … learning,"* Nature, vol. 578, pp. 397--402, 2020.

What about credible intervals?

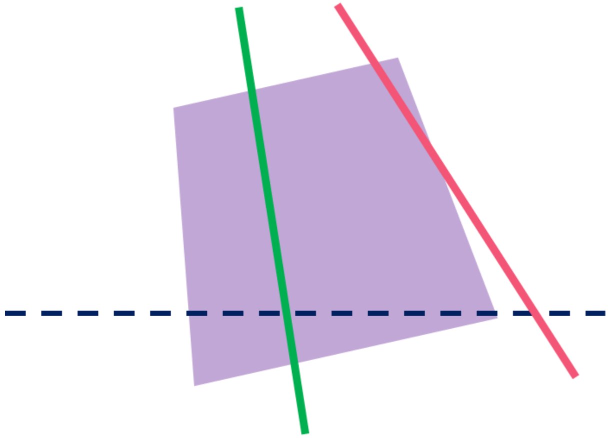


Calibration score (CS) for EoL = 0.75

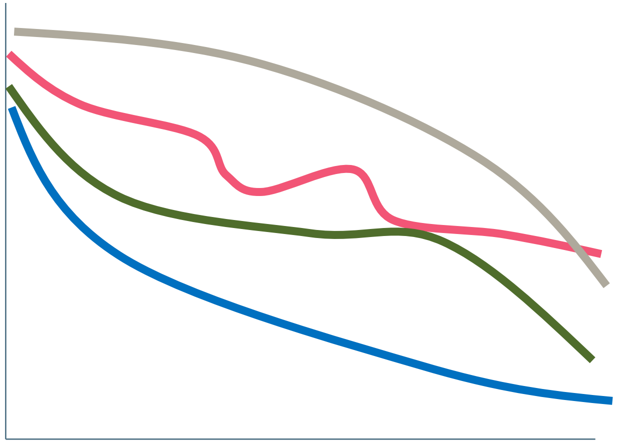


Severson 2019: Severson et al., *"Data-driven … degradation,"* Nature Energy, vol. 4, pp. 383--391, 2019.
Attia 2020: Attia et al., *"Closed-loop … learning,"* Nature, vol. 578, pp. 397--402, 2020.

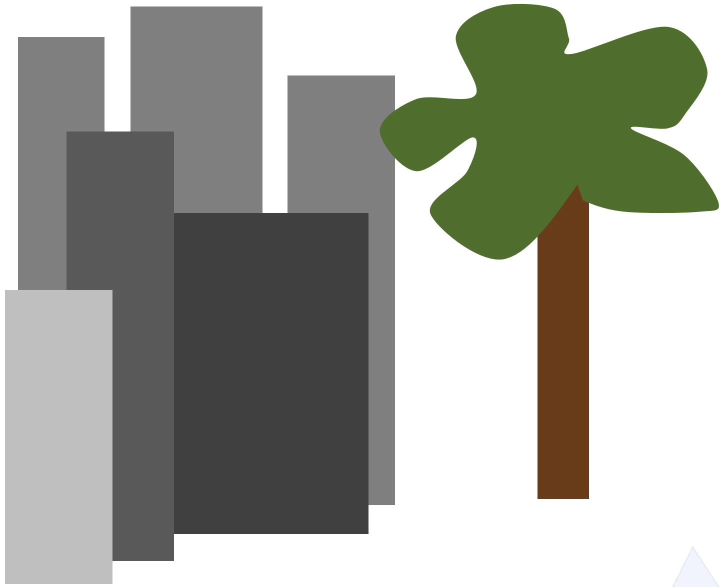
Where do we go from here?



End of life and capacity confidence



More data sets



The real world?

Thank you for listening

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