

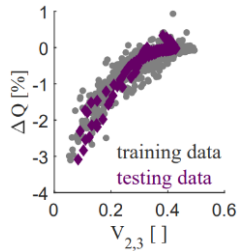
Predicting the onset of rapid degradation using data-driven approaches

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

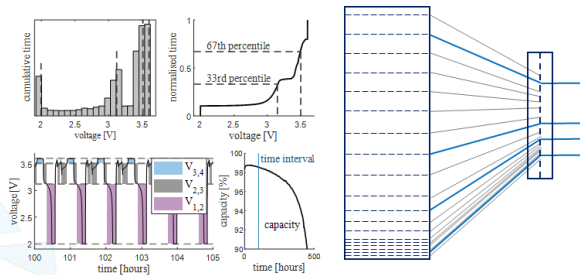
Samuel Greenbank and Dr. David Howey

NASA Battery Workshop 2020

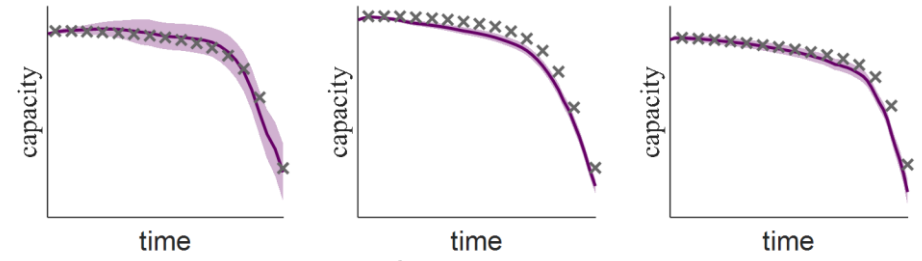
The background of my group and this work



Detailed look at the automated techniques used

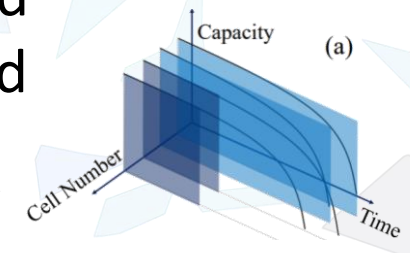
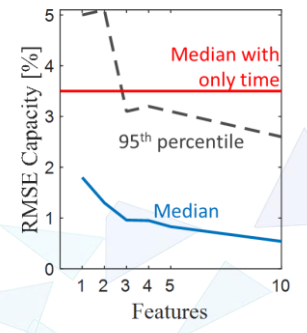


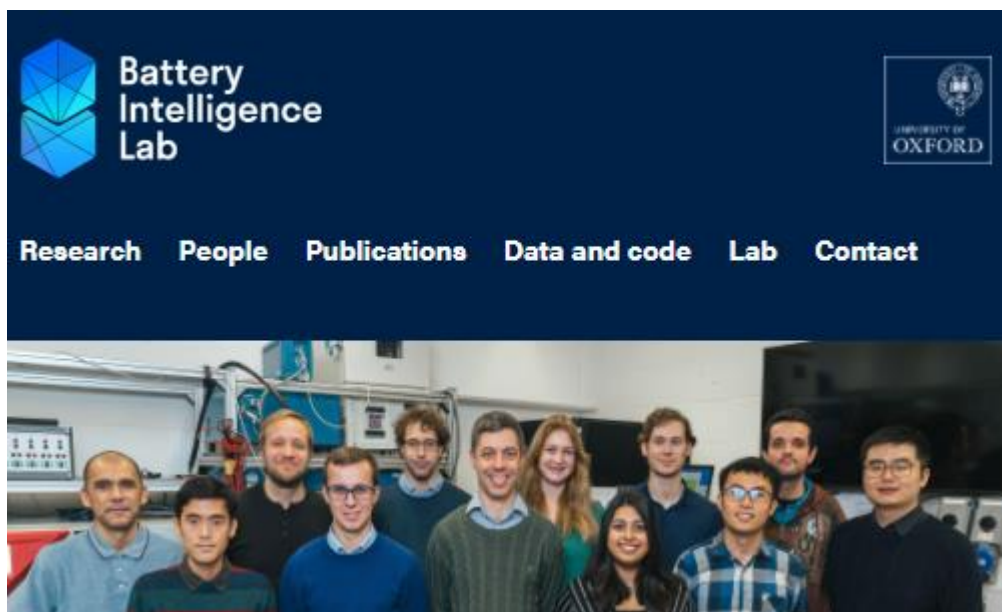
- < 1
- 2 >
- < 3
- 4 >



Initial presentation of results

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](#)

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](#)

Journal of Energy Storage

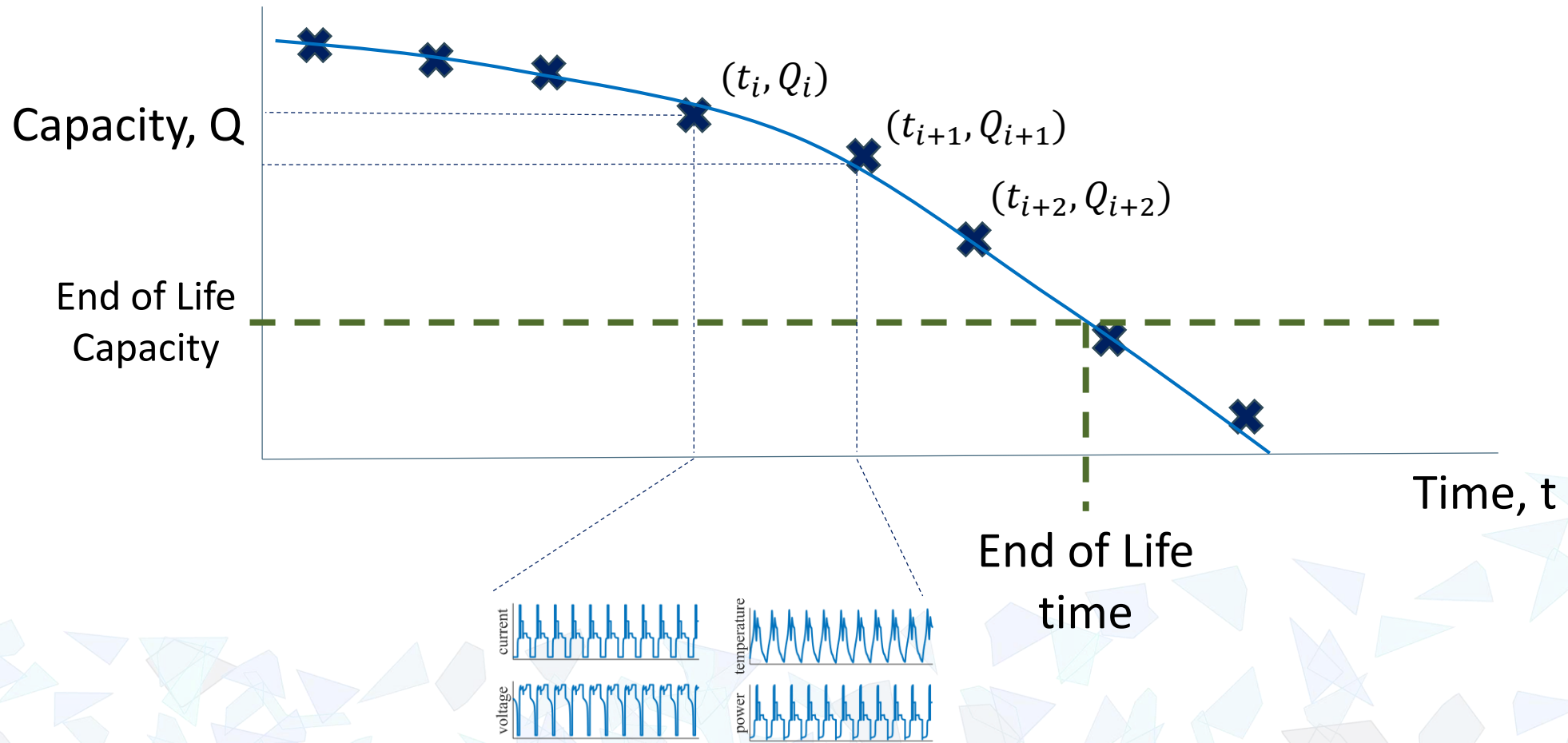
journal homepage: www.elsevier.com/locate/est

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

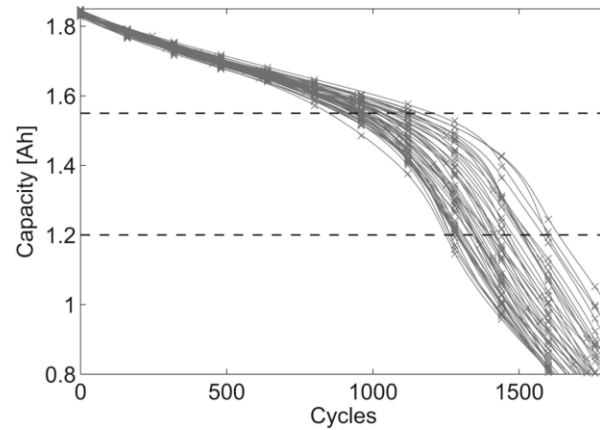
Robert R. Richardson, Michael A. Osborne, David A. Howey*

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

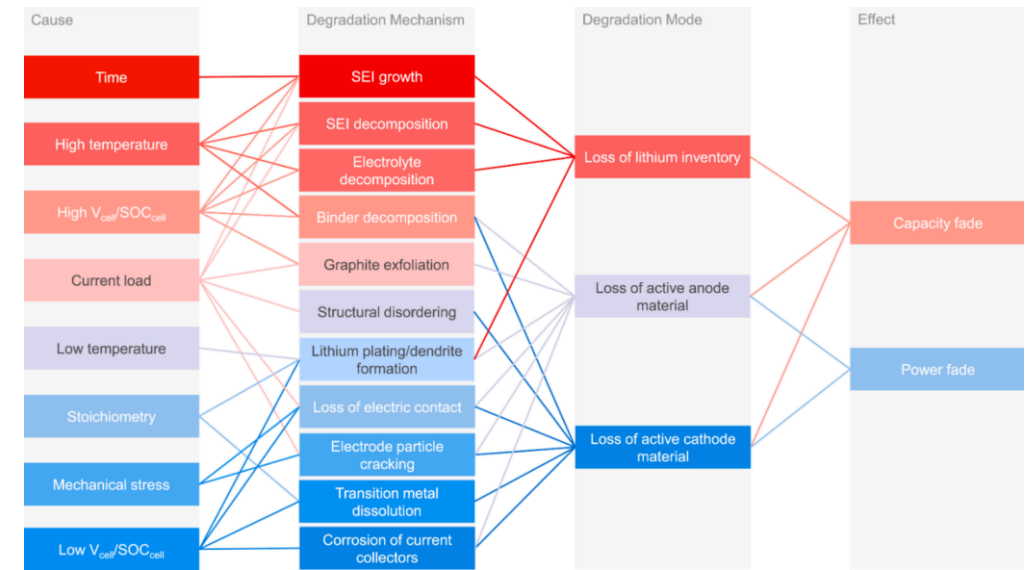
State of health, capacity and end of life



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.



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

Particle filters

Interacting multiple model particle filter for prognostics of lithium-ion batteries

Xiaohong Su^a, Shuai Wang^{a,*}, Michael Pecht^b
^a School of Computer Science and Technology, Harbin Institute of Technology
^b Center for Advanced Life Cycle Engineering (CALCE), University of Maryland

Remaining Useful Life Prediction for Lithium-Ion Batteries Based on Exponential Model and Particle Filter

LIJUN ZHANG¹, ZHONGQIANG MU^{1,2}
¹ National Center for Materials Service Safety, University of Science and Technology of China
² School of Chemistry and Biological Engineering, University of Science and Technology of China
Corresponding author: Lijun Zhang (lijunzhang@usth.edu.cn)

Interacting multiple model particle filter for prognostics of lithium-ion batteries

Xiaohong Su^a, Shuai Wang^{a,*}, Michael Pecht^b

Battery Remaining Useful Life Prediction with Inheritance Particle Filtering

Lin Li^a, Alfredo Alan Flores^a
^a Industry 4.0 Artificial Intelligence Research Center, Dongguan University of Technology
* Correspondence: Yun.Li@dgut.edu.cn

Battery Health Prognosis Using Brownian Motion Modeling and Particle Filtering

Guangzhong Dong^a, Student Member, IEEE
Jingwen Wei^a, Student Member, IEEE
Chang Liu, Yujie Wang, Zonghai Chen^a
^a Department of Automation, University of Science and Technology of China, Hefei 230027, P.R. China

Neural Networks

An Adaptive Recurrent Neural Network for Useful Life Prediction of Lithium-Ion Batteries

Jie Liu¹, Abhinav Saxena², Kai Goebel³, Bhaskar Sah⁴

Remaining Useful Life Prediction for Lithium-Ion Battery: A Deep Learning Approach

LEI REN^{1,2} (Member, IEEE), LI HAO WANG^{3,4} (Member, IEEE), JIE LIU¹
¹ School of Automation Science and Electrical Engineering

Long Short-Term Memory Recurrent Neural Network for Remaining Useful Life Prediction of Lithium-Ion Batteries

Yongzhi Zhang^a, Student Member, IEEE
Hongwen He^b, Senior Member, IEEE

Remaining useful life prediction for lithium-ion battery using a recurrent neural network model combining the long short-term memory and Elman neural network

Liang Guo^a, Naipeng Li^a, Feng Jia^a, Yaguo Lei^{a,b,*}, Jing Lin^a
^a State Key Laboratory for Manufacturing Systems Engineering, Xi'an Jiaotong University
^b State Key Laboratory of Traction Power, Southwest Jiaotong University

Lithium-ion Battery Remaining Useful Life Prediction with Long Short-term Memory Recurrent Neural Network

Yuefeng Liu¹, Guangquan Zhao², Xiyuan Peng³, Cong Hu⁴

Gaussian Process regression

Gaussian process regression for forecasting battery state of health

Robert R. Richardson, Michael A. Osborne, David A. Howey^a
^a Department of Engineering Science, University of Oxford, Oxford, UK

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

Robert R. Richardson, Michael A. Osborne, David A. Howey^a, Xiaoyu Li^{a,b}, Zhenpo Wang^{a,b,c,*}, Jinying Ya^a
^a National Engineering Laboratory for Electric Vehicles, School of Mechanical Engineering, University of Oxford, Oxford, UK
^b Collaborative Innovation Center of Electric Vehicles in Beijing, Beijing Inst of Technology, Beijing, China
^c Chemical Engineering, Royal Institute of Technology, Stockholm, Sweden

Remaining Useful Life Prediction of Lithium-Ion Batteries Based on Health Indicator and Gaussian Process Regression Model

JIAN LIU AND ZIQIANG CHEN^{a,1}
^a State Key Laboratory of Ocean Instrumentation, Collaborative Innovation Center of Electric Vehicles in Beijing, Beijing Institute of Technology, Beijing 100084, China
Corresponding author: Ziqiang Chen (zqchen@bit.edu.cn)
This work was supported by the National Natural Science Foundation of China (Grant No. 51575402).

Deep Gaussian process regression for lithium-ion battery health prognosis and degradation mode diagnosis

Piyush Tagade^a, Krishnan S. Hariharan^a, Arunava Naha^a, Subramanya Mayya Kolli^a
^a State Key Laboratory of Automotive Safety and Health, School of Mechanical Engineering, Tsinghua University, Beijing 100084, China
^b Battery Group, Samsung Electronics Corporation, Seoul, Republic of Korea

Model for state-of-health estimation of lithium-ion battery using modified Gaussian process regression and nonlinear regression

Di Zhou¹, Hongtao Yin¹, Ping Fu¹, Xianhua Song², Wenbin Lu³, Lili Yuan², and Zuoxian Fu²

Relevance Vector Machines

Prognostics Methods for Battery Health Monitoring Using a Bayesian Framework with an optimized Relevance Vector Machine algorithm with incremental learning

Bhaskar Saha, Member, IEEE, Kai G. Van Horn^a

An integrated unscented kalman filter and relevance vector regression approach for lithium-ion battery remaining useful life and short-term capacity prediction

Xiujuan Zheng, Huajing Fang^a
^a School of Automation, Huazhong University of Science & Technology, 1037 Luoyu Road, Wuhan, China

Lithium-ion Battery Remaining Useful Life Prediction with Deep Belief Network and Relevance Vector Machine

Guangquan Zhao, Gaochun Zhang, Yuefeng Liu
^a Department of Automatic Test and Control, Harbin Institute of Technology, Harbin, China
hit53hao@hit.edu.cn

An Optimized Relevance Vector Machine with Incremental Learning Strategy for Lithium-ion Battery Remaining Useful Life Estimation

Bin Zhang
^a Department of Electrical Engineering, University of South Carolina, Columbia, SC, USA
zhangbin@eec.sc.edu

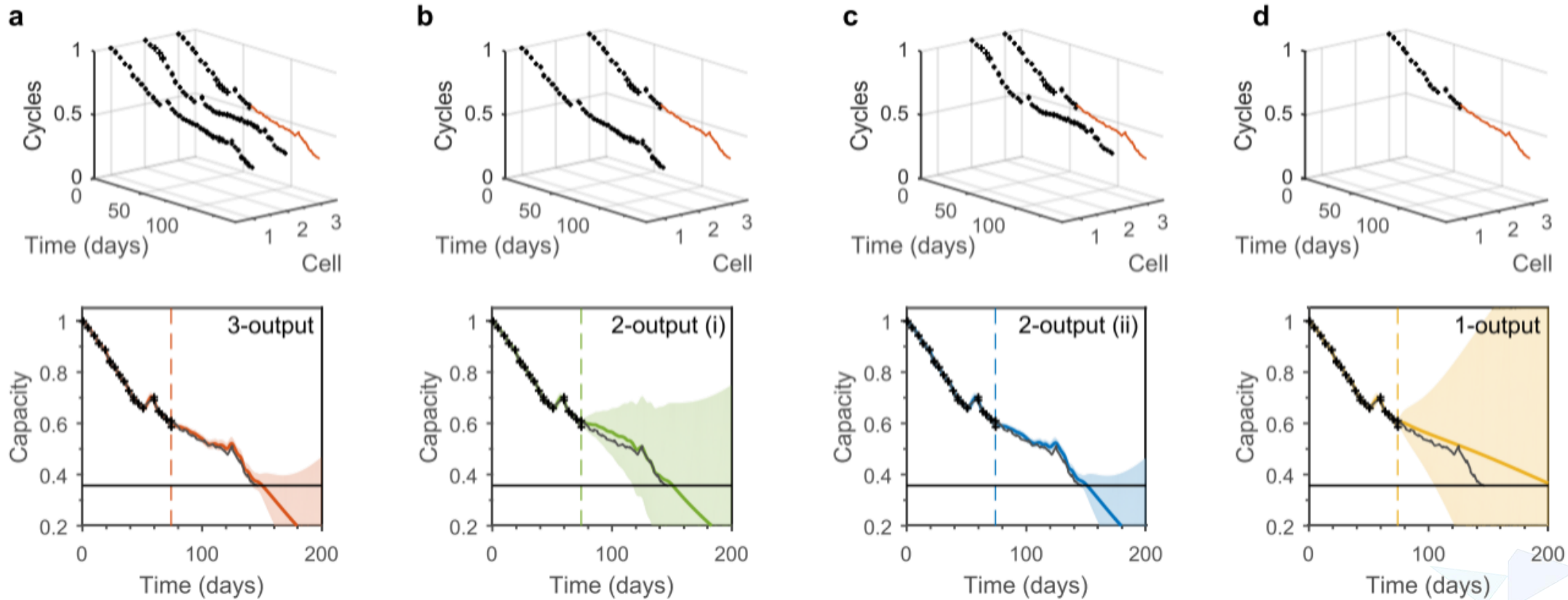
Jianbao Zhou, Datong Liu, Yu Peng, Xiyuan Peng
^a Department of Automatic Test and Control, School of Electrical Engineering and Automation, Harbin Institute of Technology (HTT), Harbin, China
Email: zhoujianbao@163.com

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.

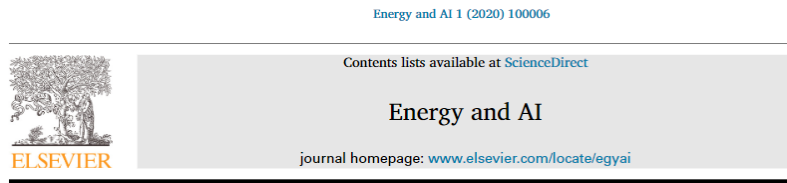
or...

Garbage in → Garbage out



$$\begin{aligned}
 (a) &\approx (c)+(b) \\
 &\approx (c) \\
 &> (b) \\
 &\gg (d)
 \end{aligned}$$

So how to forecast the “knee”?



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,*}



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

Weiping Diao^{*}, Saurabh Saxena^{MD}, Bongtae Han^{MD} and Michael Pecht

Journal of Power Sources 360 (2017) 28–40



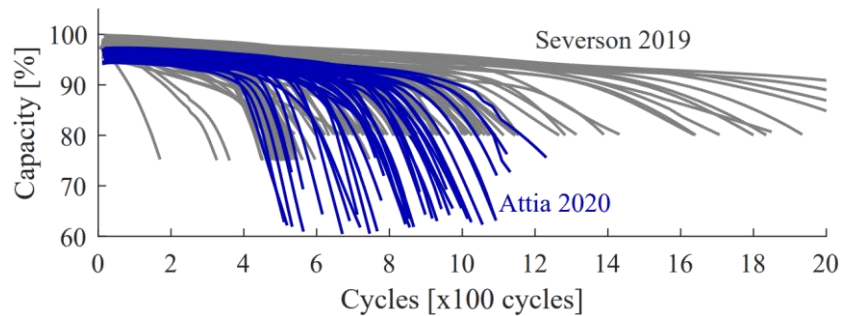
Modeling of lithium plating induced aging of lithium-ion batteries: Transition from linear to nonlinear aging

Xiao-Guang Yang^{a,*}, Yongjun Leng^a, Guangsheng Zhang^a, Shanhai Ge^b, Chao-Yang Wang^{a,b,**}



$(t_{\text{knee}}, Q_{\text{knee}}) ???$

Good results were achieved by prioritising work on the inputs



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%

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 Jin², Nicholas Perkins², Benben Jiang¹, Zi Yang², Michael H. Chen², Muratahan Aykol³, Patrick K. Herring³, Dimitrios Fraggedakis¹, Martin Z. Bazant¹, 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/s41560-020-1994-5>

Received: 6 August 2019

Accepted: 19 December 2019

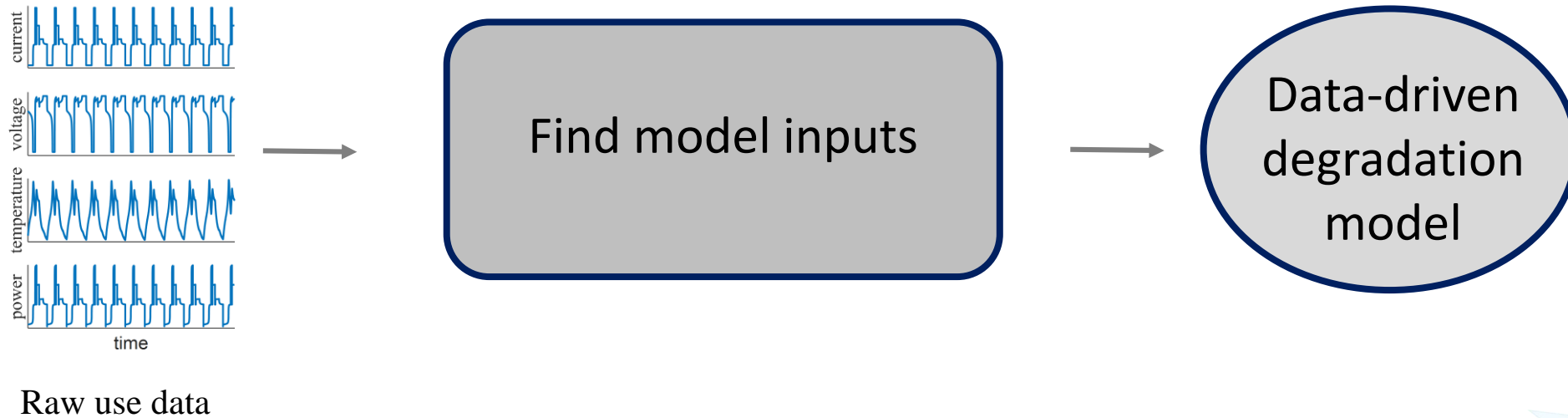
Published online: 19 February 2020

Peter M. Attia^{1,7}, Aditya Grover^{2,7}, Norman Jin¹, Kristen A. Severson⁷, Todor M. Markov⁷, Yang-Hung Liao¹, Michael H. Chen¹, Bryan Cheong^{1,2}, Nicholas Perkins¹, Zi Yang¹, Patrick K. Herring¹, Muratahan Aykol¹, Stephen J. Harris^{1,3}, Richard D. Braatz^{2,5}, Stefano Ermon^{2,5} & William C. Chueh^{1,6,8}

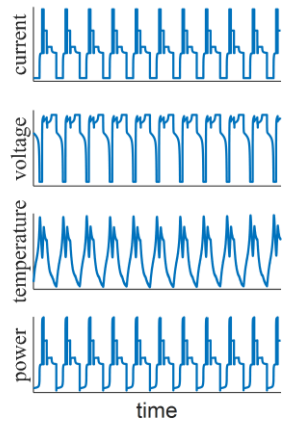
Automating feature generation and selection

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

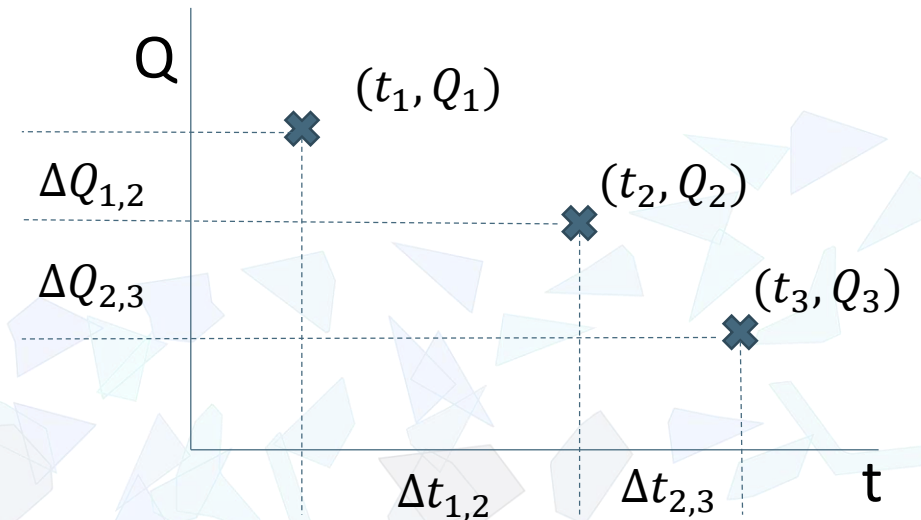
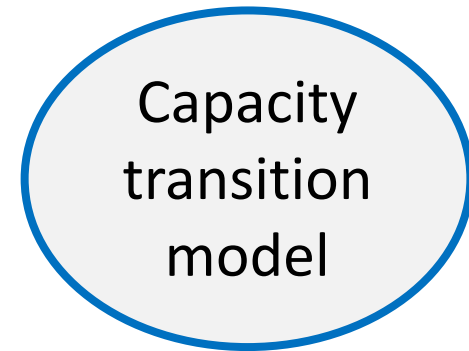
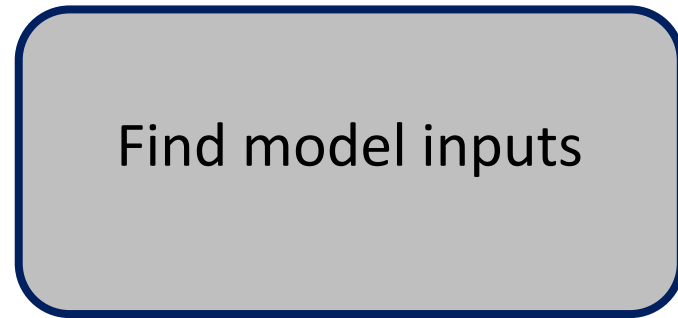
We propose to automate the process prior to modelling.



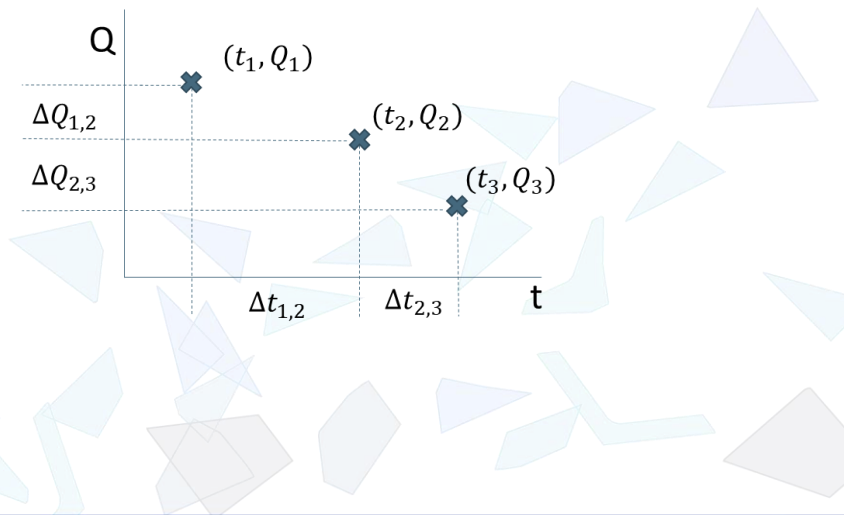
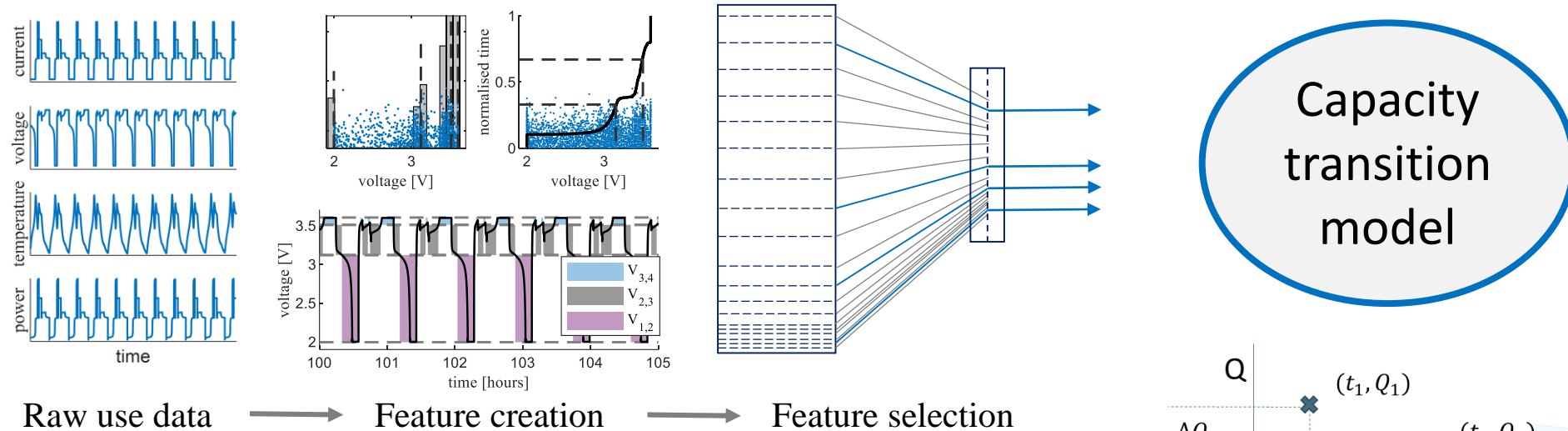
We propose to automate the process prior to modelling.



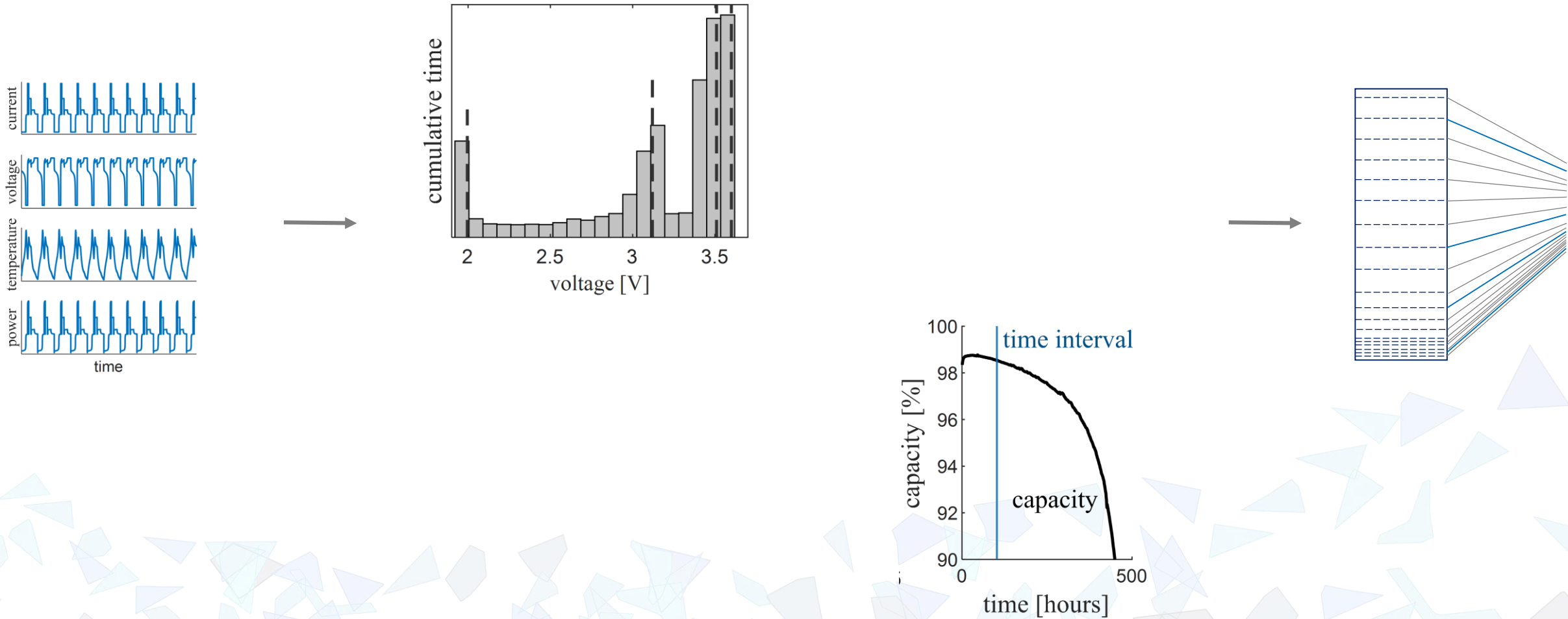
Raw use data



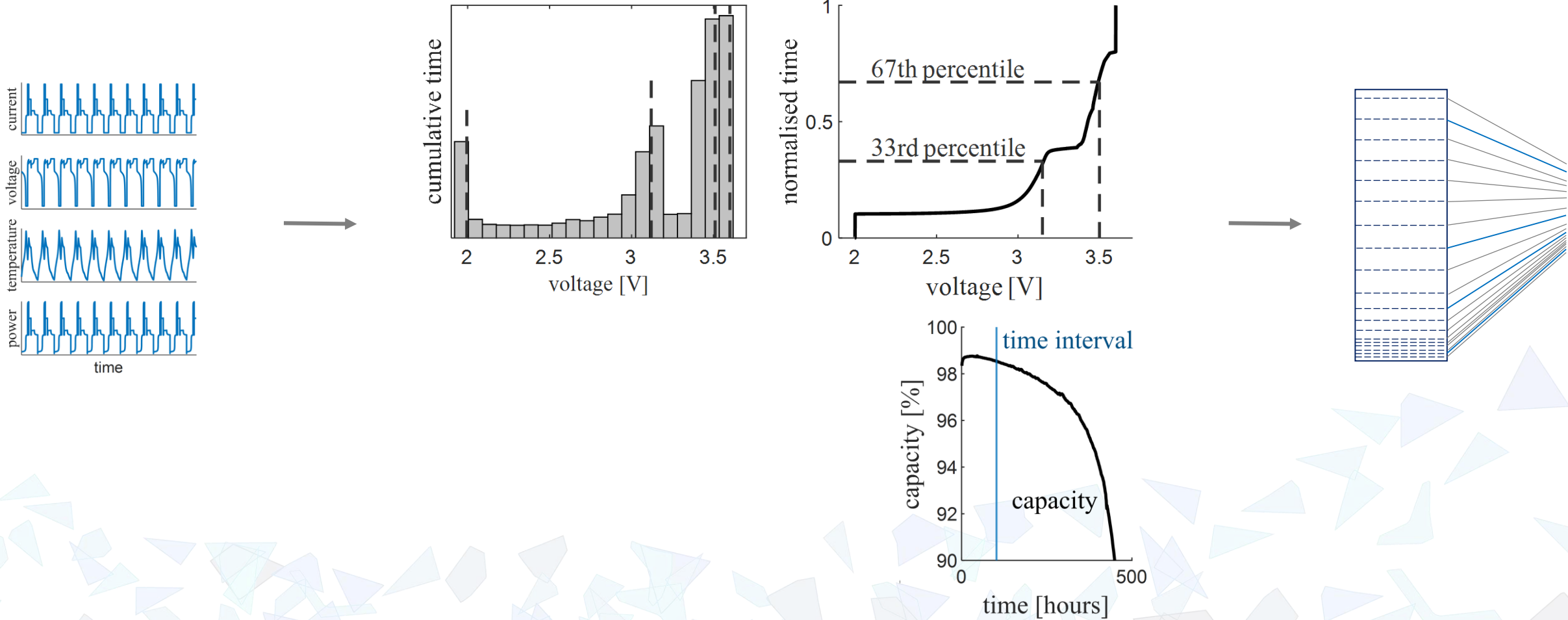
We propose to automate the process prior to modelling.



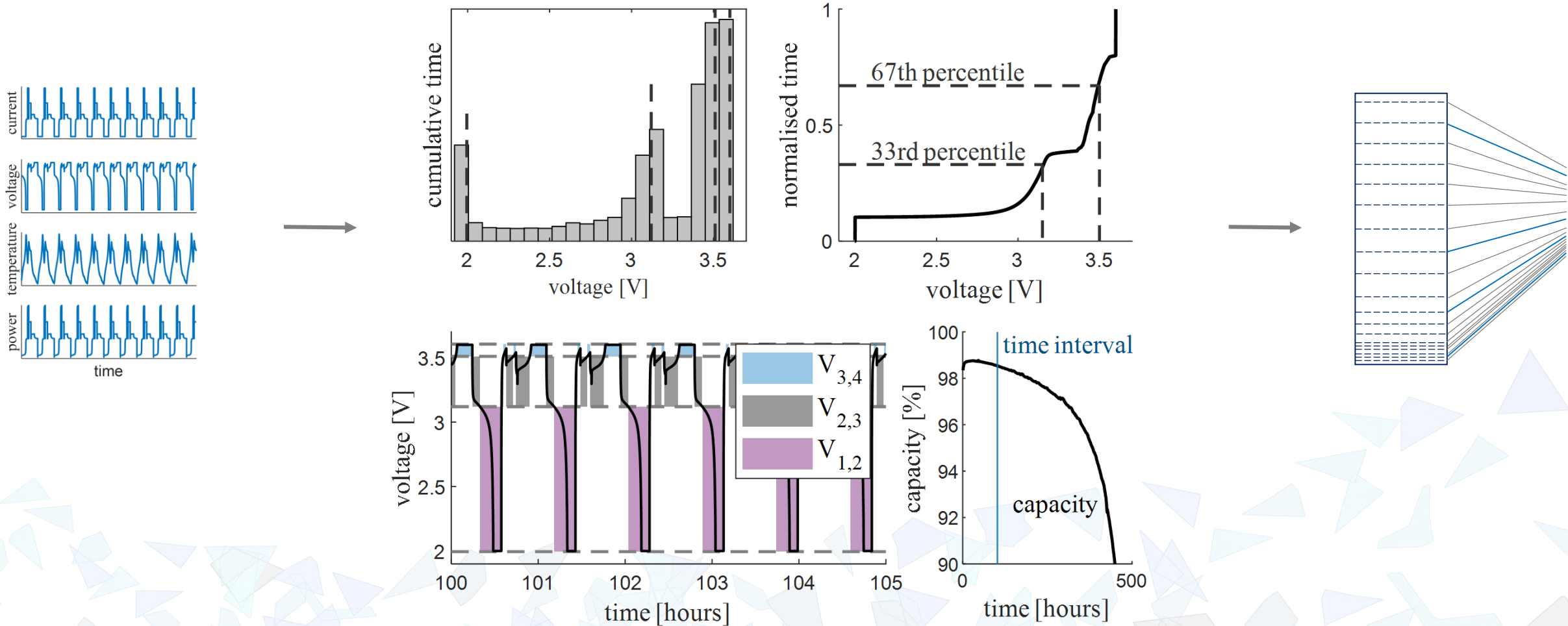
Model inputs (features) are calculated based on time spent in different regions.



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



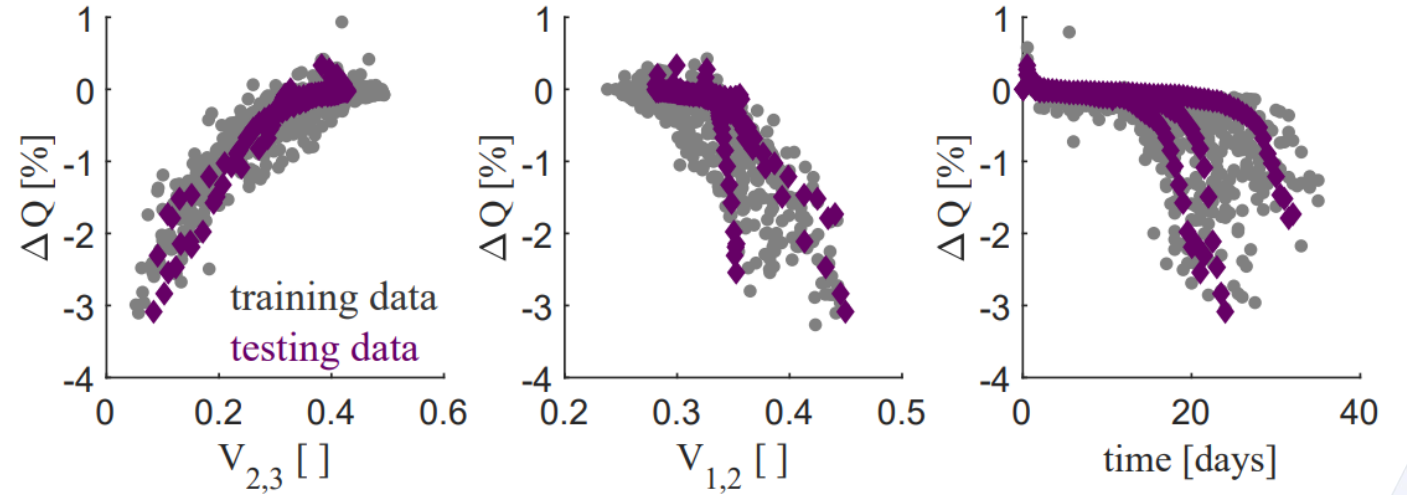
Model inputs (features) are calculated based on time spent in different regions.



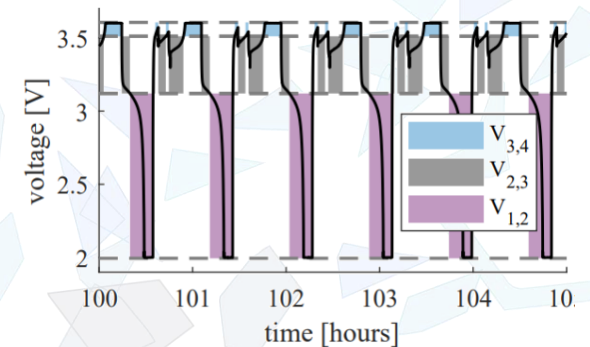
Pearson's rank produces a reliable set of inputs.

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
time	$V_{2,3}$	$T_{1,4}$	$V_{1,2}$	$I_{2,3}$	$P_{2,4}$	ΔQ	

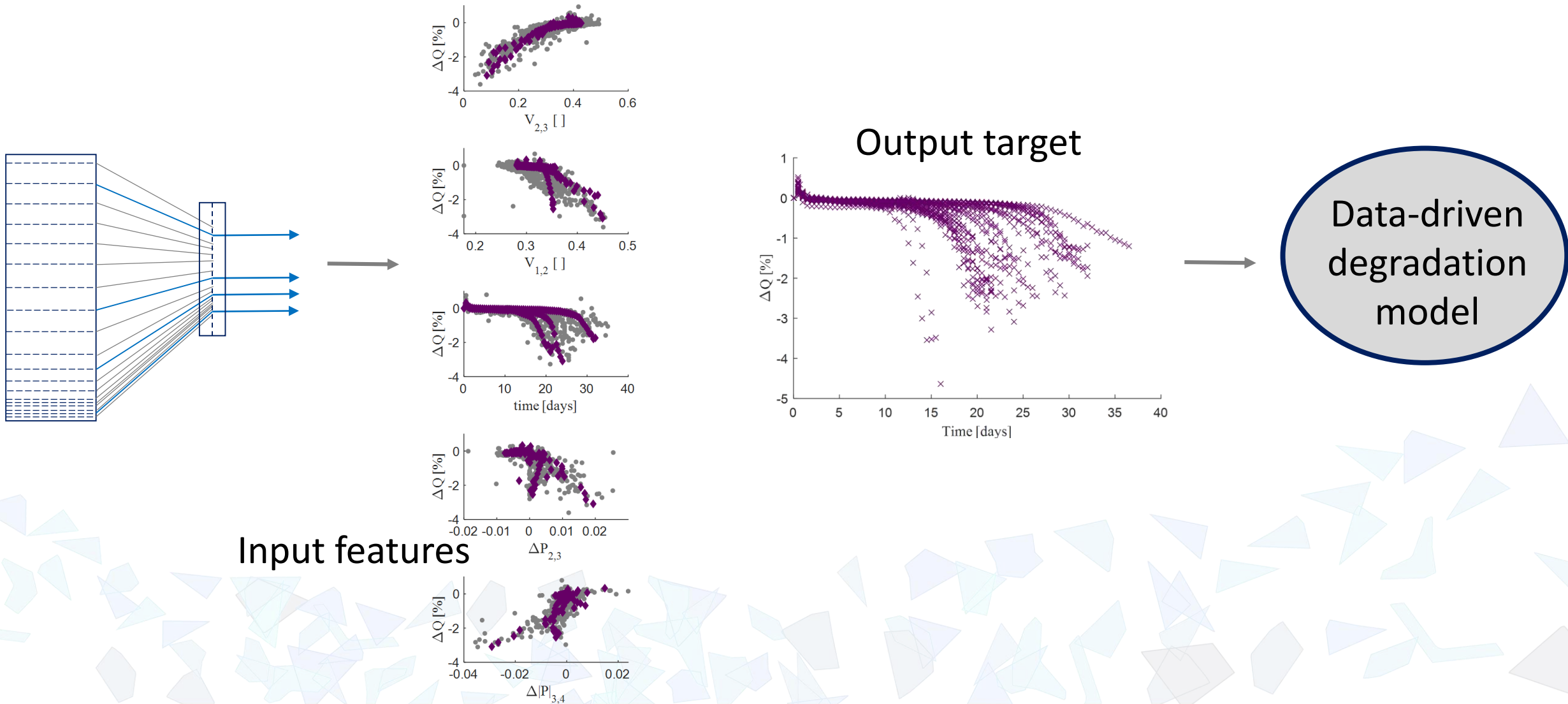
Correlation matrix



Selected features

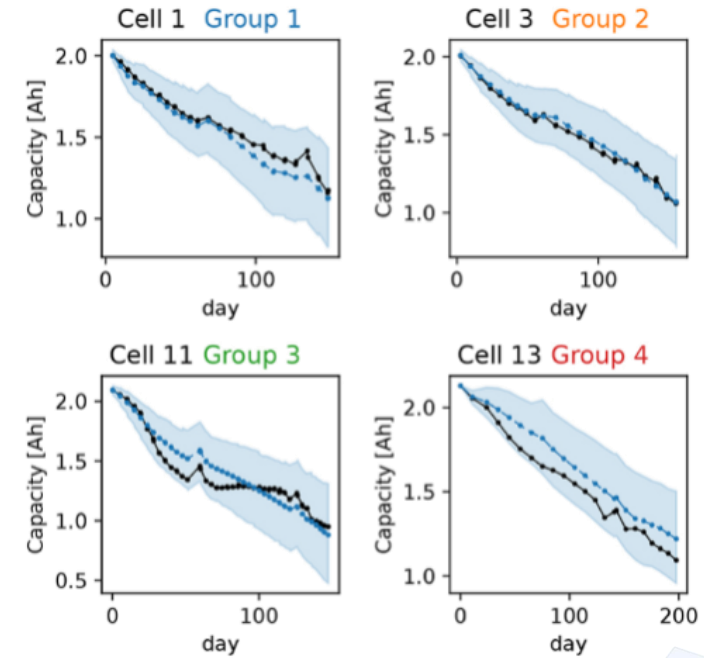
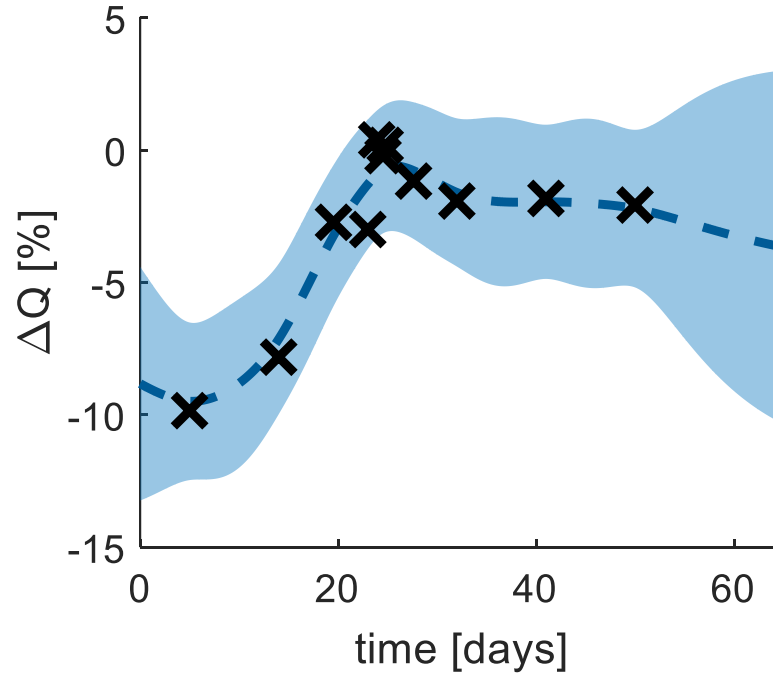


5 varied features can then be passed to the degradation model

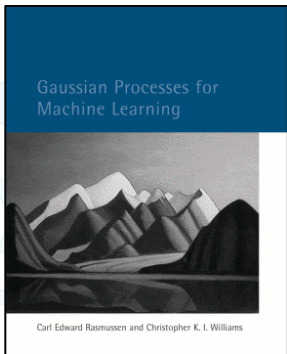


Gaussian processes are known to be effective for batteries.

Data-driven
degradation
model

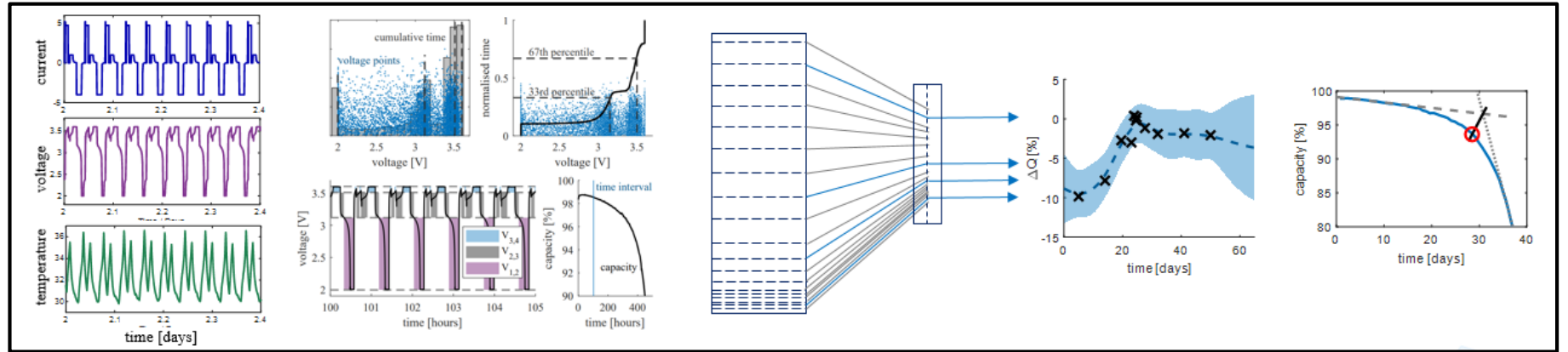


Richardson et al., "Battery ... model", Journal of Energy Storage, vol. 23, pp. 320-328, 2019



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

Testing

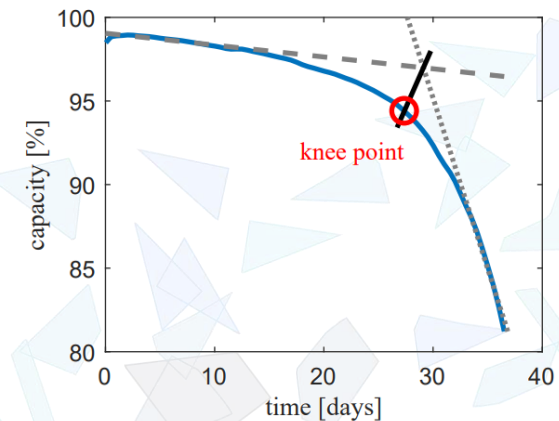
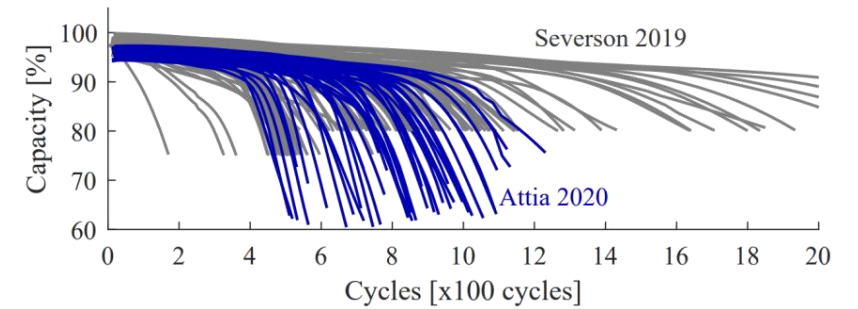


100 training cells
30 test cells
Repeat 20 times

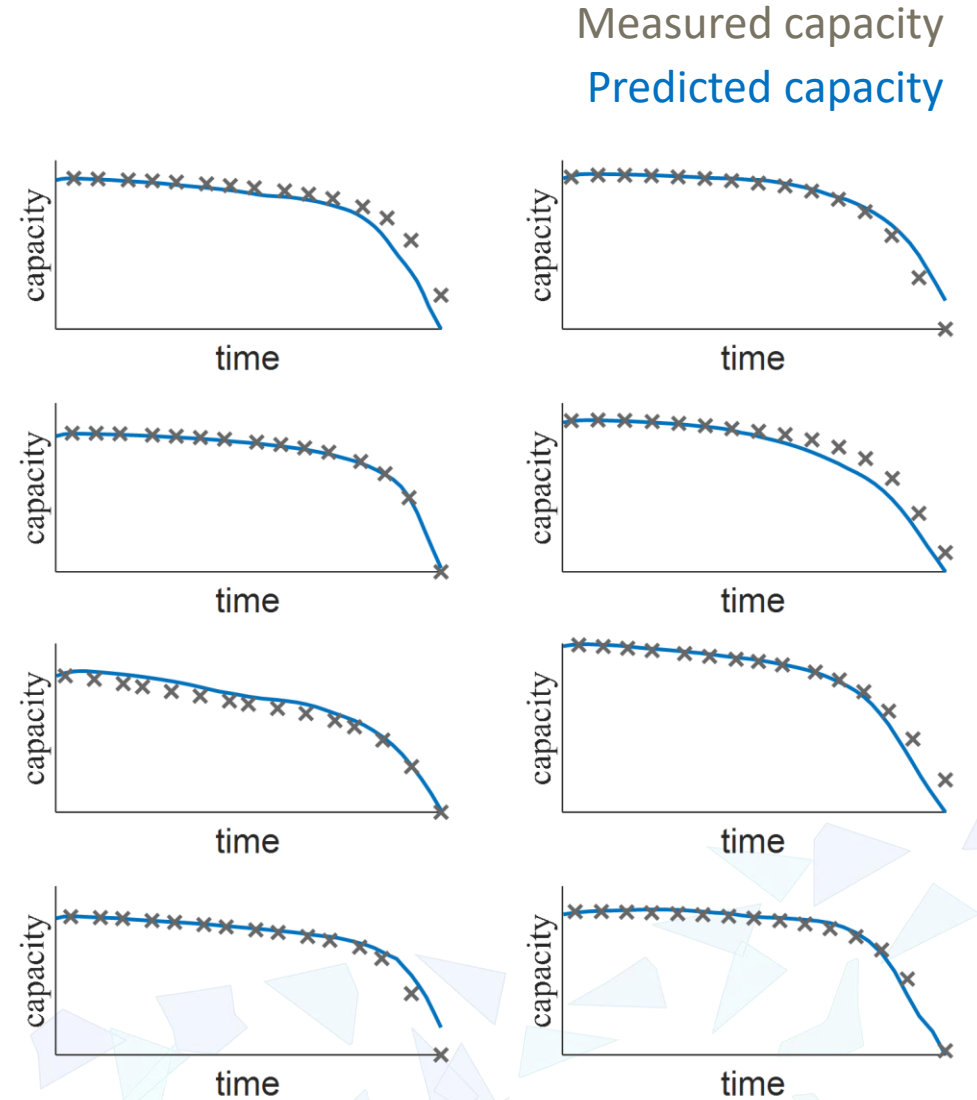
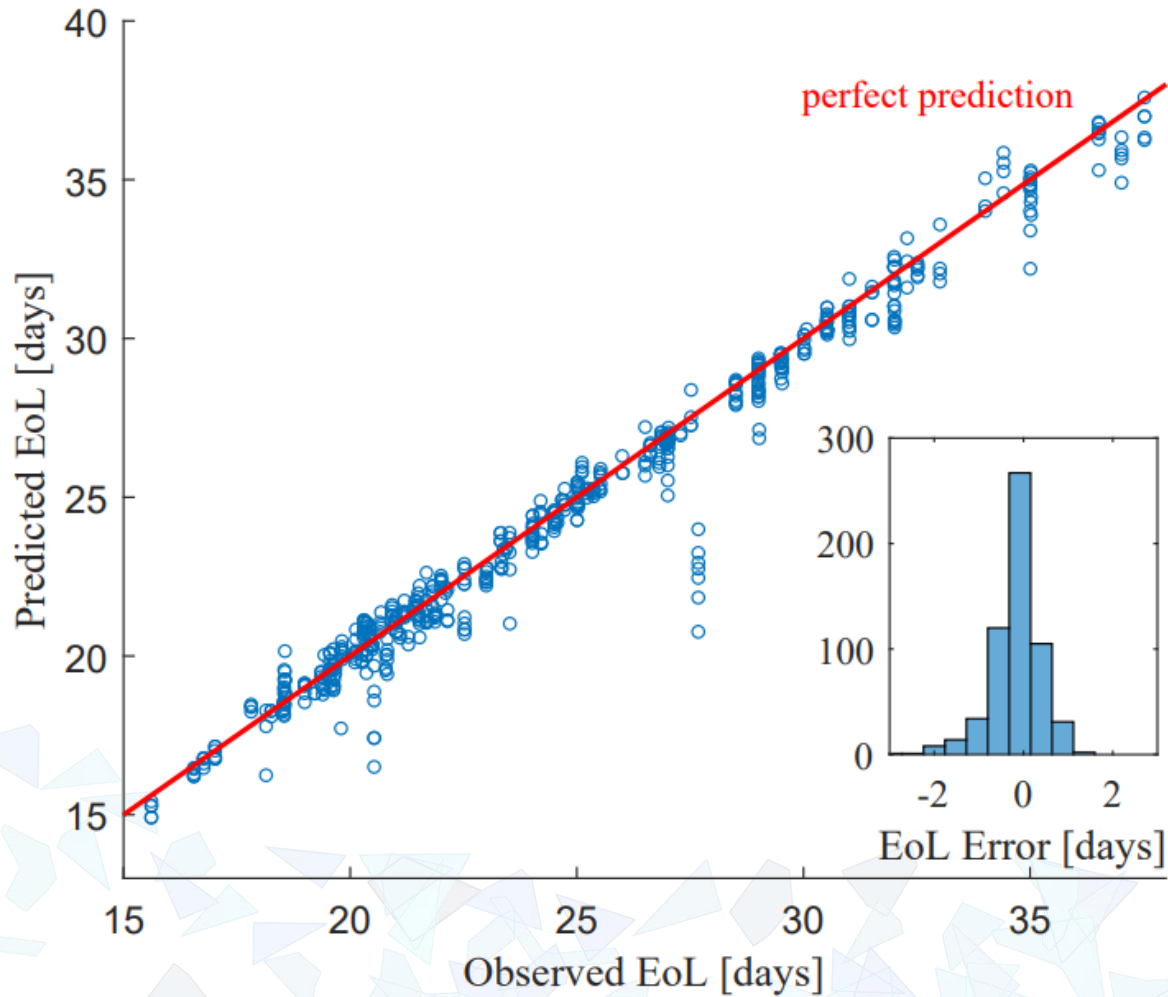
600 trials

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

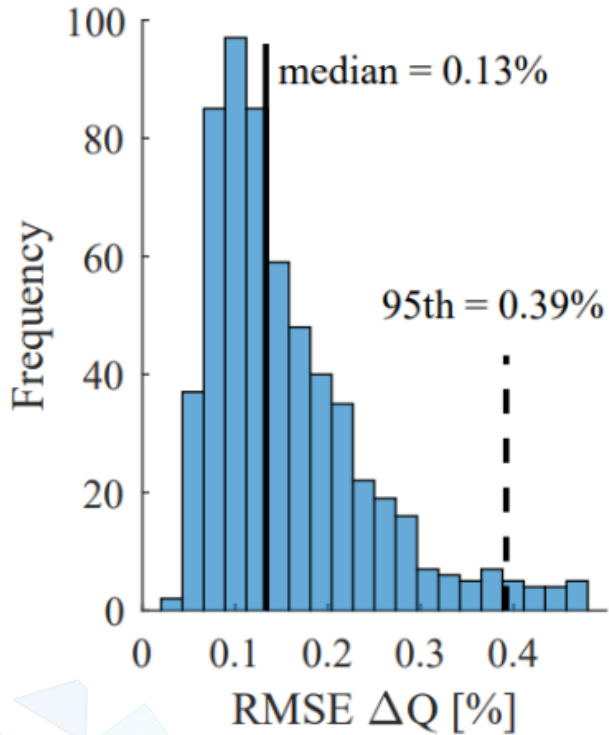
147 cells in total from Severson 2019 and Attia 2020



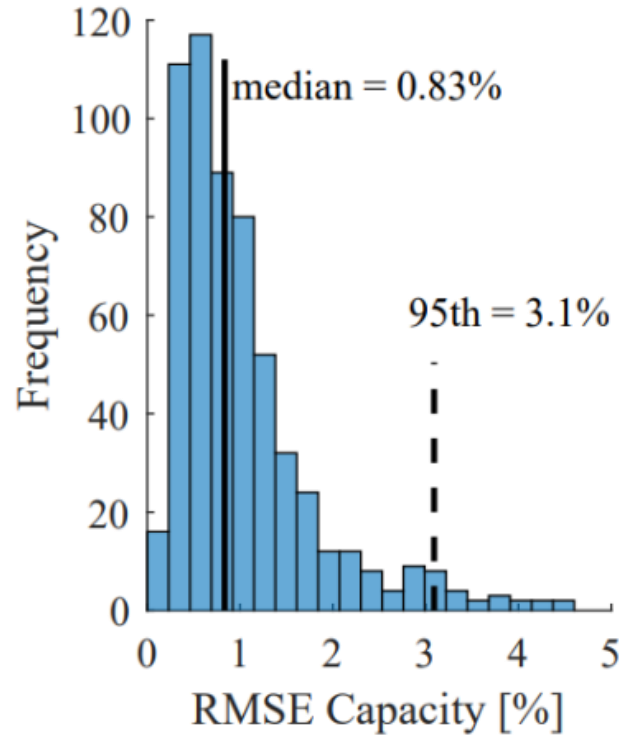
End of life scatter



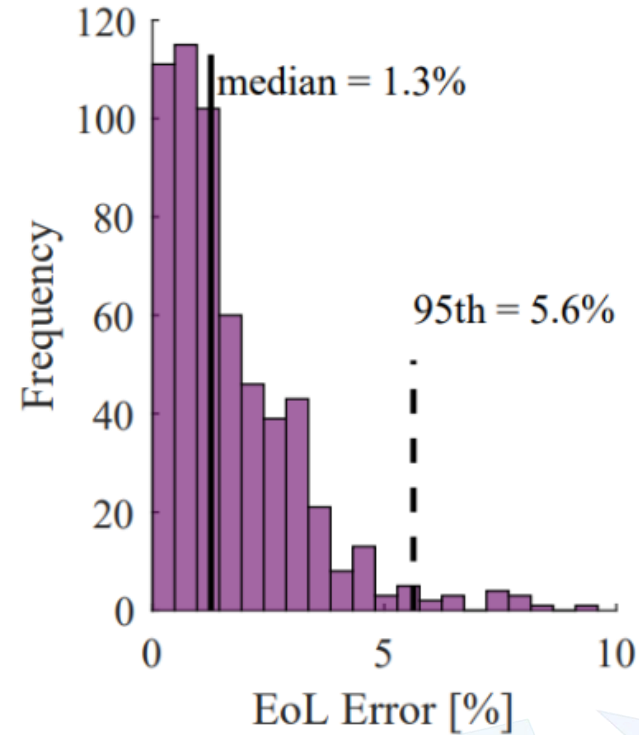
We see tight profiles and consistent knee forecasts.



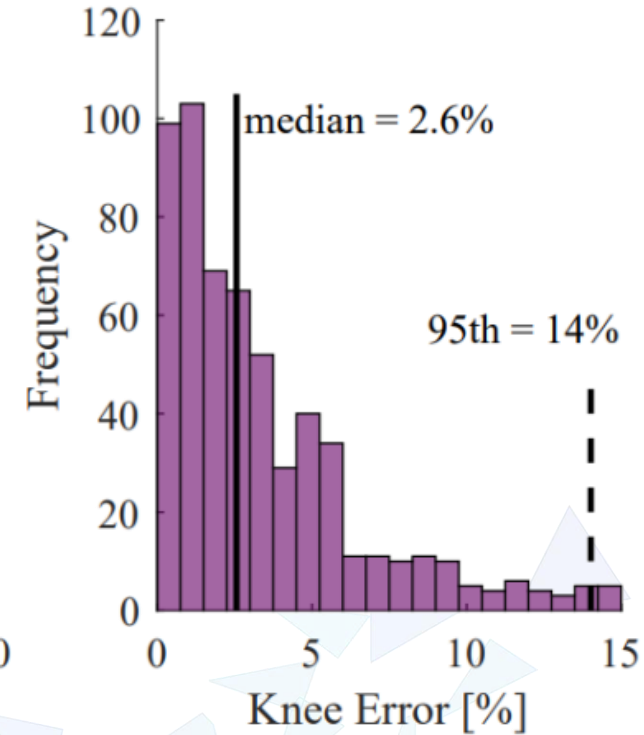
Model performance



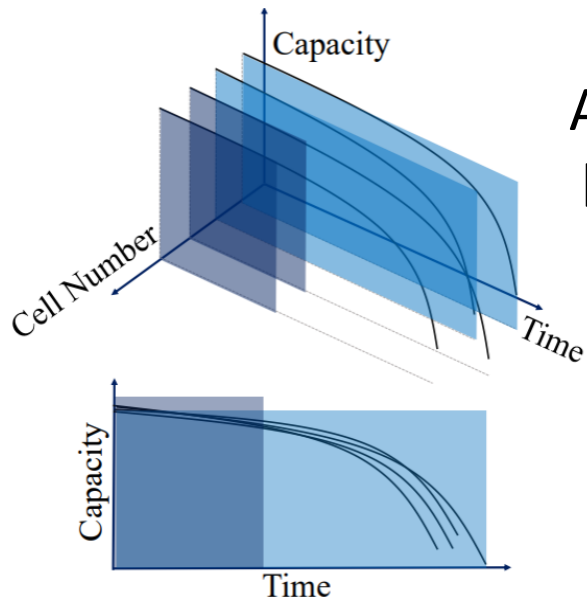
Capacity accuracy



Lifetime estimation
(Mean = 2.0%)



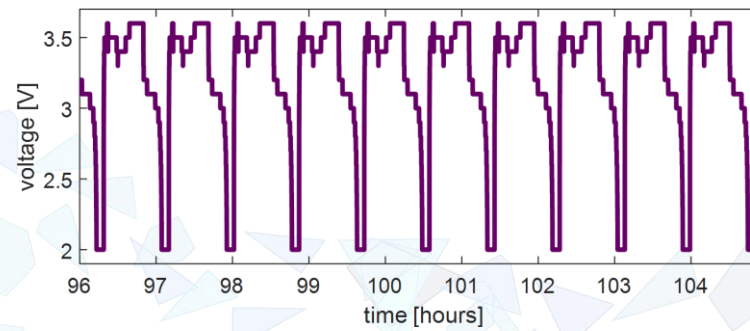
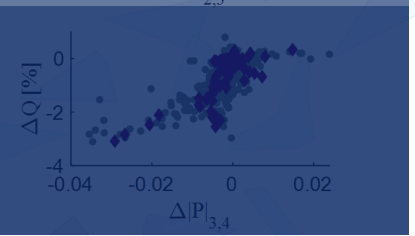
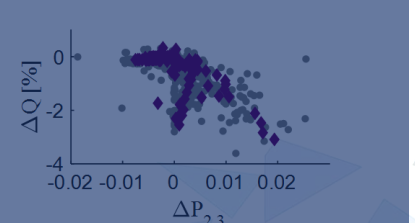
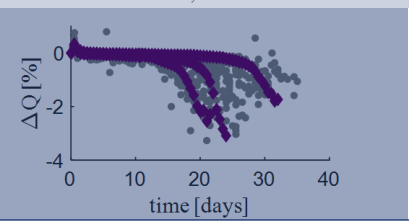
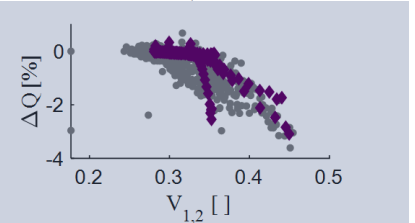
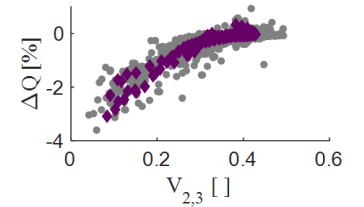
Knee point forecasts



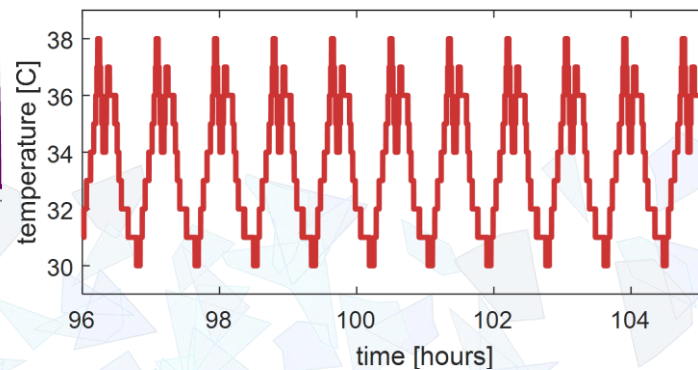
Availability of late-life data

Number of features

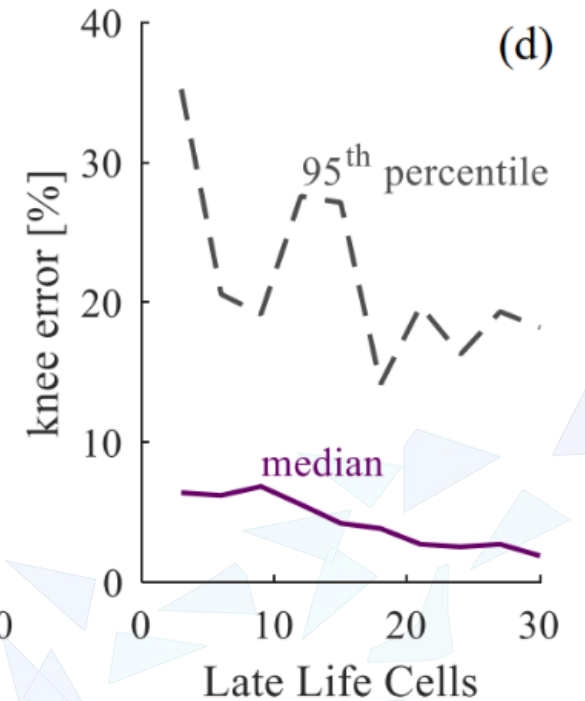
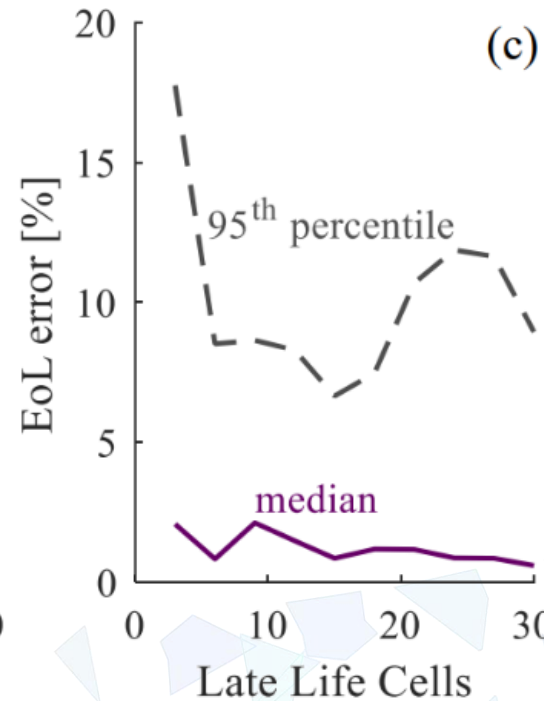
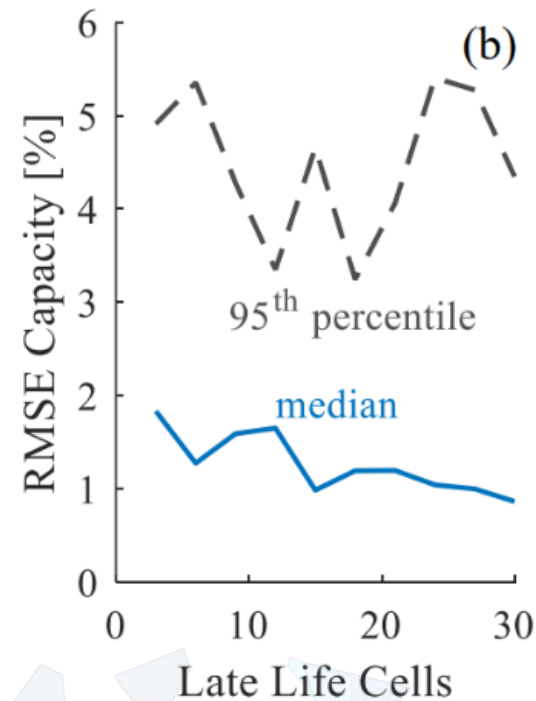
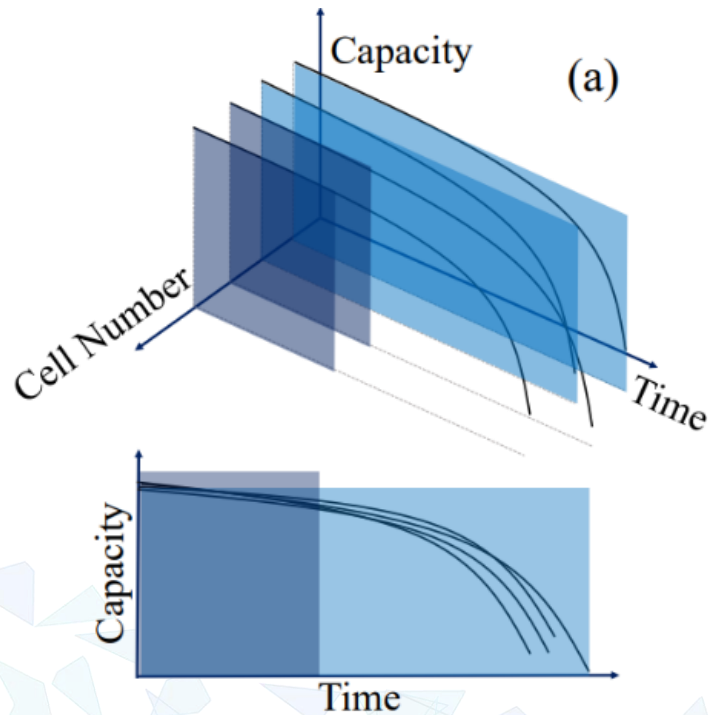
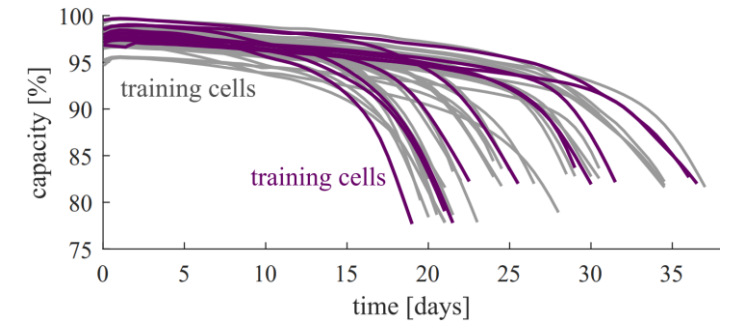
How to test further?



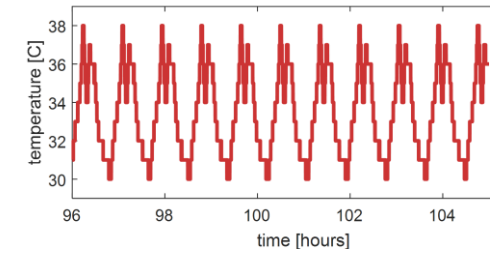
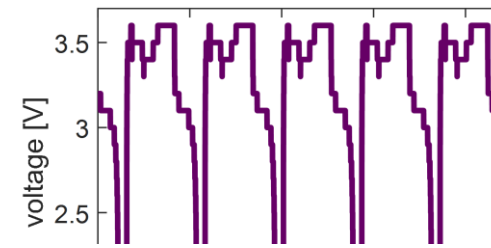
Precision of input



Whole process coped with reduced late-life data

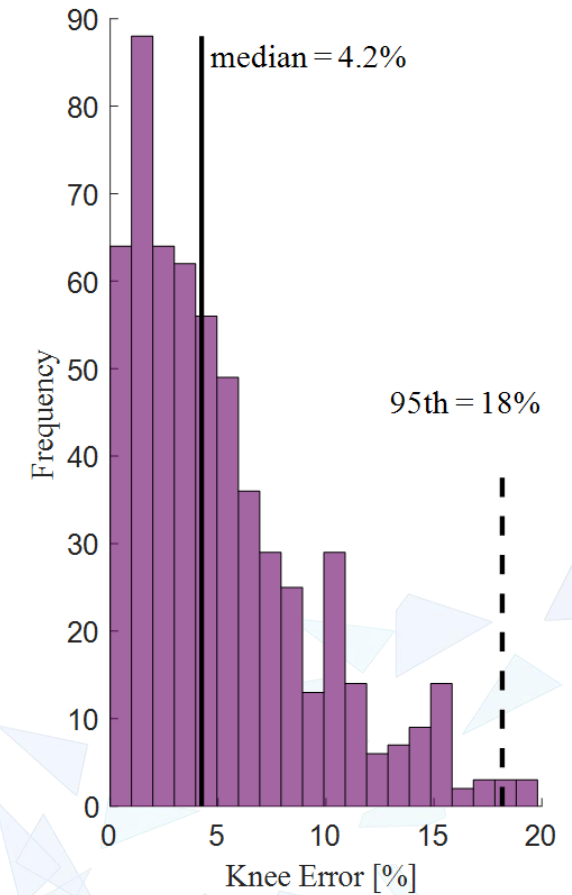
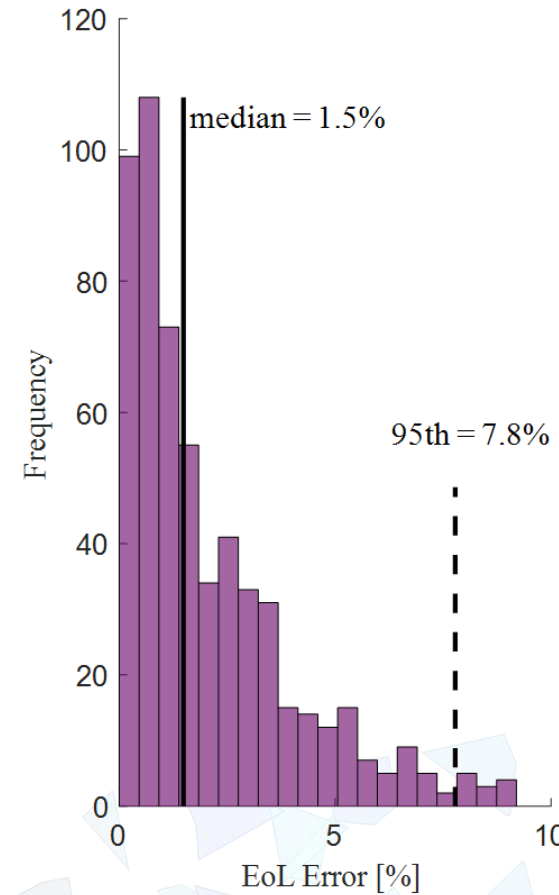
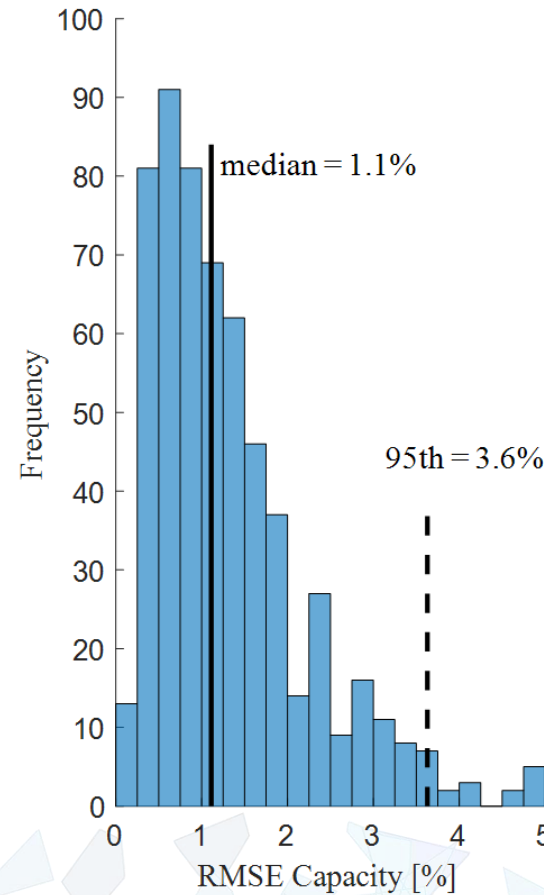


50 training cells, but rounded raw data

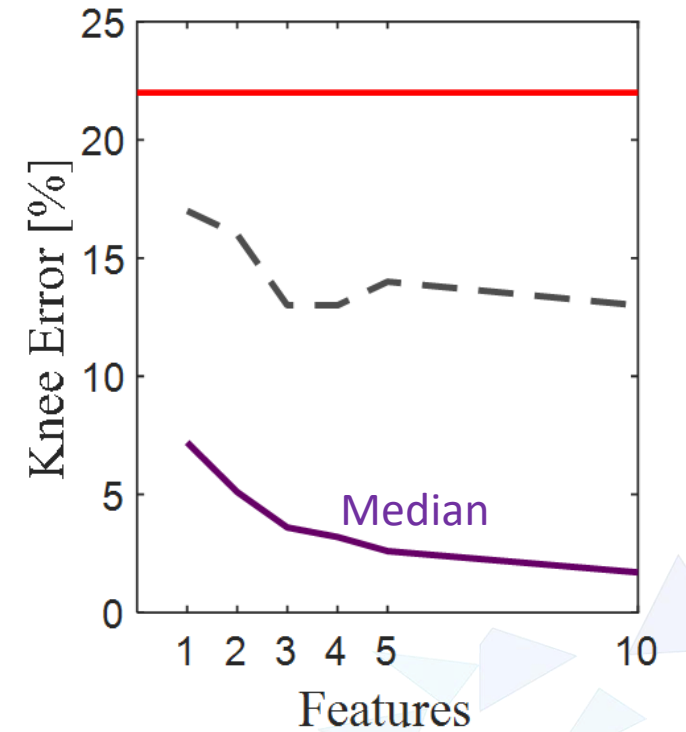
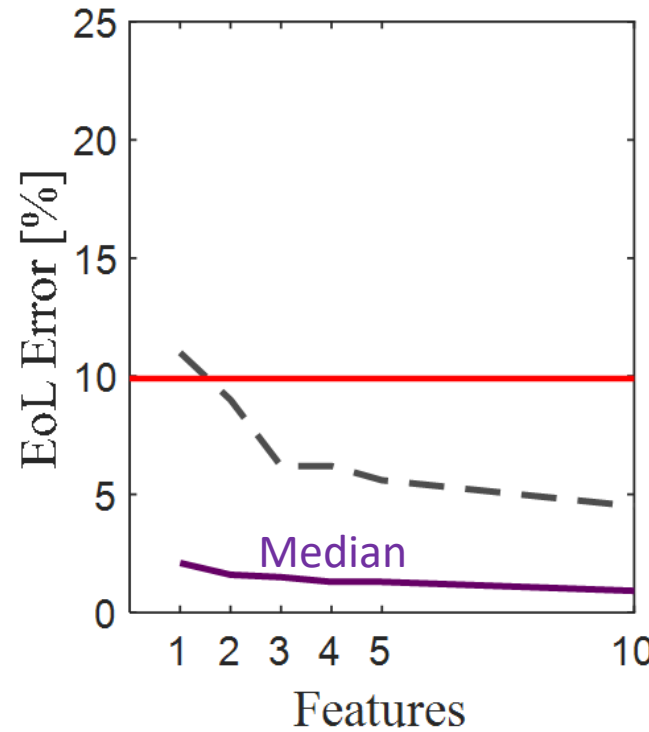
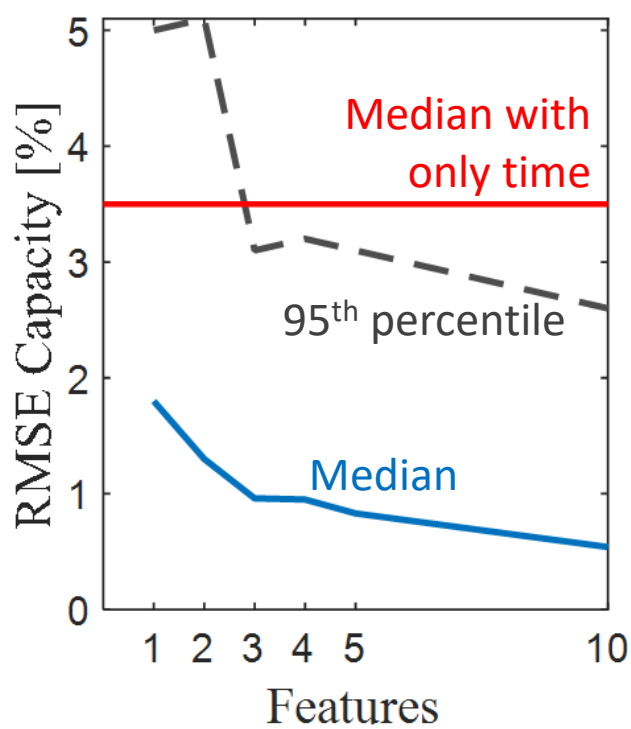
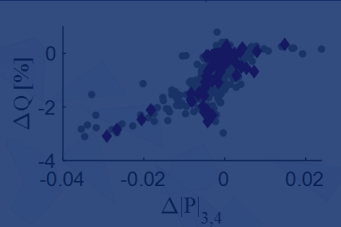
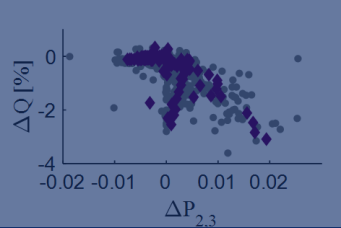
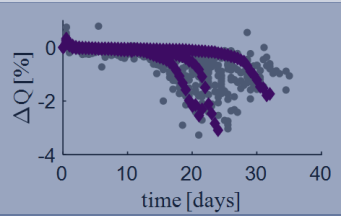
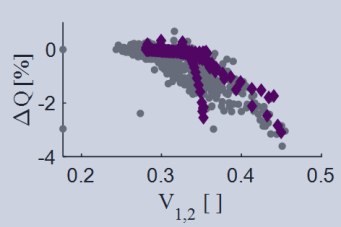
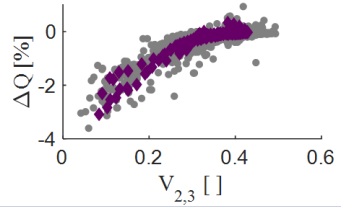


Rounding current and temperature to integers and voltage to 2 s.f.

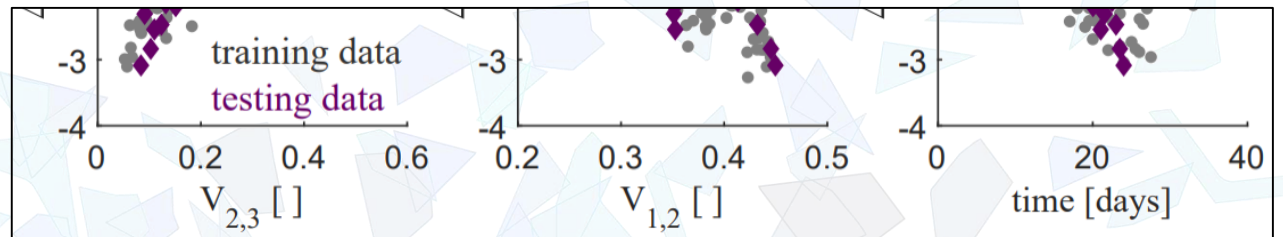
Still fairly successful for EoL estimation, but higher degradation rates were poorly predicted.



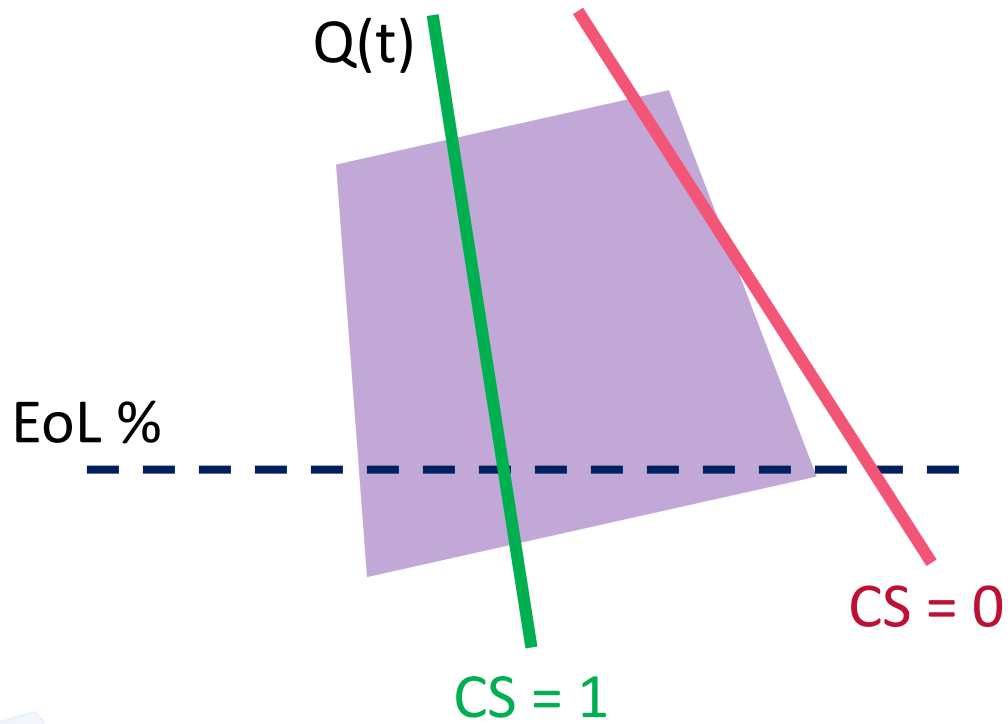
Automated approach is quite robust to reducing features.



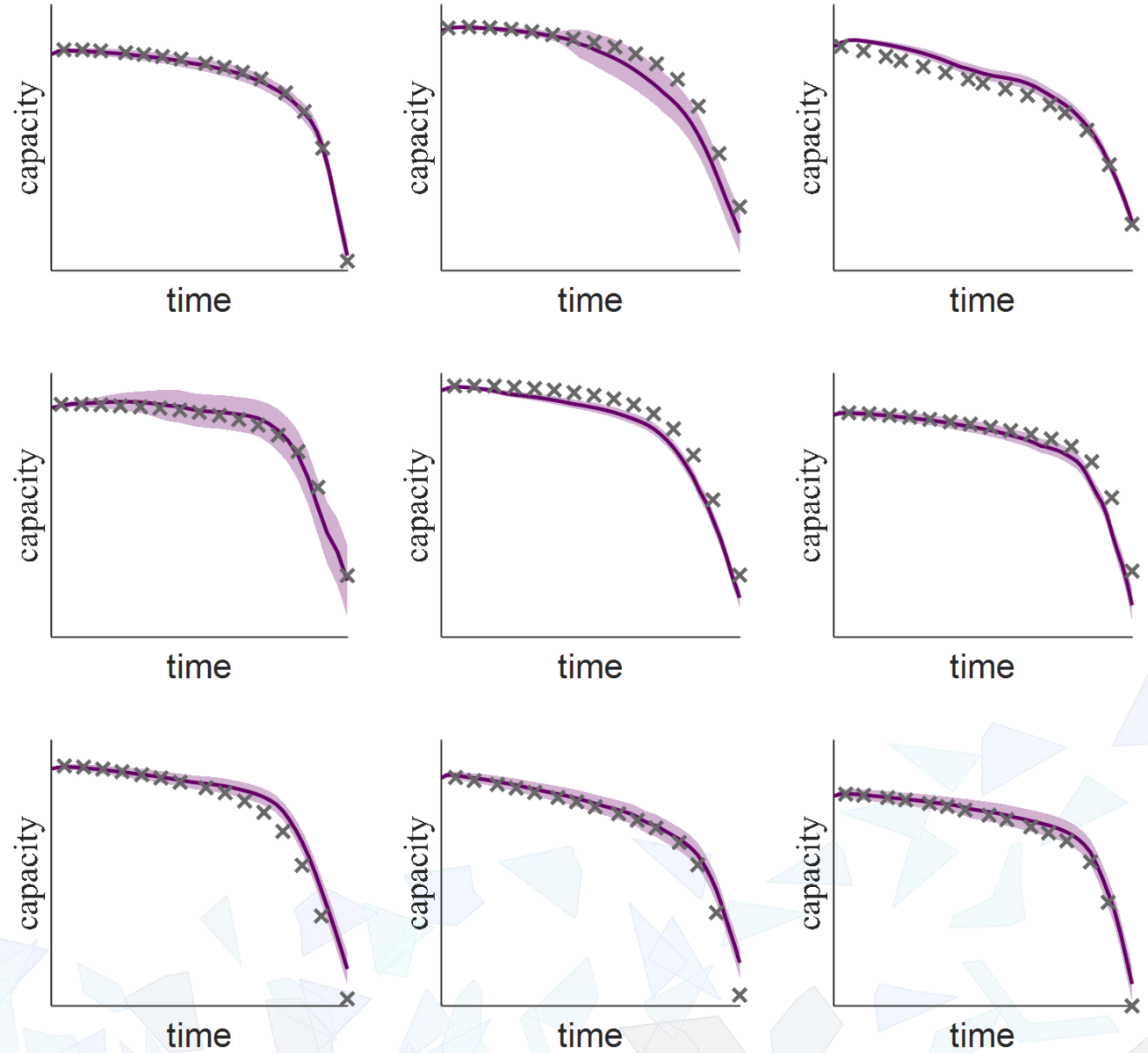
Most common selection of three inputs:



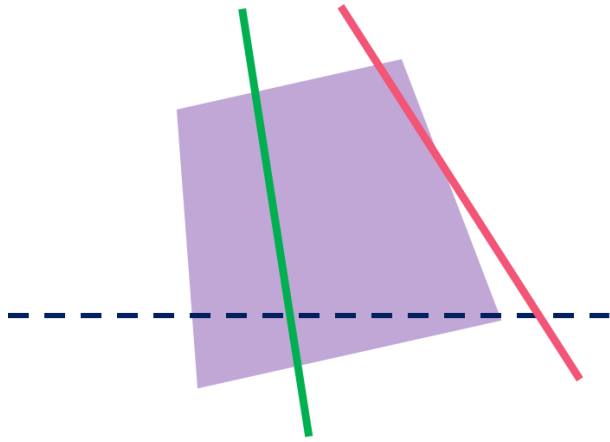
What about credible intervals?



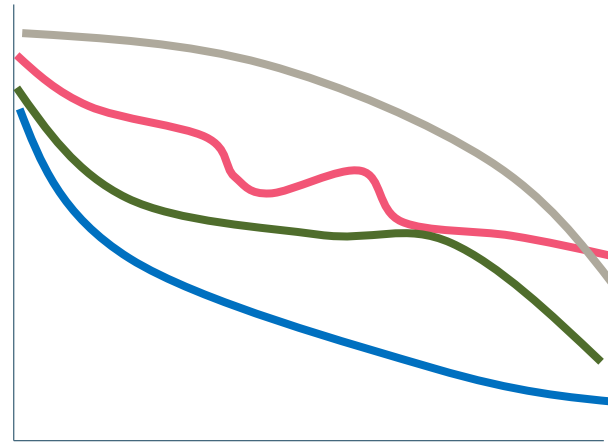
Calibration score (CS) for EoL = 0.75



Where do we go from here?



End of life and capacity confidence



More data sets



The real world?

Thank you for listening



**Battery
Intelligence
Lab**

EPSRC

Engineering and Physical Sciences
Research Council

SIEMENS

Ingenuity for life

Twitter: [@segreenbank](https://twitter.com/segreenbank)

Email: samuel.greenbank@eng.ox.ac.uk

Website: <http://howey.eng.ox.ac.uk/>

