Real-world performance of small off-grid solar systems in Africa

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Oxford Energy Day, October 2024

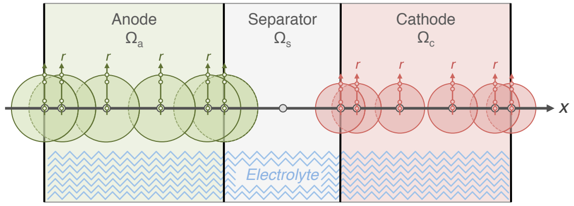
Battery Intelligence Lab

UNIVERSITY OF OXFORD

Outline

1. Introduction

- Group overview

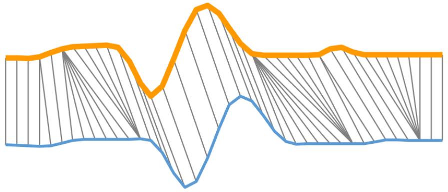


2. Battery health from field data

- Motivation
- Existing approaches
- Results—detection of failing batteries from operational data

3. Usage clustering

- Aims and methods
- Results—including changes in usage over time



Bottom image by Romain Tavenard, https://rtavenar.github.io/blog/dtw.html, 2021

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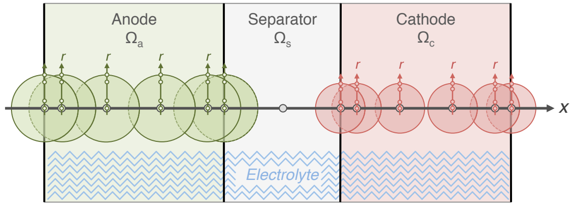

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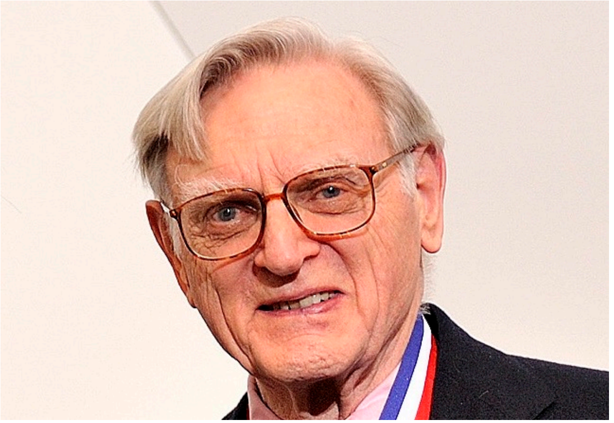
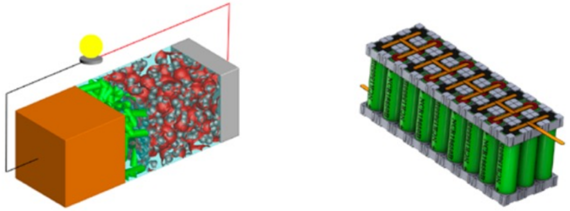
Oxford has a critical mass of battery research activities

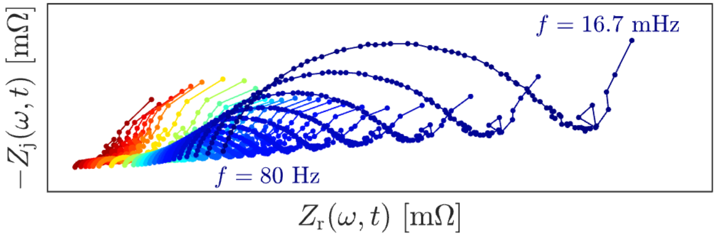
1980

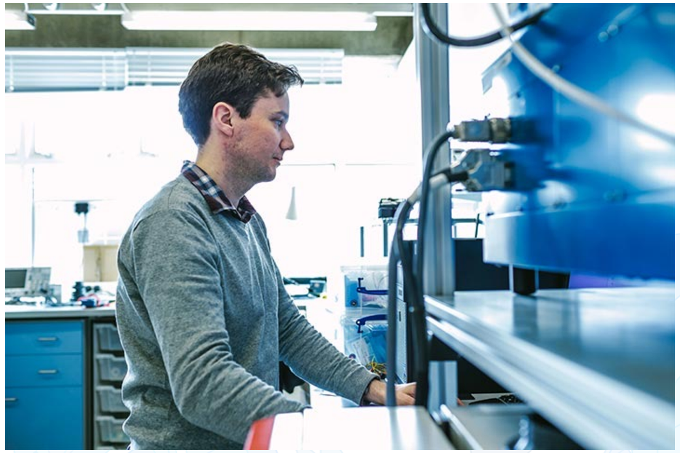


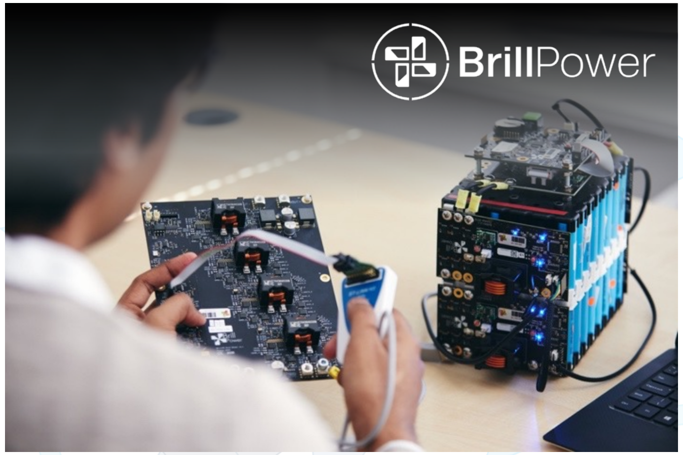
2023: 25 faculty, 50+ postdocs, 80+ PhD students
Materials: Patrick Grant, Peter Bruce, Saiful Islam, Mauro Pasta;
Engineering/Maths: Paul Shearing, Charles Monroe, Jon Chapman, myself

BIL: Modelling, control, diagnostics, data





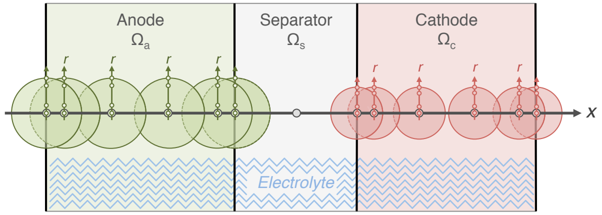




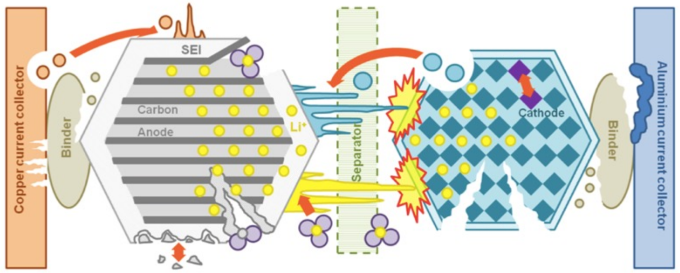
Images: Goodenough public domain (US DOE), Plaque CC BY 3.0 license by Kastrel; Models Howey et al., 2020 Electrochem. Soc. *Interface* 29(4):30-34 (by A. Mistry); EIS, Noel Hallemans; lower photos Brill Power and Ian Wallman.

We’ve had several successes in ‘battery engineering’

Adrien Bizeray: Fast P2D model, Samsung Applied Institute of Technology, Korea, 2015

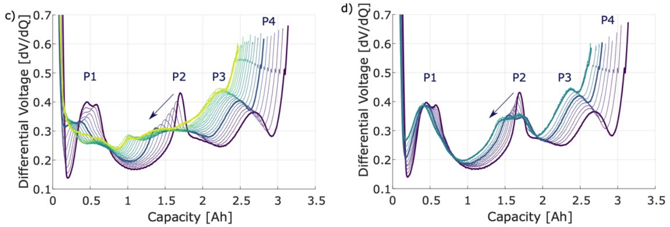


Christoph Birkl: Tracking electrode-specific degradation modes, 2017 (with JLR)



Damien Frost: Decentralised modular batteries/BMS, 2016/17

Trishna Raj: Measuring path-dependent aging, 2020 (with JLR)



FI Project on UK gigafactories, 2019 (with McKinsey)

Jorn Reniers, Volkan Kumtepeli: Impact of usage on revenue & life of grid storage (2020-)

Energy Superhub Oxford

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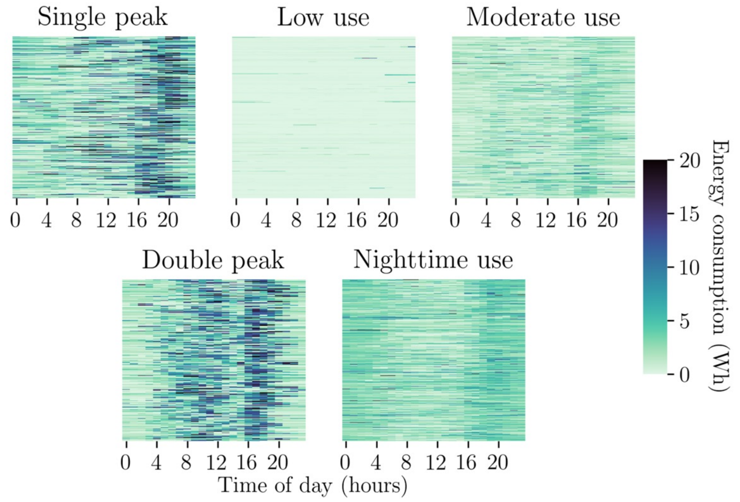
Papers: Birkl, C.R., Roberts, M.R., McTurk, E., Bruce, P.G., & Howey, D.A. (2017). Journal of Power Sources, 341, 373-386; Raj, T., Wang, A.A., Monroe, C.W., & Howey, D. A. (2020). Batteries & Supercaps, 3(12), 1377-1385; Reniers, J. M., Mulder, G., & Howey, D. A. (2021), Journal of Power Sources, 487, 229355. Top centre photo: Brill Power. Bottom R: ESO.

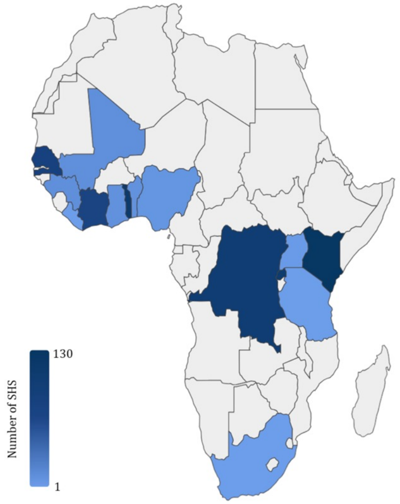
Energy access is an ongoing research theme

Long-term relationship with BBOXX

Supporting DPhil students and research:

- **Valentin Sulzer**, 2015-19, modelling lead-acid batteries
- **Antti Aitio**, 2018-22, battery health estimation
- **Becky Perriment**, 2021-25, energy use and battery life
- **MaxBatt project**, 2024-25, life extension (?)





Papers: Aitio and Howey, Joule 5(12):3204-3220, 2021 + arXiv Preprint 2304.13666, 2023. Photos and images also thanks to BBOXX and Becky Perriment.

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Battery health prediction is important, but challenging

Electric car owner	Investor in a 50 MWh battery	Off-grid system supplier in Kenya

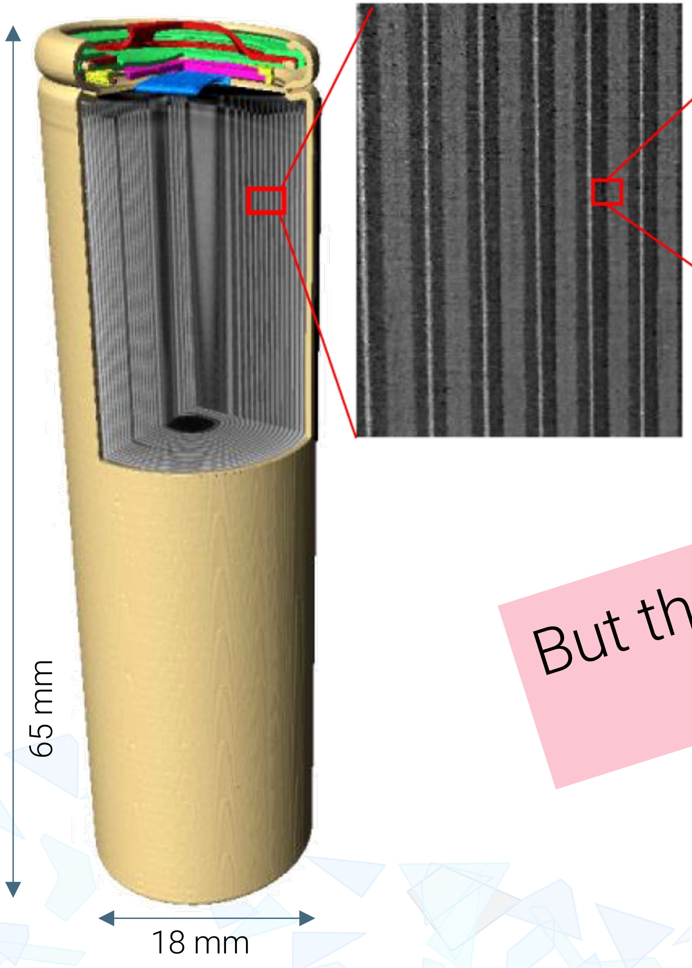
How much will it be worth in 5 years?

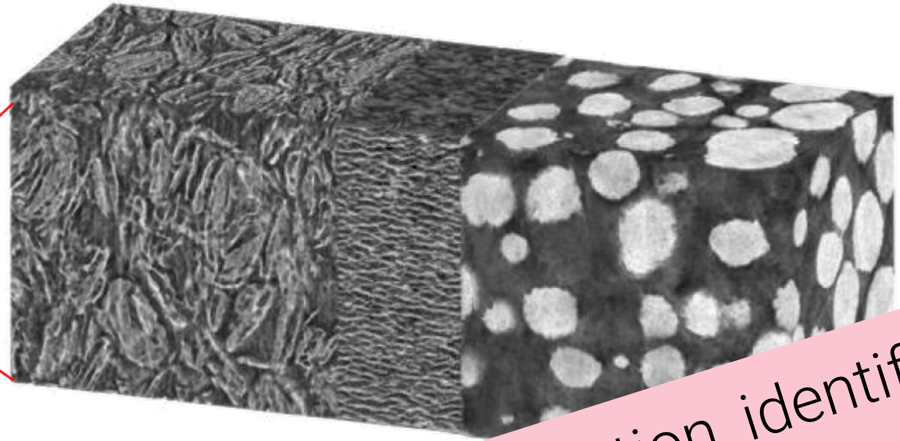
What's the return on investment?

How many spare batteries should I order next month?

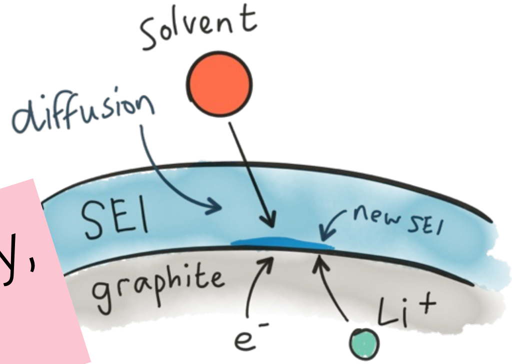
Physics-based models enable plausible long-term scenario testing

Li-ion cell

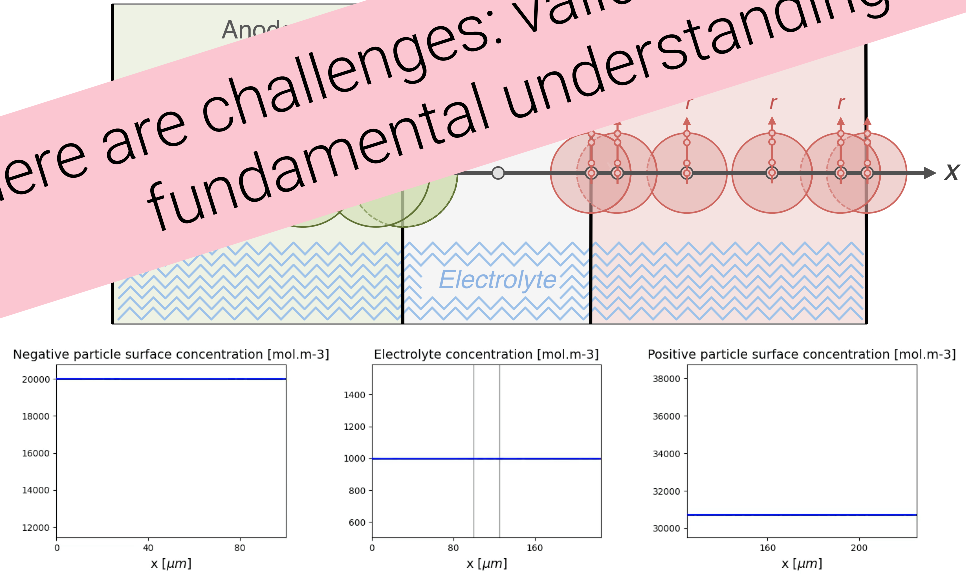


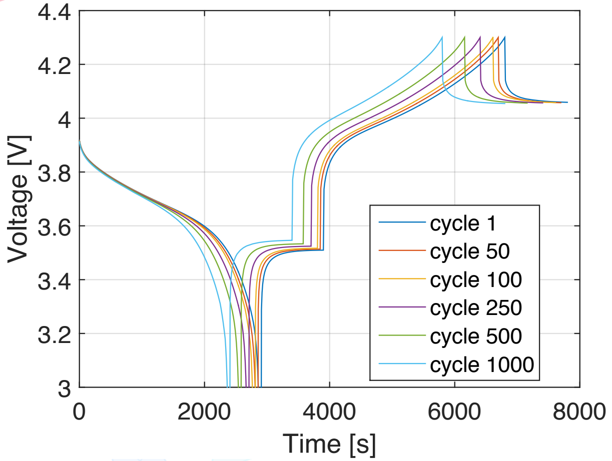


Anode degradation



But there are challenges: validation, identifiability, fundamental understanding



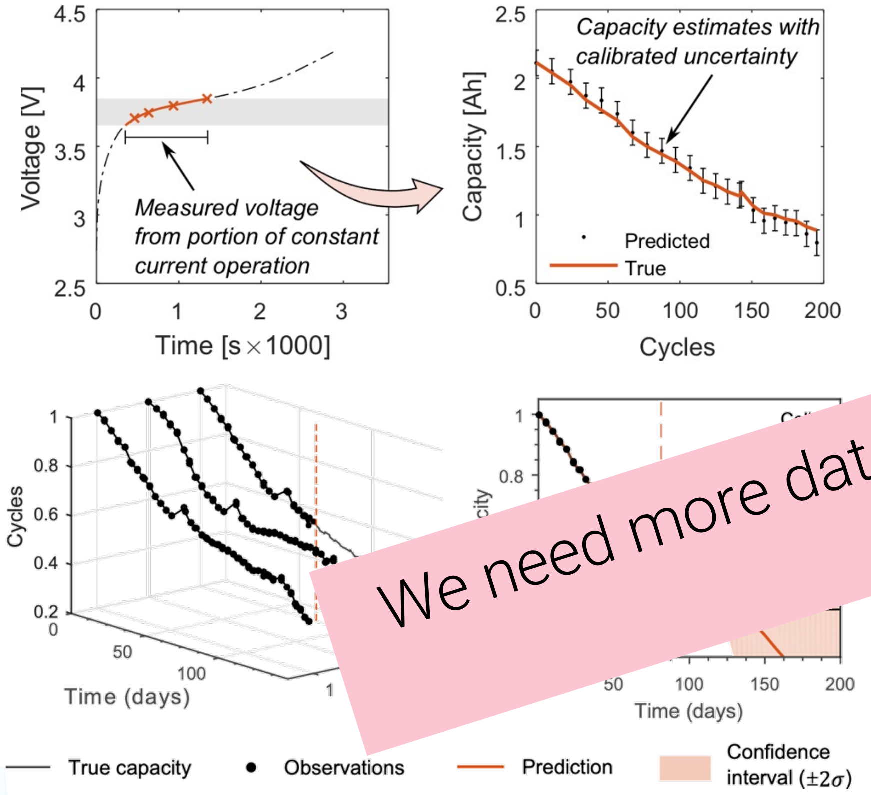


PyBaMM

Images: LHS adapted from Lu, Bertei, Finegan et al. Nat Commun 11, 2079 (2020) CC BY 4.0 license, middle bottom and RHS: Adrien Bizeray

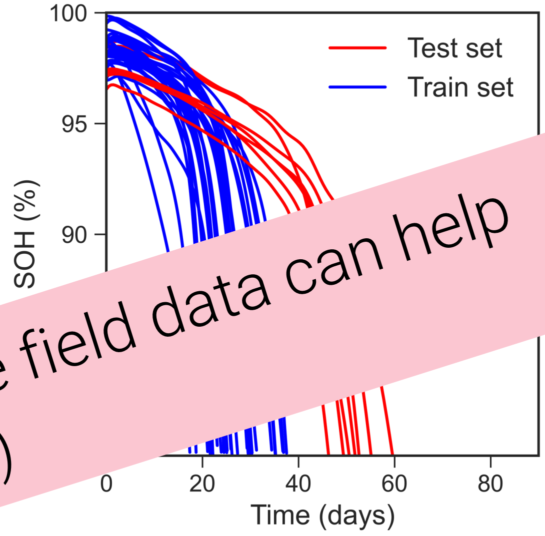
Machine learning is interesting – but only if you have enough (good) data

- ML can be used for diagnostics and prognostics



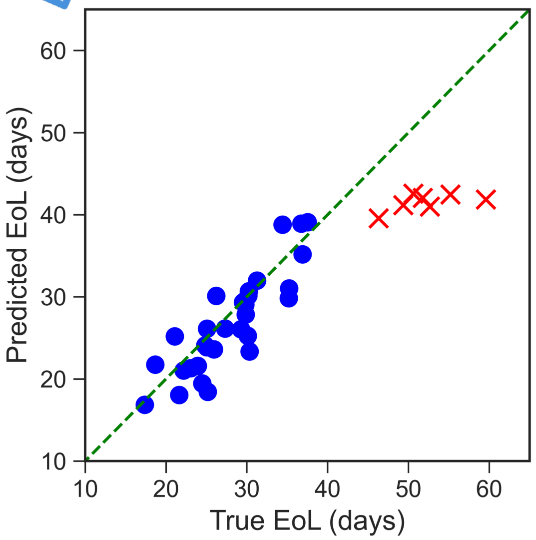
Richardson, R.R., Osborne, M.A., & Howey, D.A. (2017). "Gaussian process regression for forecasting battery state of health". J Power Sources, 357, 209-219 and Richardson, R.R., Birkl, C.R., Osborne, M.A., & Howey, D.A. (2018). "Gaussian Process Regression for In Situ Capacity Estimation of Lithium-Ion Batteries". IEEE Transactions on Industrial Informatics, 15(1), 127-138.

- But generalization requires large, rich datasets



We need more data! Maybe field data can help (BUT ...)

Toy example: train model on one condition but use it at another condition.



So much can change!

- temperature, C-rate
- SOC range
- energy/power cell
- chemistry
- application
- rest periods...

Figures kindly generated by Zihao Zhao

Learning battery health from field data (with *very* simple models!)

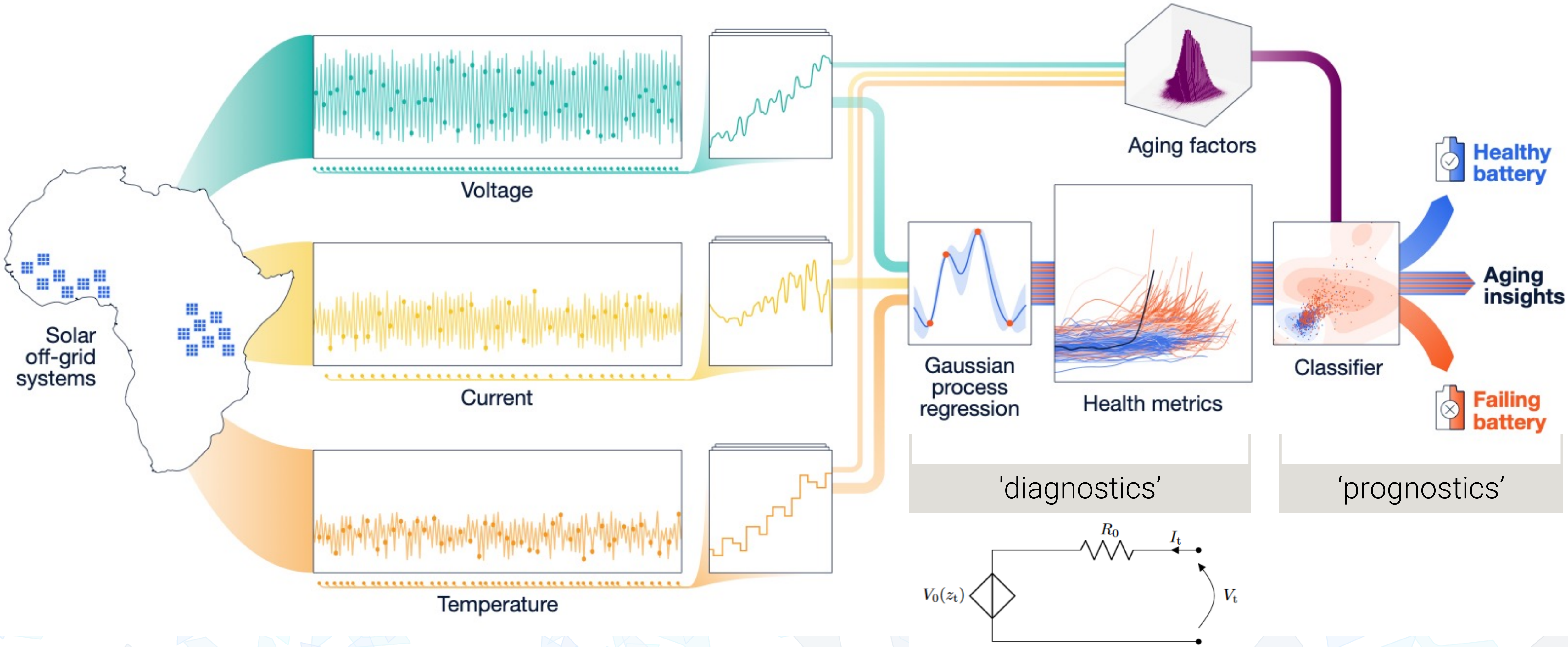
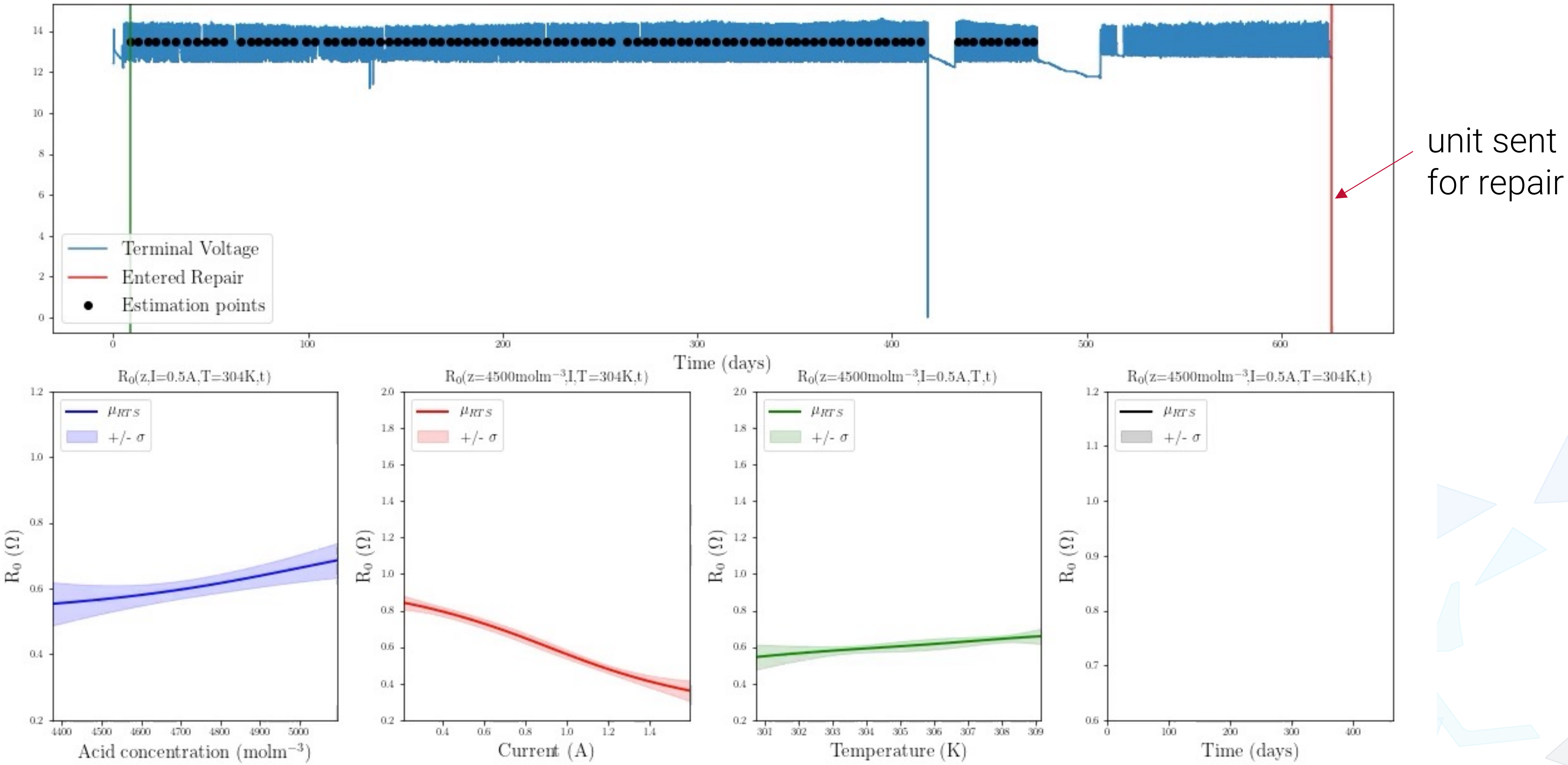


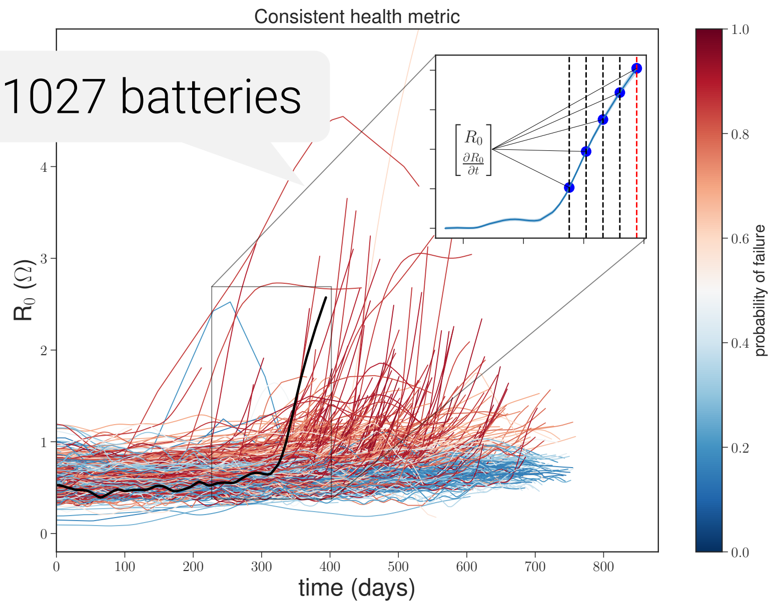
Figure reprinted from Aitio and Howey, Joule 5(12):3204-3220, 2021

From field data, learn the dependence of R_S on SOC, T, I, t



Voltage data: BBOXX; Video: Antti Aitio

To predict failure, train a classifier with independent validation data



1027 batteries

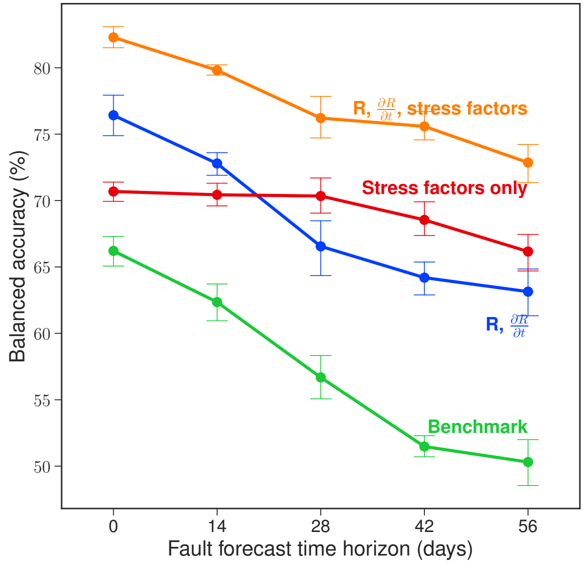
Stress factors, i.e. cumulative:
- Age
- Charge throughput
- Cycles
- Mean temperature
- Mean voltage
- …

Classifier

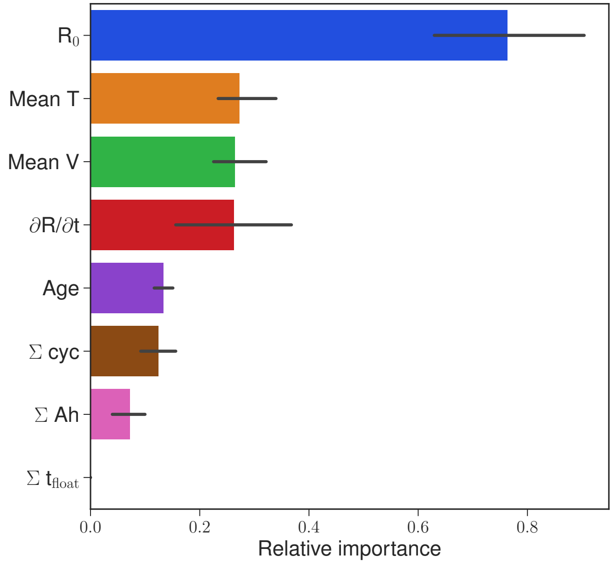
fault predictor:

Balanced accuracy =

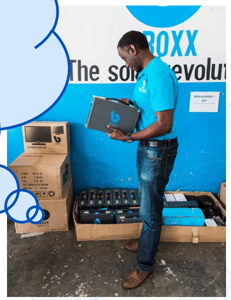
$$\frac{1}{2}(\text{Sensitivity+ Specifty}) = \frac{1}{2}\left(\frac{\text{TP}}{\text{TP+FN}} + \frac{\text{TN}}{\text{TN+FP}}\right)$$



aging model:



"Probability of failure is high for 23 batteries this month."



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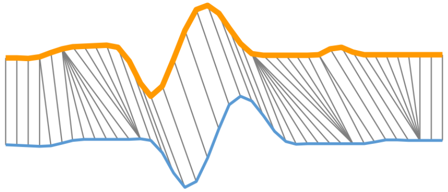
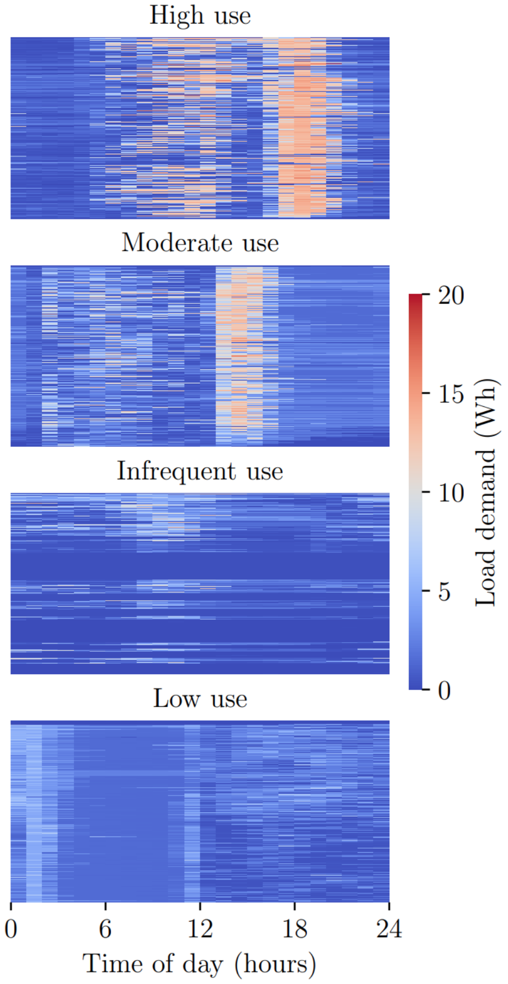


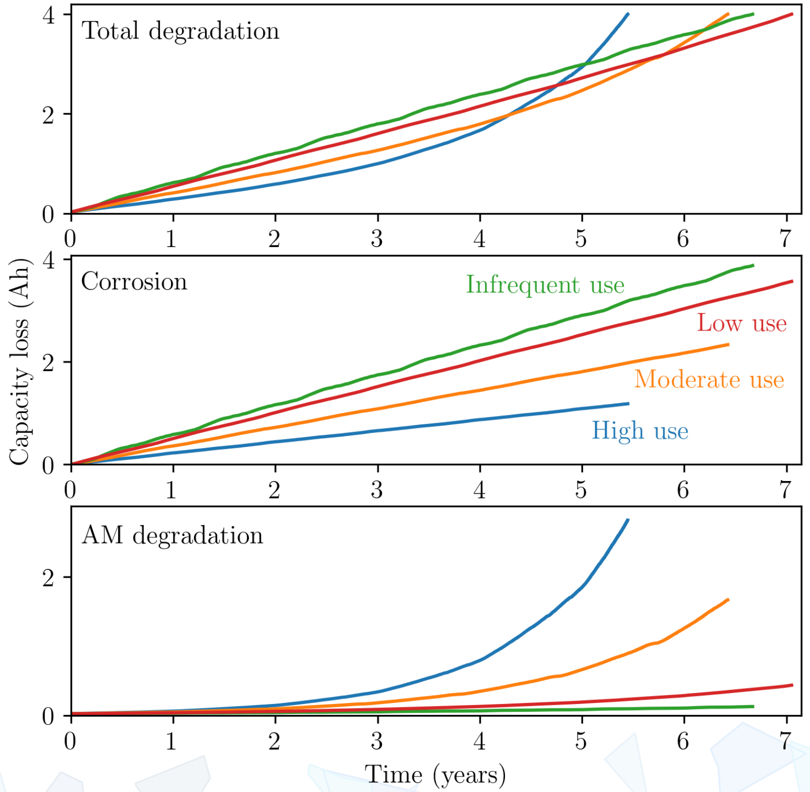
Bottom image by Romain Tavenard, https://rtavenar.github.io/blog/dtw.html, 2021

Adjusting battery controls based on usage can improve lifetime

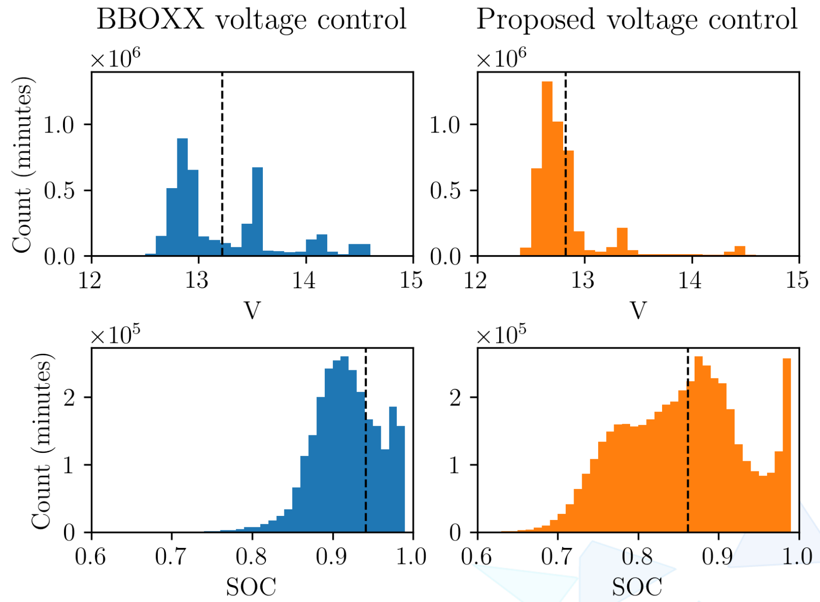
People use solar home systems differently



Batteries experience different ageing mechanisms/rates



Control ageing rates by adjusting upper voltage limit

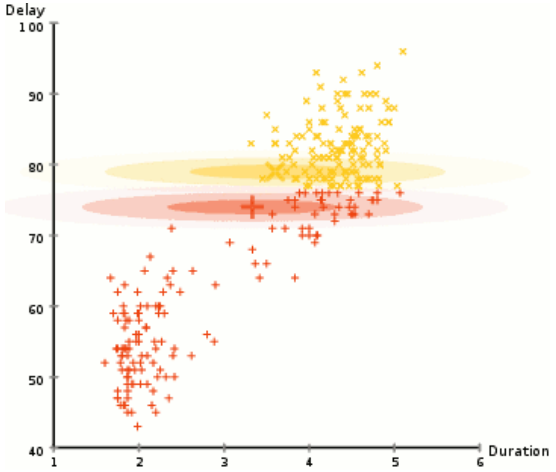


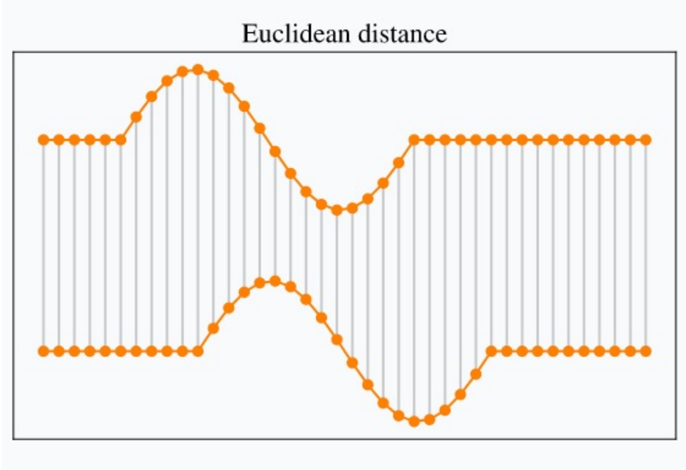
Challenge: How to extend battery lifetime without impacting user experience

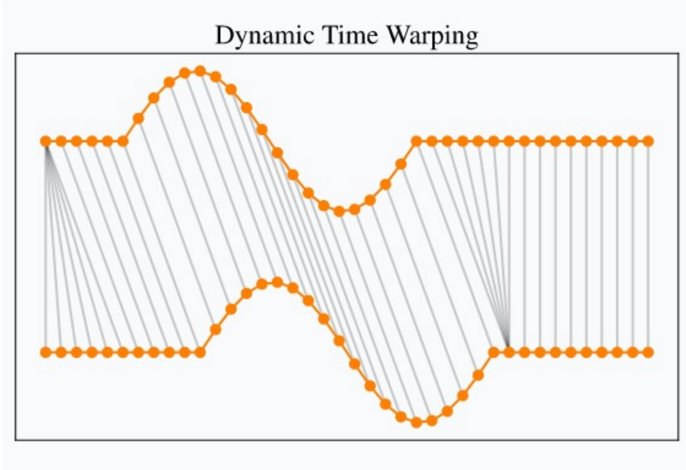
Clustering is useful for understanding time series (energy) data

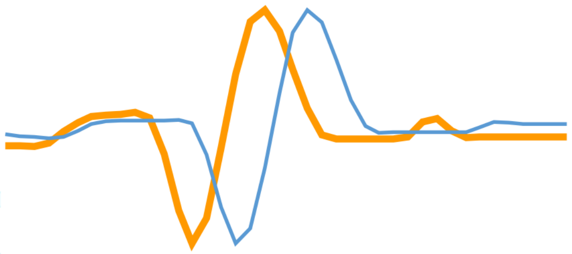
- Clustering is a key technique for unsupervised learning
- Split data into groups based on 'similarity'
- Not an exact science!

- Time series are tricky – what distance to use?

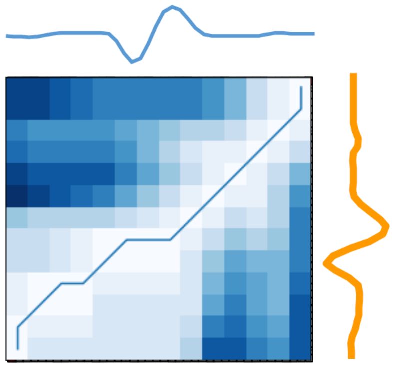




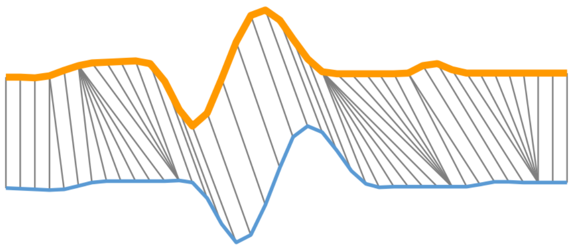




Original time series



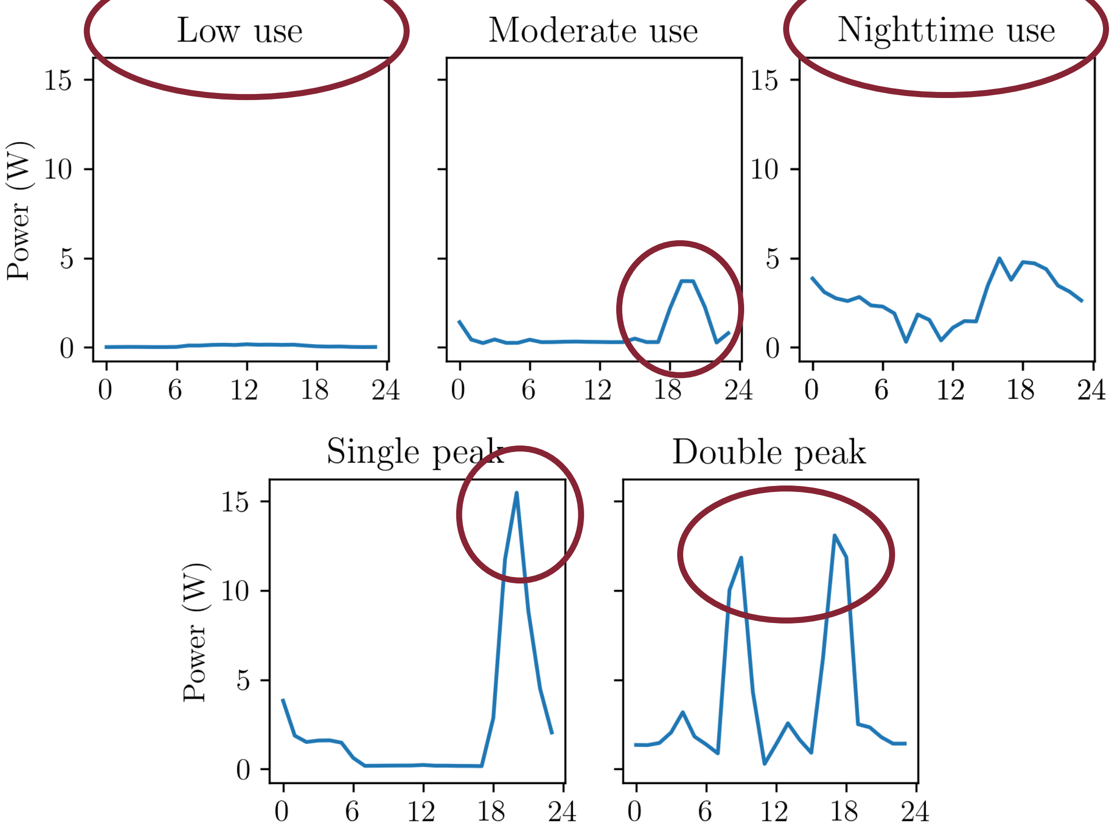
Optimal shifting

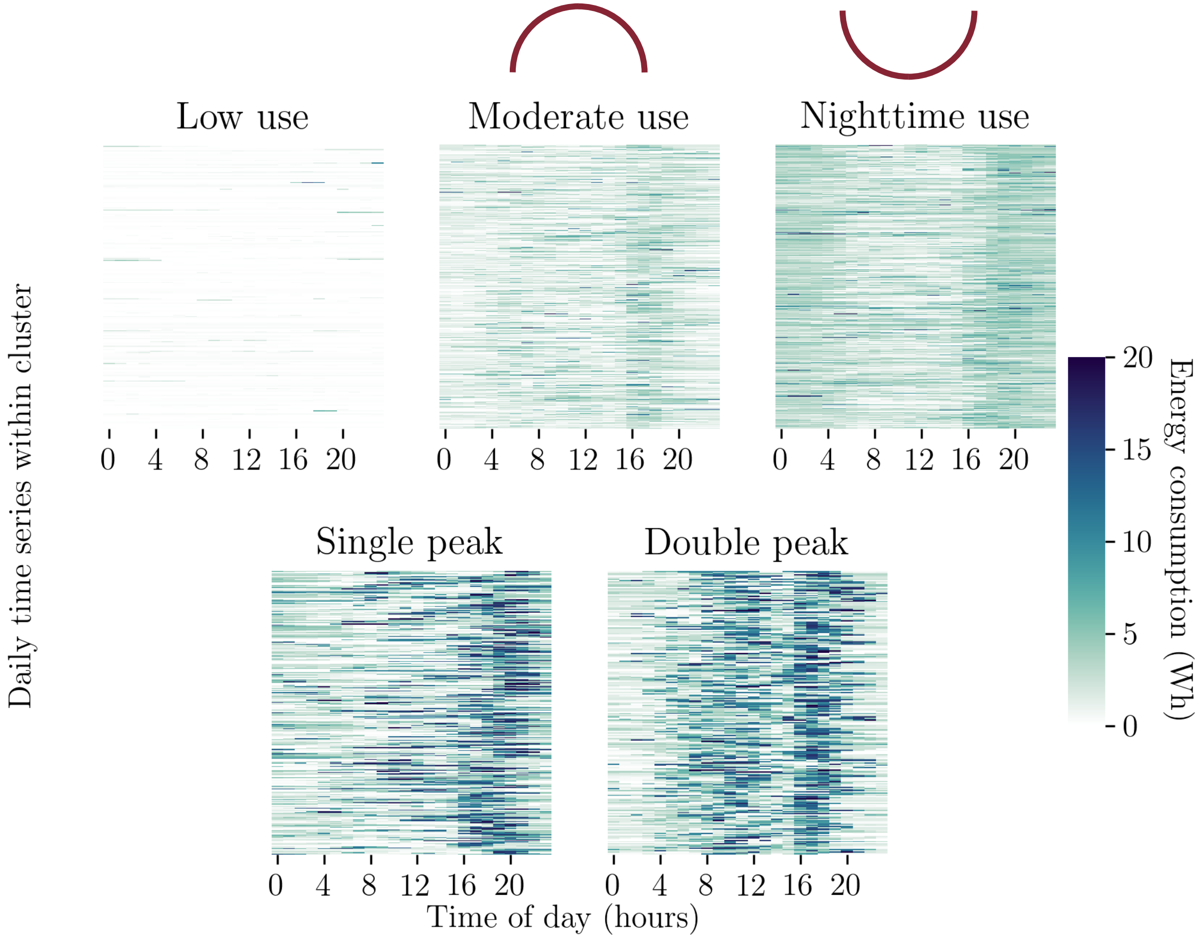


Matched time series

Five clusters of electricity use show up in rural off-grid systems

We clustered the daily load profiles of over 1,000 BBOXX SHS customers

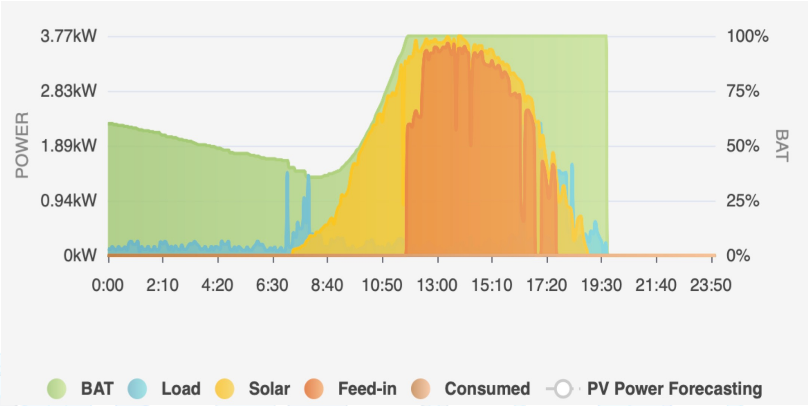


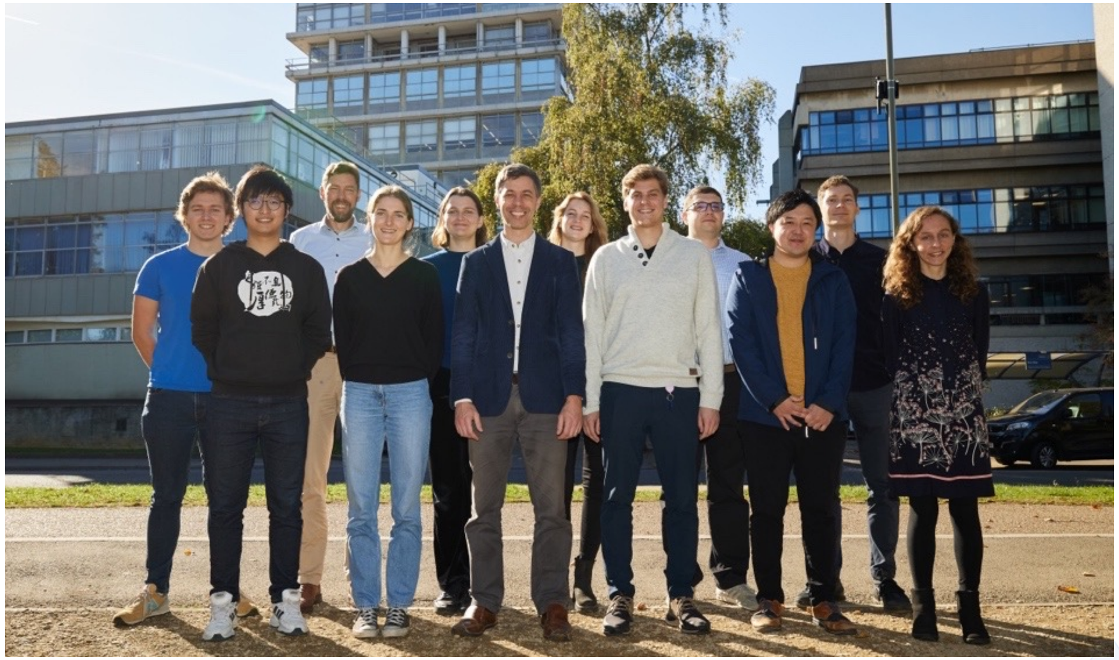


Perriment et al., "Clustering Load Demand of Off-Grid Solar Home Systems in Sub-Saharan Africa: Insights on Payment and Long-Term Behaviour", *Paper under development*

Summary and outlook

- We're still learning how batteries perform 'in the wild'. Lab tests often don't compare well to field data.
- Combining aging models and usage data is key to extending life.
- Also true for larger systems, e.g….





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