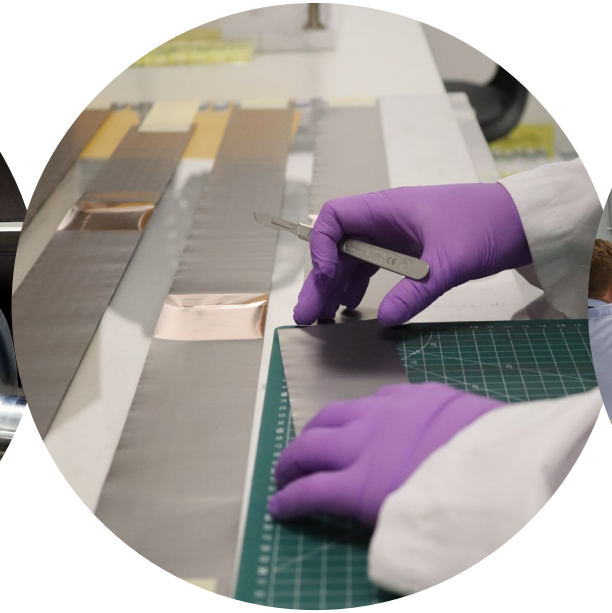
Introducing UKBIC



Manufacturing Scale-up



Product Development



Testing and Analysis



Workforce Development

Why predict cycle life?

Cycle testing is slow and costly

Cut costs

Long cell cycling is expensive

Save time

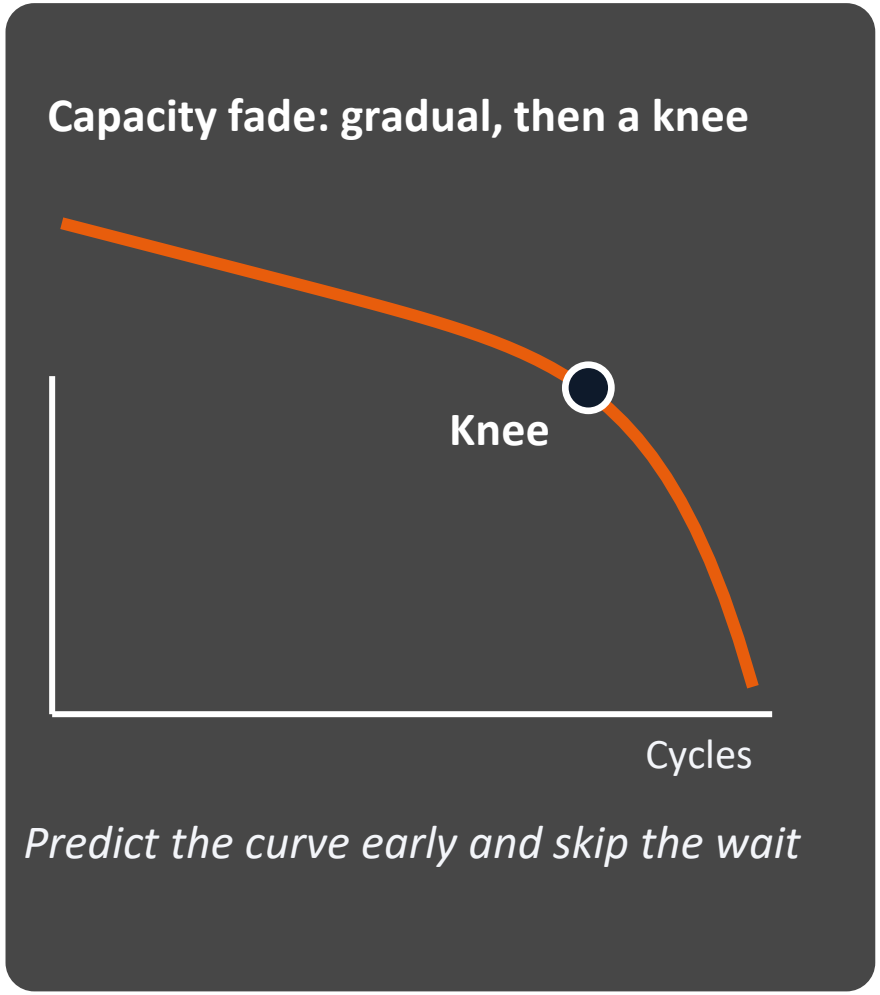
Cycling takes months to years of testing

See mechanisms earlier

Understand cell degradation mechanics earlier

Screen designs and protocols

Evaluate design decisions and gain insights



Three ways to predict cycle life

Physics-based

- Electrochemical models: DFN, SPM, SPMe
- Semi-empirical fade laws
- Equivalent-circuit models with aging
- Degradation-mode (LLI and LAM) models

Data-driven

- Feature-engineered regression
- Gaussian processes and tree ensembles
- Deep sequence models: LSTM, CNN, Transformer
- Impedance and relaxation-based models

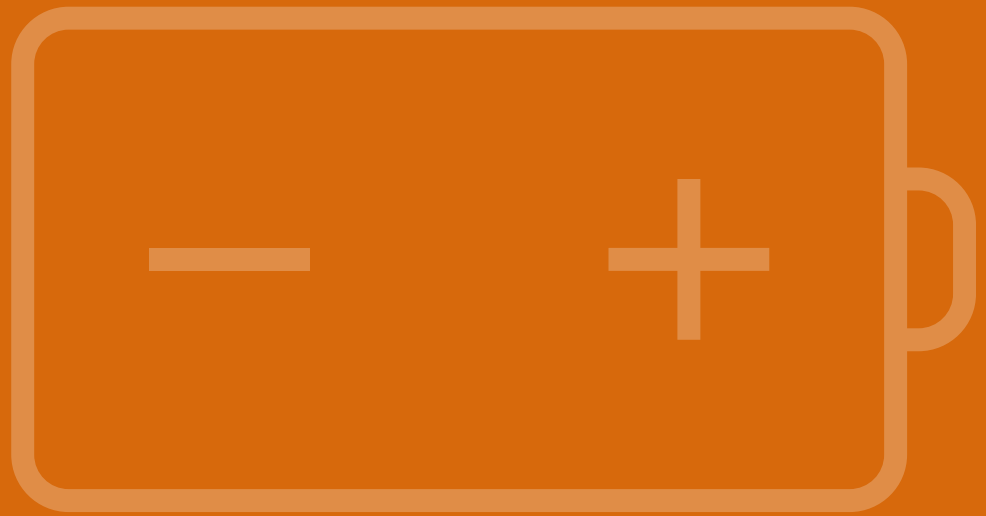
PIML

- Physics trend plus ML residual
- ML-estimated physics parameters
- Physics-informed neural networks
- Neural surrogates of simulations

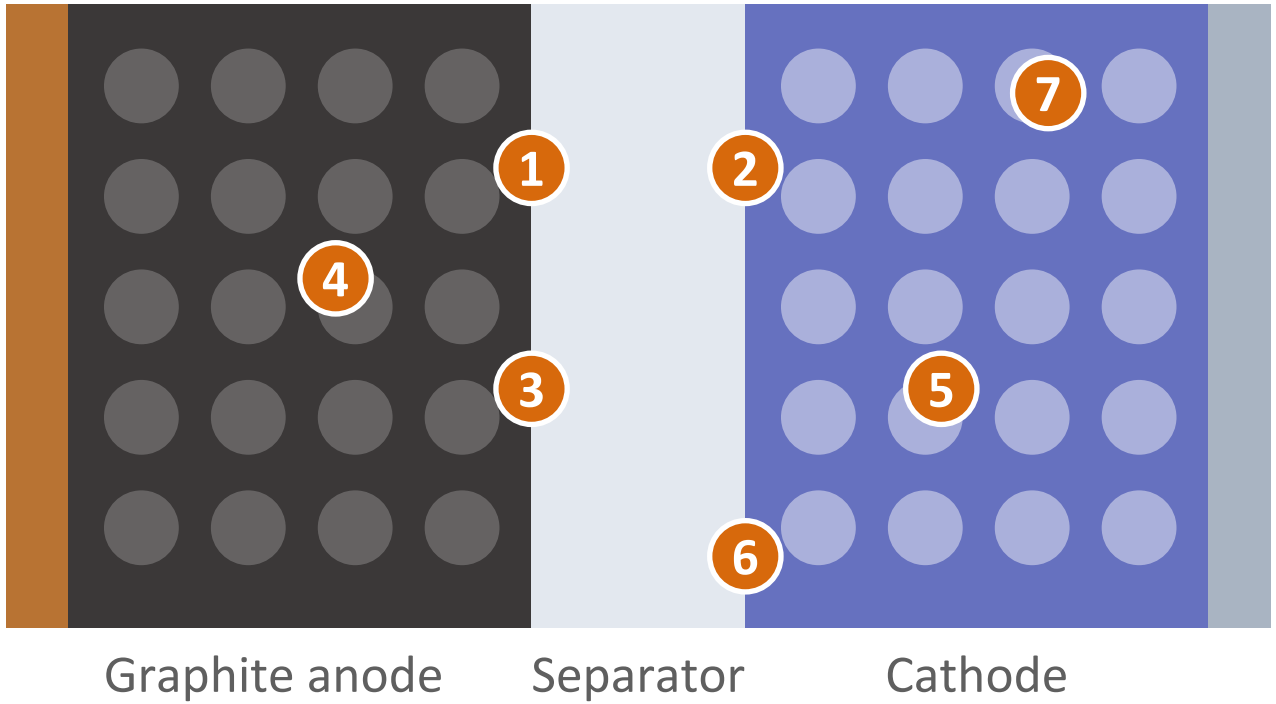
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External speaker slots

Richard Robinson



Physics models to capture seven degradation mechanisms



1. SEI growth on the anode surface
2. CEI growth on the cathode surface
3. Lithium plating on the anode
4. Particle cracking in the anode
5. Cathode cracking and surface reconstruction
6. Transition-metal dissolution
7. Electrolyte oxidation and gas at the cathode

More than one degradation mechanism can be combined in a single model

Every mechanism ends as one of three losses

LLI

Loss of lithium inventory

Cyclable lithium is consumed by side reactions such as SEI growth and plating, so less is left to shuttle between the electrodes

Drives capacity fade

LAM

Loss of active material

Electrode particles crack, lose electrical contact or change structure, so part of the host material can no longer store lithium

Drives capacity fade

RESISTANCE

Rising internal resistance

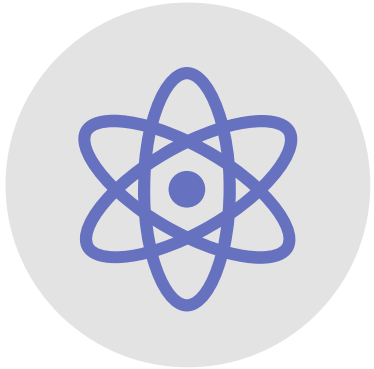
Thicker films, lost contacts and a drying electrolyte slow charge transfer and ion transport, which cuts power

Drives power fade

Capacity fade is mainly LLI and LAM. **Power fade** is mainly resistance rise

Degradation sub-models are attached to DFN, SPM, SPMe or ECM

The advantages: physics-based models explain the why



First principles



Answers the why question



Interpretable



Generalised



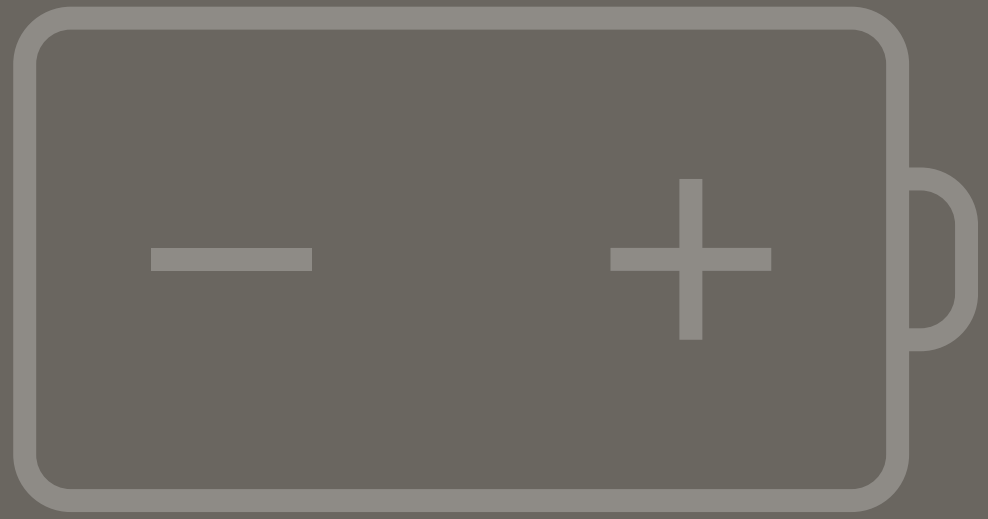
Highly accurate

The challenges: they're complex, slow and costly to build

- Model parameters
- Multi-scale
- Complexity
- Domain knowledge
- Computation time
- Cost

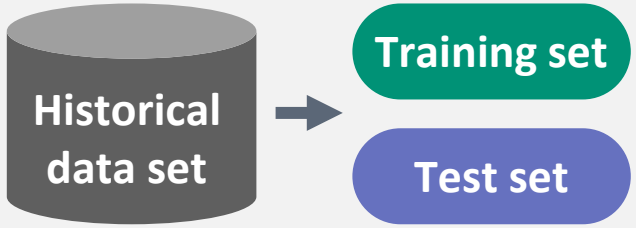
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Data-driven models



ML workflow: from historical data to deployed model

1 Preprocessing



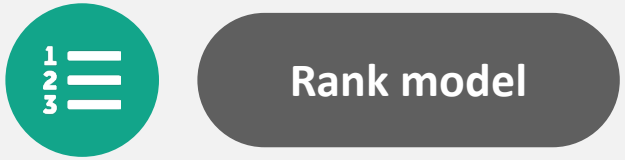
- Data cleaning
- Partition data
- Data exploration
- Feature selection

2 Train and test model



- Model selection
- Parameter tuning
- Apply model
- Optimise model

3 Performance evaluation



- Score model
- Check for overfitting
- Validate model
- Deploy model

Machine learning: deep sequence models learn the features themselves

1

LSTM and GRU

Recurrent networks on capacity or voltage time series, suited to trajectory forecasting

2

Temporal CNN and transformer

Convolutions or attention over windows of cycles, capturing long-range context

3

MLP, SVM and XGBoost

Simplicity and fast inference, and capability to learn nonlinear model

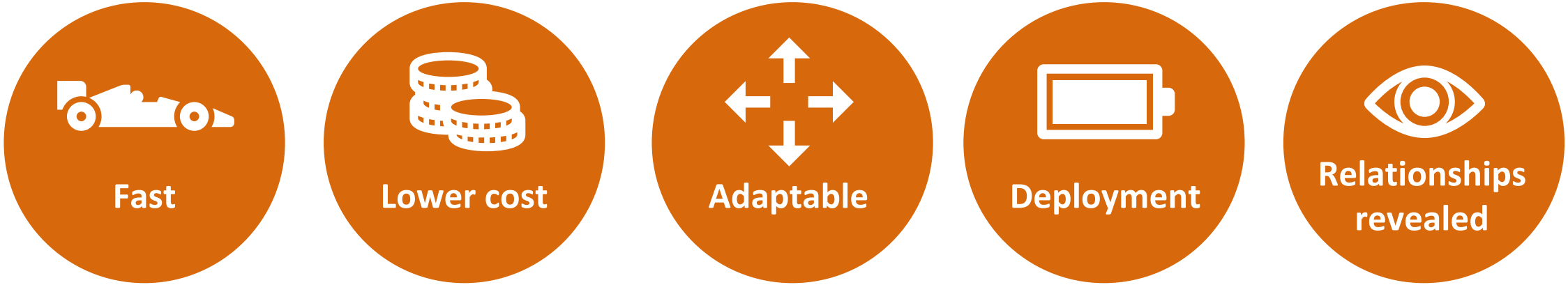
Advantage

Learns features automatically and handles whole trajectories

Disadvantage

Needs far more cells than regression and can overfit to one batch

The advantages: ML models are fast, cost effective and adaptable



Three learning modes

1

Supervised learning

Predicts cell properties from known material descriptors

2

Unsupervised learning

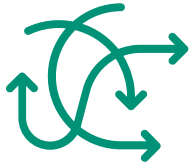
Clusters materials by latent structure, revealing hidden relationships

3

Transfer learning

Applies knowledge from related domains to sparse battery datasets

The disadvantages: ML models stumble on data, trust and extrapolation



Poor interpretability

Black-box nature



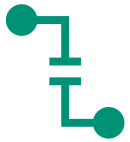
Lack of generalisation

The same model architecture can give different outcomes in different applications



Data availability

Data hunger. Scarce and sparse data. IP and data protection rules. No standardised dataset



Bias and reproducibility

Proprietary or unrepresentative data can perpetuate performance gaps across material classes



Data integrity

Bad data = bad model

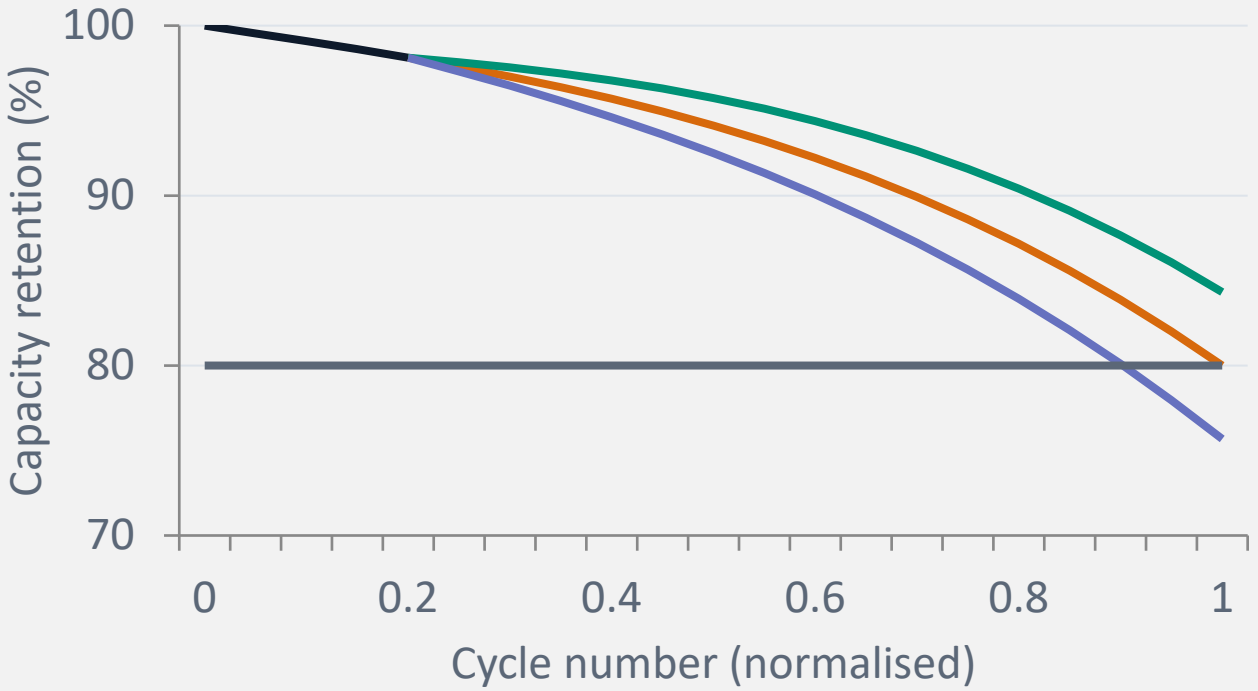


Poor extrapolation

Pure data-driven models break down outside their training distribution, giving highly inaccurate predictions

The workflow: from early-cycle data to a forecast with uncertainty

1. **Early cycle data**
   Split data into training and validation sets
2. **Build model**
   Physics-based or ML models
3. **Model evaluation**
   Evaluate model against early-life data
4. **Forecast**
5. **Uncertainty quantification**



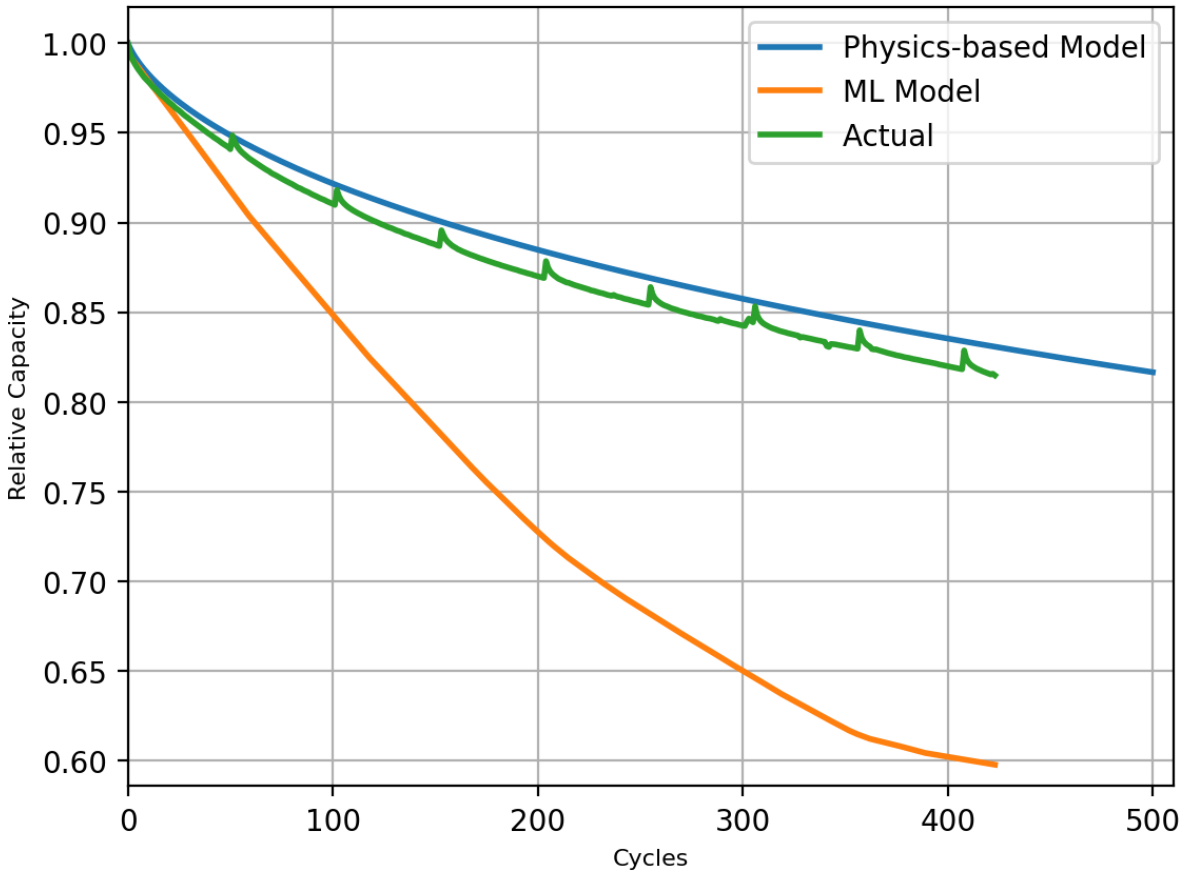
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Case studies

Prediction results, model accuracy and challenges



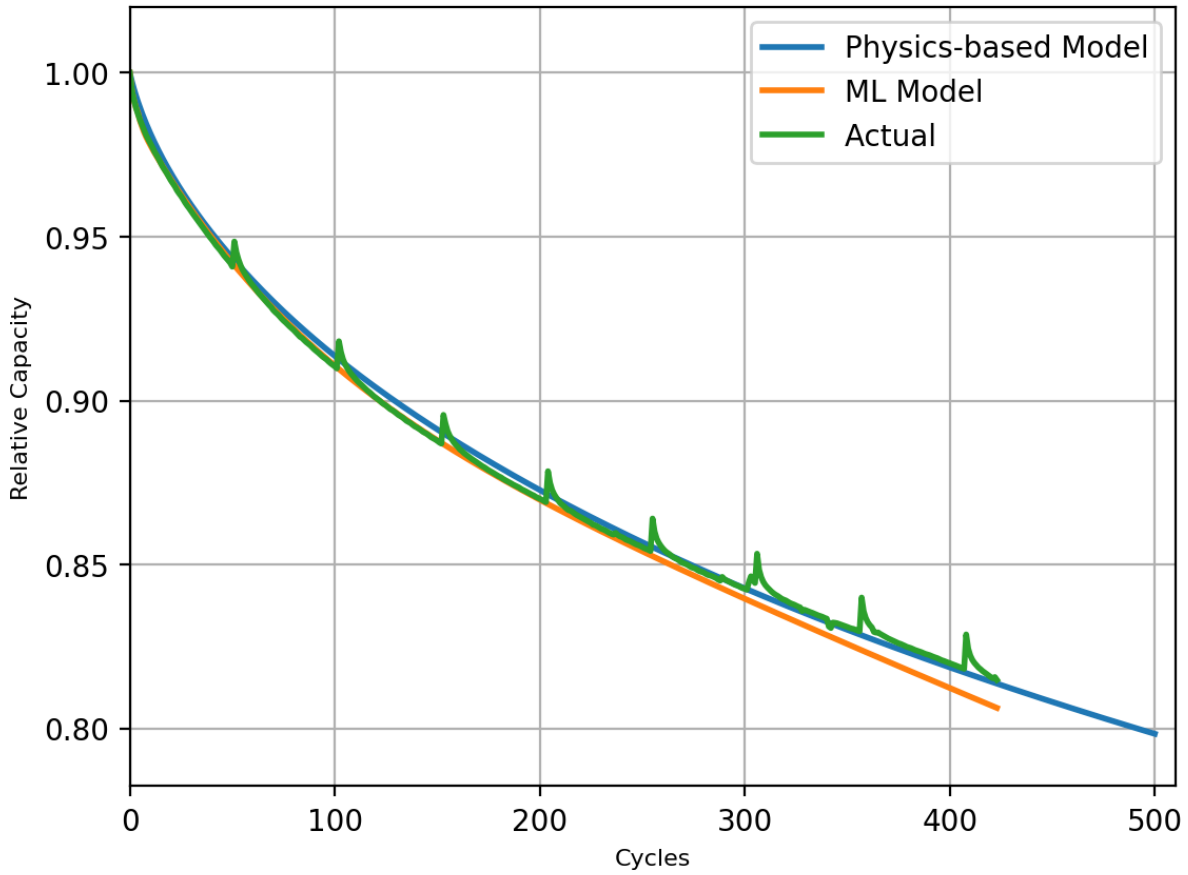
With 2% of the data, machine learning is fast but 15.2% off



	ML model	Physics-based
PREDICTION ERROR (RMSE)	15.2%	1.25%
RUN TIME	5 minutes	1 week

Model trained or tuned with 15 full cycles, about 3% of the total data

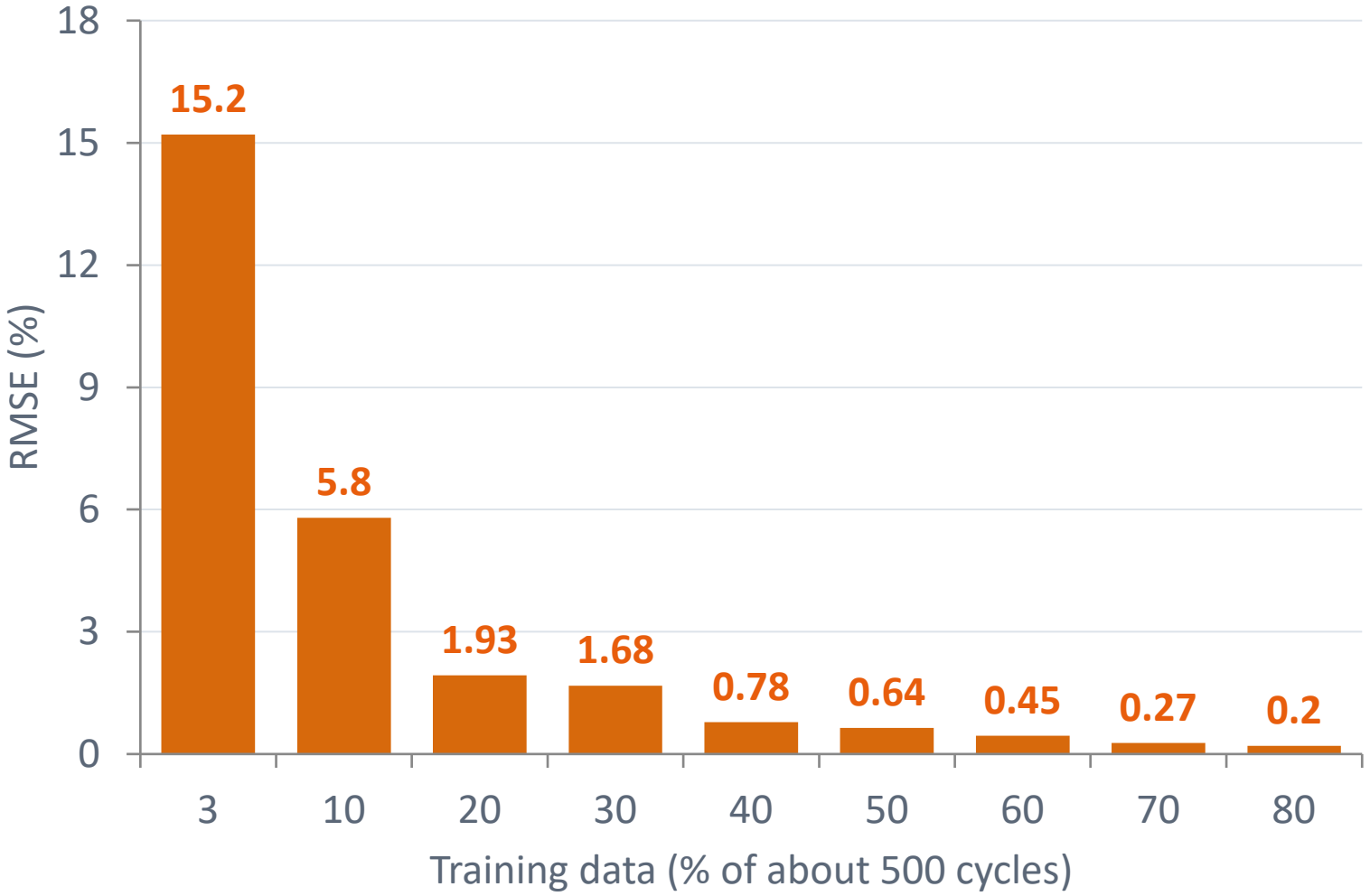
With 20% of the data, machine learning error falls to 1.93%



	ML model	Physics-based
PREDICTION ERROR (RMSE)	1.93%	0.27%
RUN TIME	5 minutes	1 week

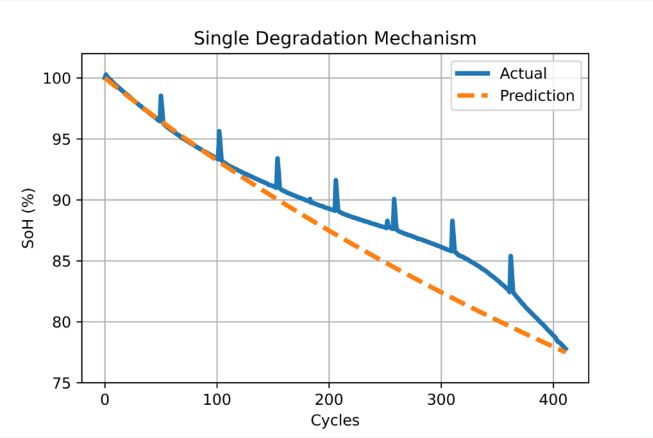
Model trained or tuned with 100 full cycles, about 20% of the total data

More training data drives machine learning data error from 1.2% to 0.2%



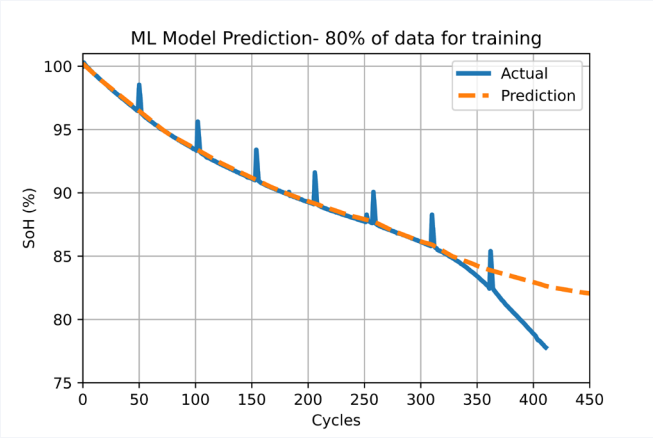
ML accuracy can match or surpass physics-based accuracy, but it needs a large volume of valid historical data

Case study: machine learning and physics both struggle to extrapolate



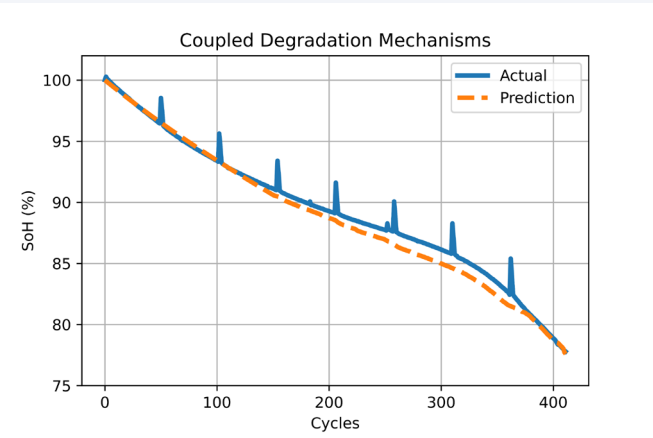
Physics-based

These models mostly explain degradation in cycling data rather than forecast it



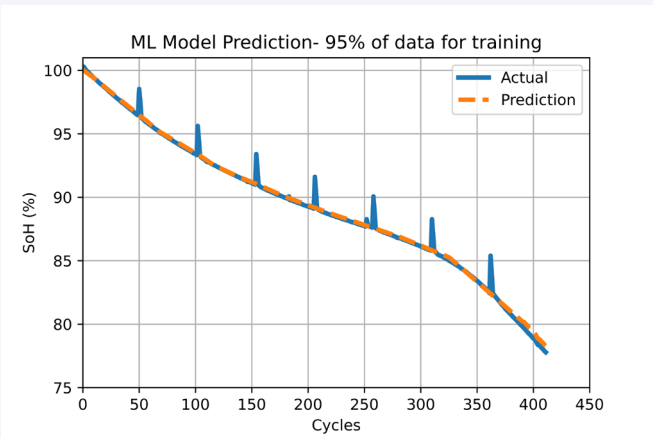
ML

ML can only extrapolate trends in its training data



Physics-based

Cell-to-cell spread means parameters need updating for every build and may not transfer



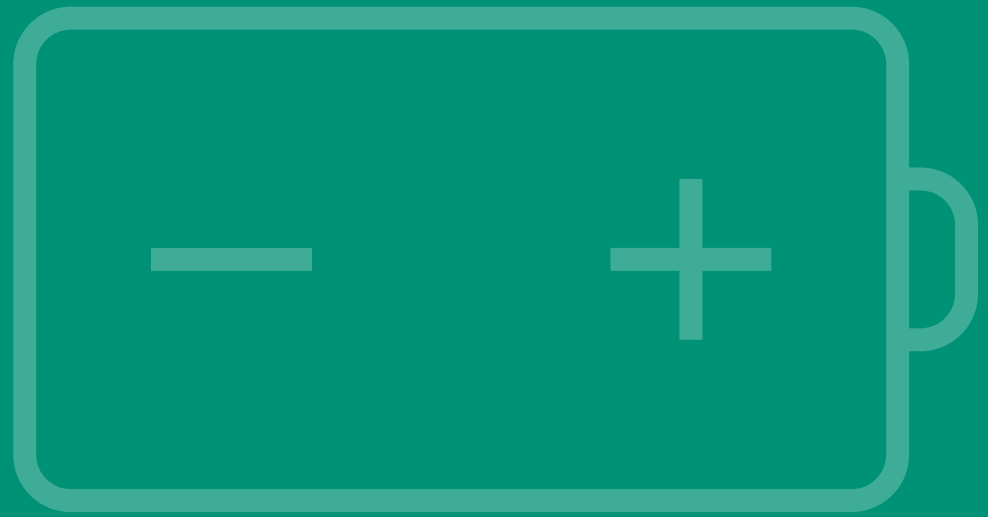
ML

ML can learn multi-degradation signals, but they appear late in the cycling data

Line about PIML models

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Physics-informed machine learning models (PIML)



Hybrid models: speed meets interpretable accuracy

ML models

Speed

Trade-offs

- Wait time and cost
- Volume of training data
- Prediction accuracy

Physics-based models

Accurate and interpretable

Must capture

- Multi-scale and multi-degradation
- Operating conditions
- Dynamics at high C-rates
- Multi-physics

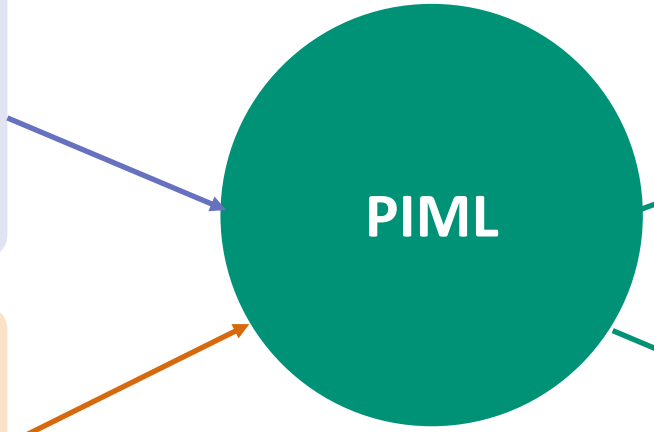
Hybrid models

The speed of ML with the accuracy and interpretability of physics

PIML: physics priors meet data-driven learning

Physical laws
Governing equations and constraints

Neural networks
Discovering patterns



Integrating priors with data

Data efficient
High performance with fewer data samples

Extrapolates better
Interpretable

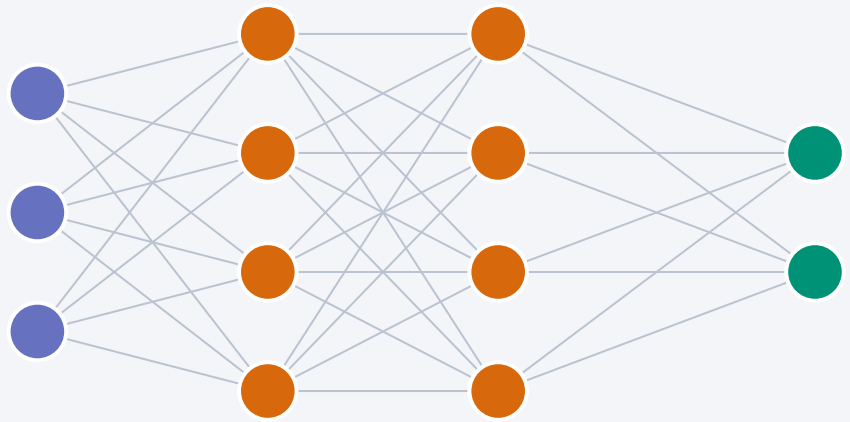
Physics enters the ML workflow through

- Features
- The loss function
- The model structure

Two techniques: embed physics or augment the data

PINN

Embed the PDE in the ML loss function

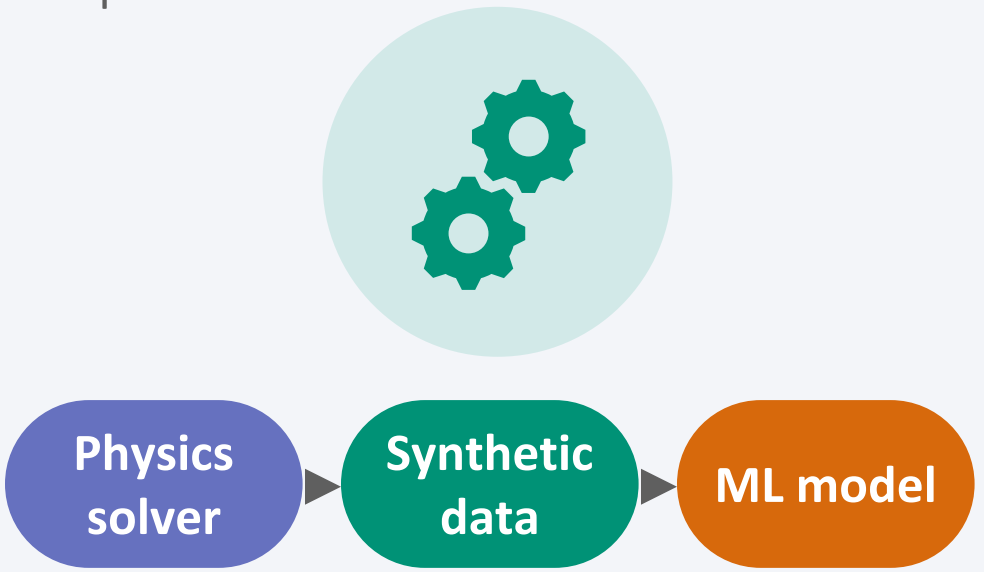


Inputs Outputs

Loss = data misfit + PDE residual

Data augmentation

Combine physics solvers and data with ML components



Real data can be blended in at each step

Closed loop: synthetic data then a physics cross-check

PHASE 1: Build on synthetic data

Validated physics-based model
Multi-modal degradation

Generate synthetic data

Train ML models

- Learn state vs cycle number
- Per-mechanism physics parameters
- Multi-mechanism signals

PHASE 2: Predict and reconcile

Sparse early-life cycle data

ML model predictions → physics parameters and RUL

Physics model predictions

Models agree?

No

Yes

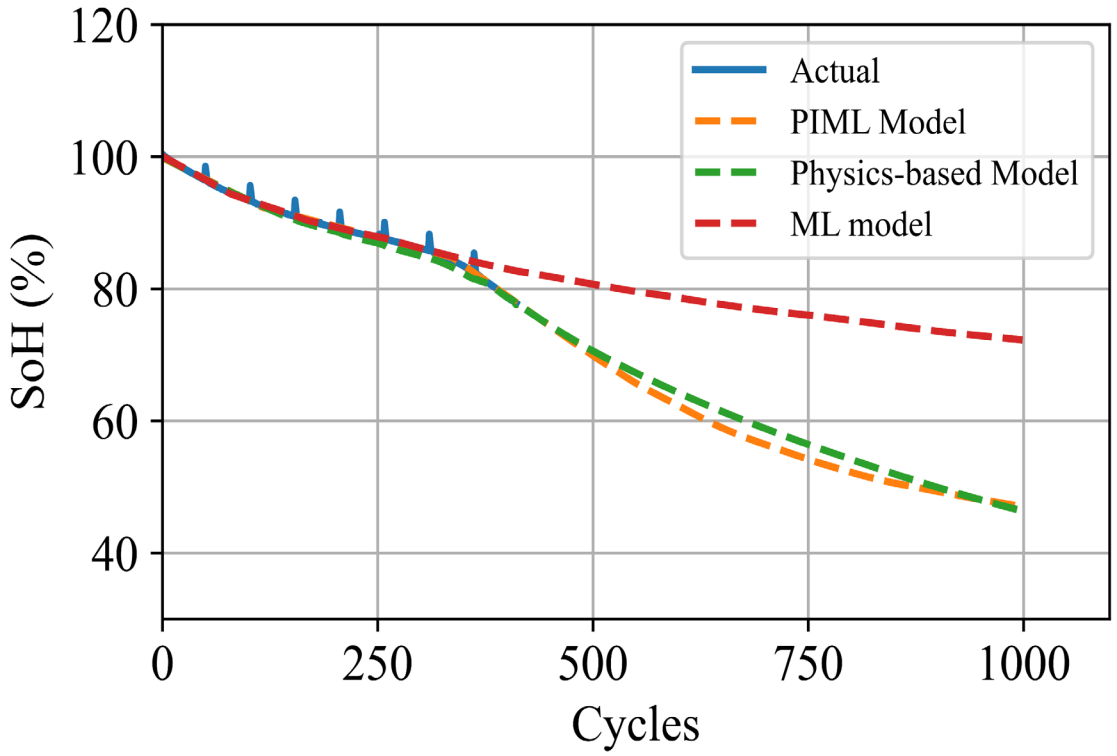
End

Prediction error and physics model parameters

→ **physics-guided loss**
→ **update network weights**

- Synthetic data removes the label bottleneck
- Per-mechanism parameters stay interpretable and measurable
- An explicit physics cross-check on every prediction
- Multi-mechanism signals inform late-life predictions

The result: PIML tracks physics accuracy in hours not weeks



Degradation trend guided by physics · 50 cycles for training

Run time

ML model
5 minutes

PIML model
2 hours

Physics-based
1 week

50 cycles for training/tuning · bar lengths on a log scale

Summary

Let physics guide the data: the speed of ML with the trust of physics

Physics- based

1 week

run time

Explains the why and is highly accurate, but complex, parameter-heavy and slow to run

Machine learning

5 minutes

run time

Fast and cheap, but data-hungry and unreliable outside its training data

Physics-informed ML

2 hours

run time

Physics guides the learning: data-efficient, interpretable and better at extrapolating

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Our capability



Data source: UKBIC cell cycling facilities

288 test channels for long-term cycling and high-accuracy characterisation

96

pouch cell channels
100 A per channel

192

cylindrical cell channels
15 A per channel



Pouch
Maximum current
100A

Cylindrical
Maximum current
15A

Operating range
Temperature
–40°C-100°C

ML prediction tools for fast state of health forecast

UPLOAD FILE

Test data

Cell_00…l_Data.csv 4.3KB × Upload

Pre-trained models

GRU.pt 53.0KB × LSTM.pt 69.9KB × MLP.pt 36.1KB × Upload

☑ Use only pre-trained models

MODEL SELECTION

GRU × LSTM × MLP ×

Select test size 0.20

Select learning rate 0.001

Select number of epochs 3000

Select number of cycles to forecast 500

RUN MODEL ☐ Save model

BEST MODEL · RMSE

LSTM

0.0144 LOWEST

WORST MODEL · RMSE

MLP

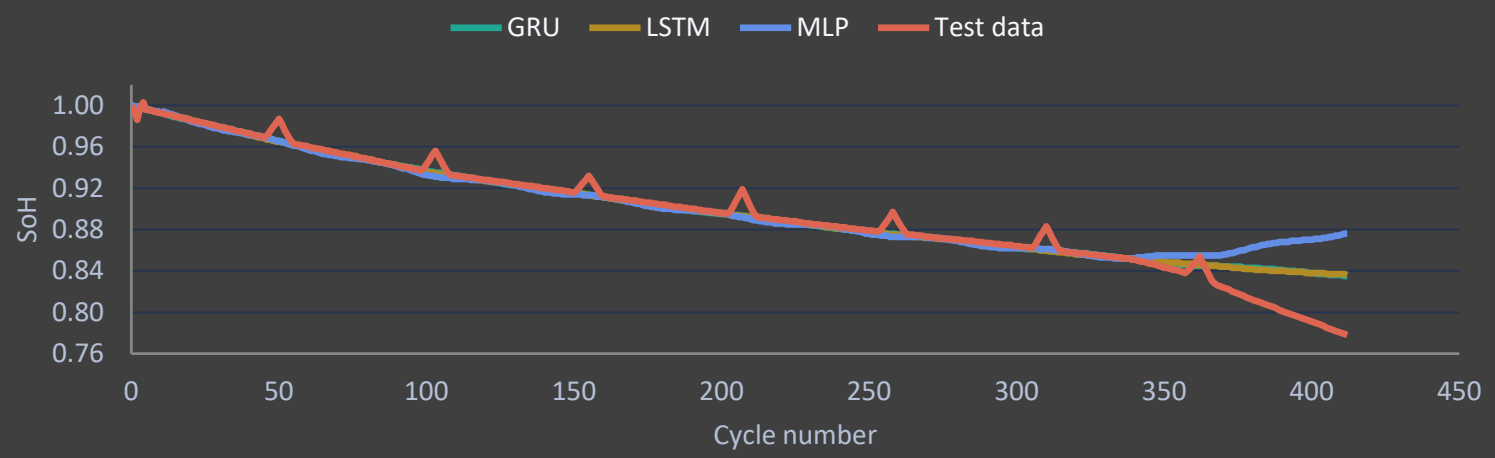
0.0225 HIGHEST

RUN

412 cycles

Test data vs 3 forecasts

STATE OF HEALTH BY CYCLE



MODEL	RMSE	MAE	R^2
LSTM BEST	0.0144	0.0066	0.9305
GRU	0.0150	0.0069	0.9246
MLP WORST	0.0225	0.0097	0.8289

Question and answer panel

Please use the Q&A function and not the Chat function



Kenneth Nwanoro
Senior Modelling & Simulation Engineer



Webinar Host:
Richard Robinson
PR & Communications Manager

Webinar: Battery Trendspotting 2026-2027: A view from the CTO



Richard LeCain

CTO

24 November 2026

Register via - www.ukbic.co.uk/webinars



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