On the use of machine learning in (Li-ion) battery degradation

May 10, 2023

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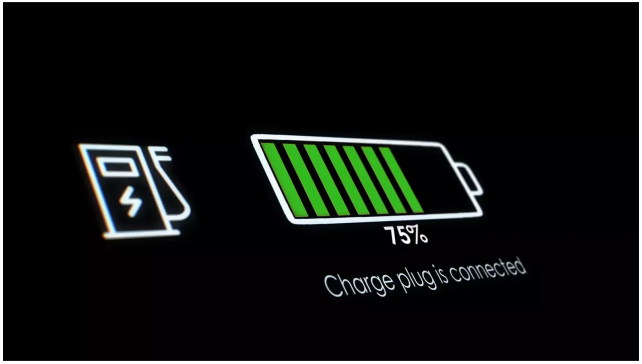
Battery degradation

What is battery degradation?



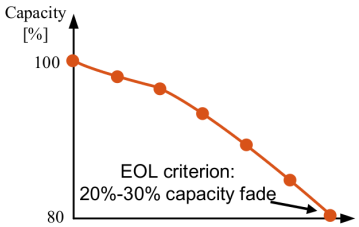
- Loss of performance during long-term operation.
- Effect is loss of power and capacity.
- In an EV the result is loss acceleration and range.
- In a laptop / phone, the result is a loss of response and charge.

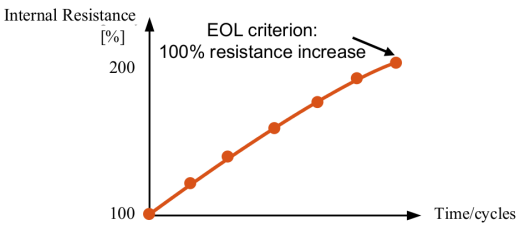
Figure from: https://www.greencars.com/greencars-101/battery-degradation-and-how-to-prevent-it

Battery degradation

What makes it difficult to measure?

- Degradation is a latent variabel – meaning that it cannot be measured directly.

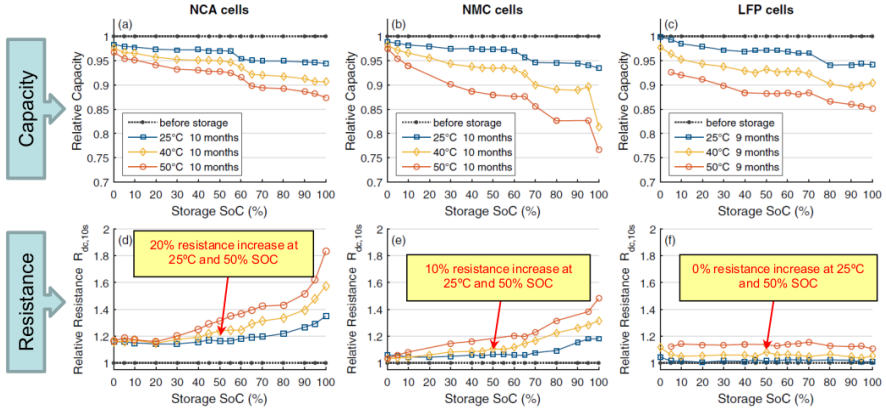




- Power and capacity are very difficult to measure during battery operation.

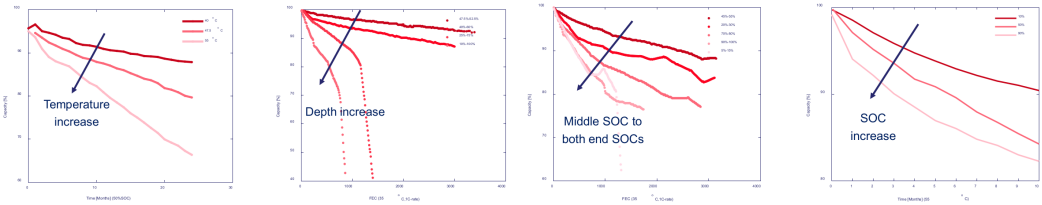
Battery degradation

What makes it difficult to model?



Battery degradation

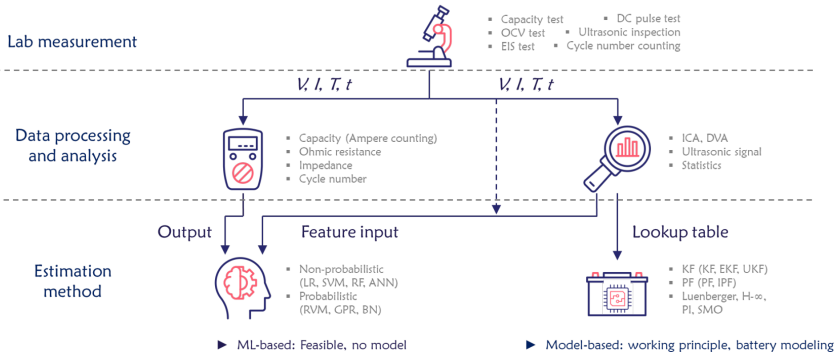
What makes it difficult to model?



- The way the battery is stored and operated has a huge influence on its degradation pattern.
- The dependence between battery health and storage/operation is complex.

Machine learning in battery degradation

Moddelling state-of-health

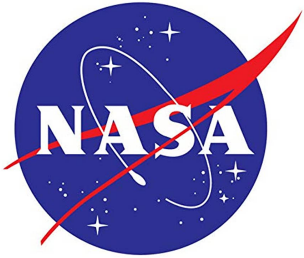


X. Sui, "Robust state of health estimation for lithium-ion batteries using machine learning," Ph.D. dissertation, Dept. Energy, Aalborg University, Aalborg, Denmark, 2022

The NASA data

The NASA data

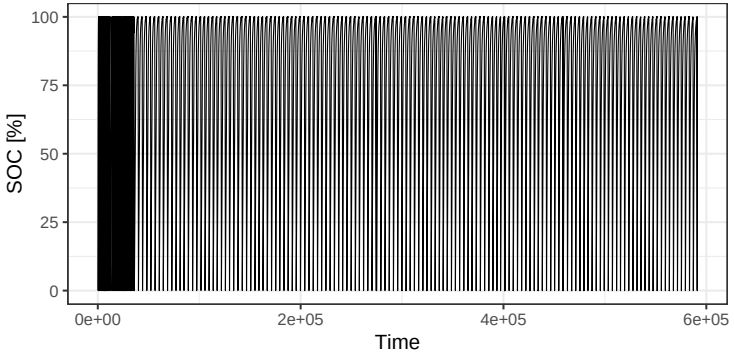
- Publically available data-set of aged battery cells.
- The cells are aged under different operating conditions – different charge/discharge profiles, temperatures, ...
- Contains capacity, resistance, and EIS measurements.



Data available at: https://data.nasa.gov/dataset/Li-ion-Battery-Aging-Datasets/uj5r-zjdb/data

The NASA data

Charge and dischage



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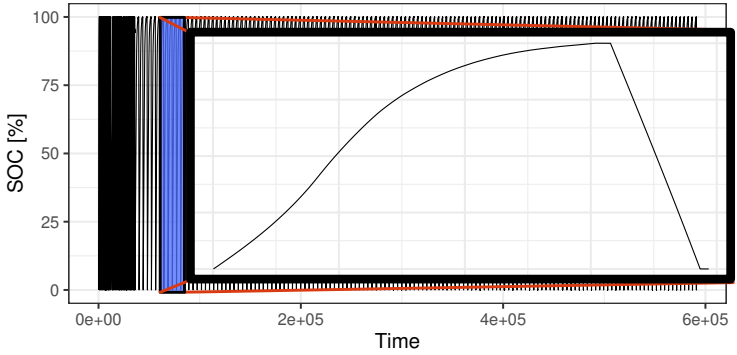

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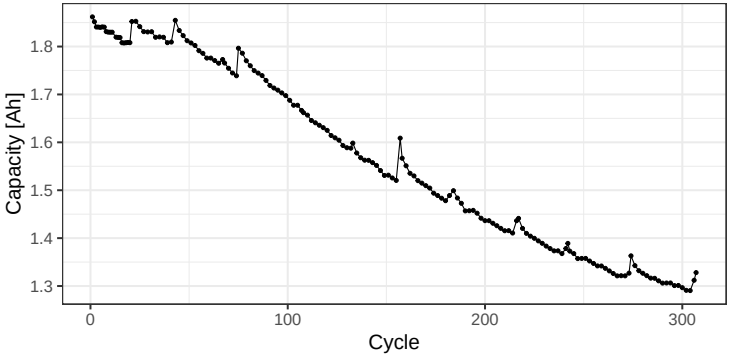
The NASA data

Degradation



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Machine learning in battery degradation

Example 1

5634 IEEE TRANSACTIONS ON INDUSTRIAL ELECTRONICS, VOL. 65, NO. 7, JULY 2018

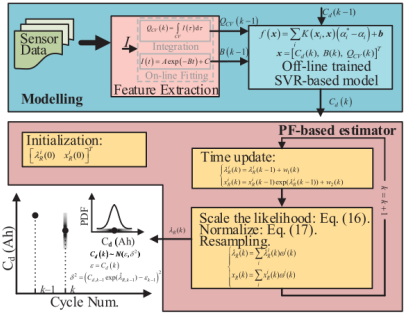
Remaining Useful Life Prediction and State of Health Diagnosis for Lithium-Ion Batteries Using Particle Filter and Support Vector Regression

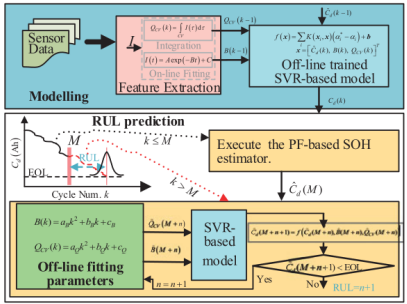
Jingwen Wei, *Student Member, IEEE*, Guangzhong Dong, *Member, IEEE*, and Zonghai Chen, *Member, IEEE*

"Remaining Useful Life Prediction and State of Health Diagnosis for Lithium-Ion Batteries Using Particle Filter and Support Vector Regression," J. Wei et al., 2018

Machine learning in battery degradation

Example 1

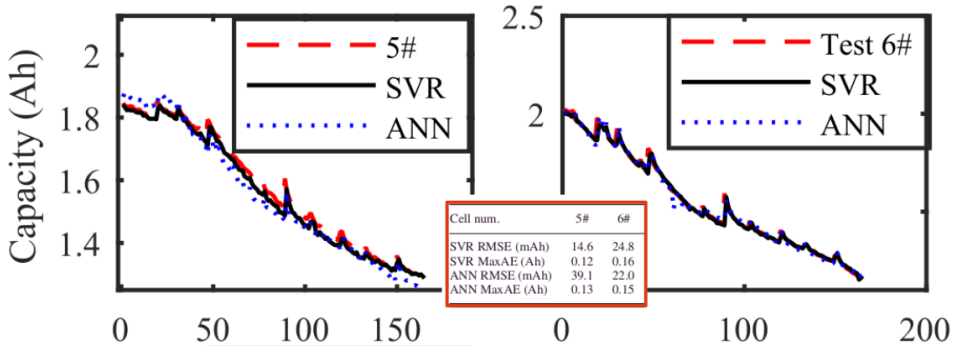




"Remaining Useful Life Prediction and State of Health Diagnosis for Lithium-Ion Batteries Using Particle Filter and Support Vector Regression," J. Wei et al., 2018

Machine learning in battery degradation

Example 1



Cell num.	5#	6#
SVR RMSE (mAh)	14.6	24.8
SVR MaxAE (Ah)	0.12	0.16
ANN RMSE (mAh)	39.1	22.0
ANN MaxAE (Ah)	0.13	0.15

"Remaining Useful Life Prediction and State of Health Diagnosis for Lithium-Ion Batteries Using Particle Filter and Support Vector Regression," J. Wei et al., 2018

Machine learning in battery degradation

Example 2

Journal of Power Sources 459 (2020) 228069

Contents lists available at ScienceDirect

Journal of Power Sources

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

Perspective

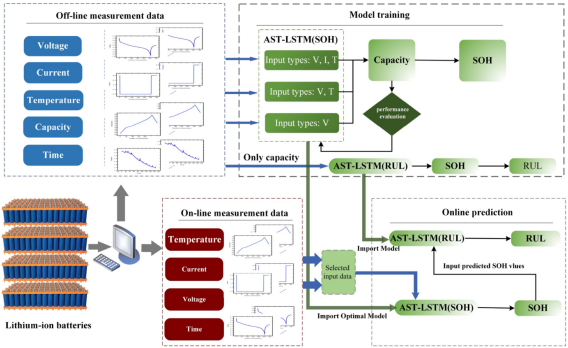
State-of-health estimation and remaining useful life prediction for the lithium-ion battery based on a variant long short term memory neural network

Penghua Li [a,*], Zijian Zhang [a], Qingyu Xiong [b], Baocang Ding [c], Jie Hou [a], Dechao Luo [d], Yujun Rong [e], Shuaiyong Li [a]

"State-of-health estimation and remaining useful life prediction for the lithium-ion battery based on a variant long short term memory neural network," P. Li et al., 2020

Machine learning in battery degradation

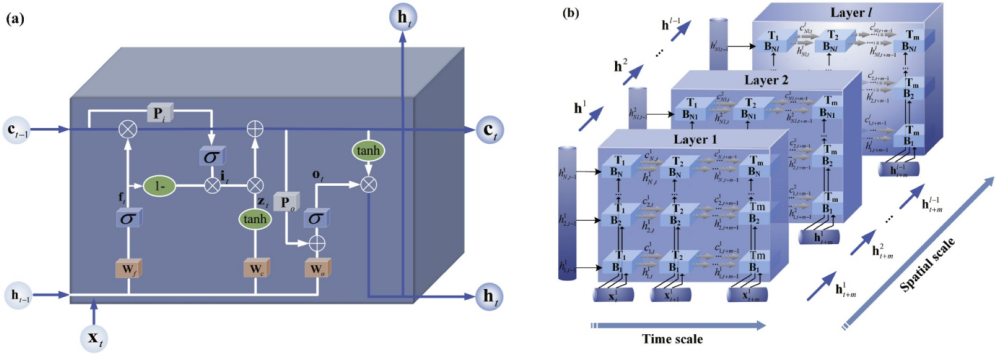
Example 2



"State-of-health estimation and remaining useful life prediction for the lithium-ion battery based on a variant long short term memory neural network," P. Li et al., 2020

Machine learning in battery degradation

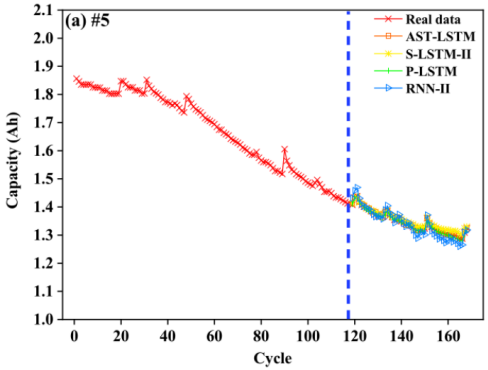
Example 2

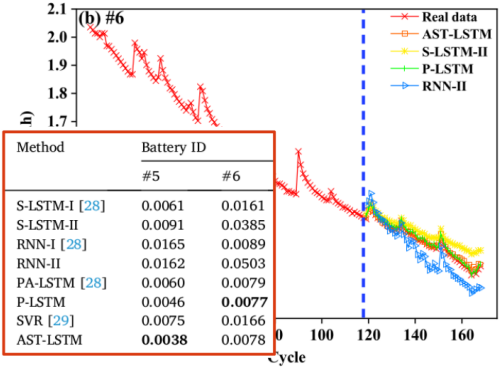


"State-of-health estimation and remaining useful life prediction for the lithium-ion battery based on a variant long short term memory neural network," P. Li et al., 2020

Machine learning in battery degradation

Example 2



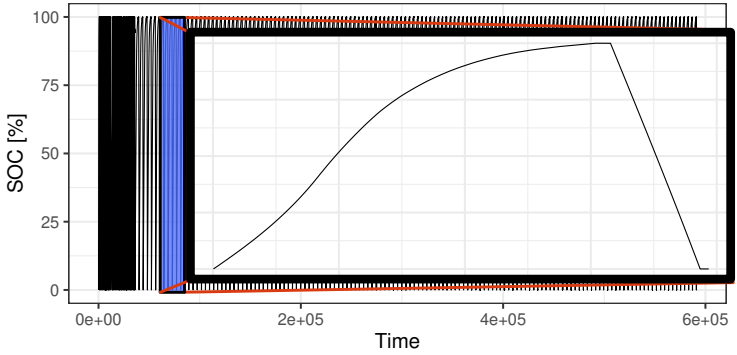


Method	Battery ID	
	#5	#6
S-LSTM-I [28]	0.0061	0.0161
S-LSTM-II	0.0091	0.0385
RNN-I [28]	0.0165	0.0089
RNN-II	0.0162	0.0503
PA-LSTM [28]	0.0060	0.0079
P-LSTM	0.0046	**0.0077**
SVR [29]	0.0075	0.0166
AST-LSTM	**0.0038**	0.0078

"State-of-health estimation and remaining useful life prediction for the lithium-ion battery based on a variant long short term memory neural network," P. Li et al., 2020

The problems with the NASA data

Who is going to use their battery like this?



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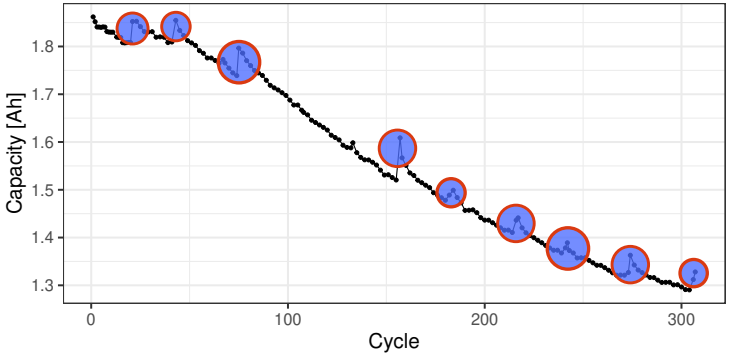
The problems with the NASA data

What is this?



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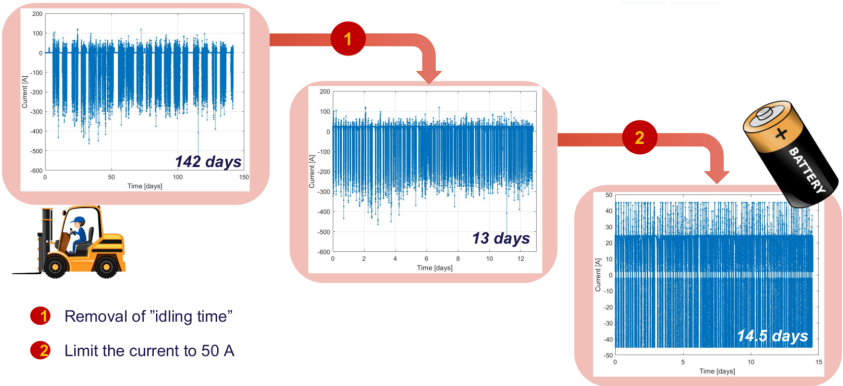
Forklifts

Forklifts

Forklifts

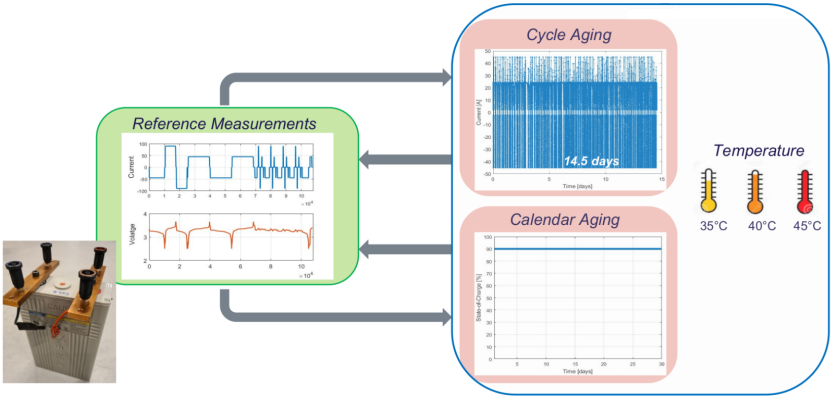
Synthetic ageing profile



1. Removal of "idling time"
2. Limit the current to 50 A

Forklifts

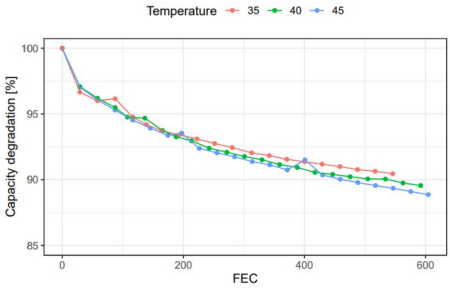
Laboratory ageing



Forklifts

Laboratory ageing results

Cycle Aging



Calendar Aging

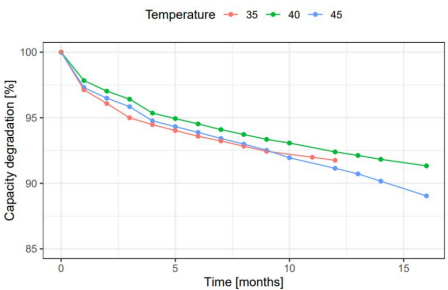
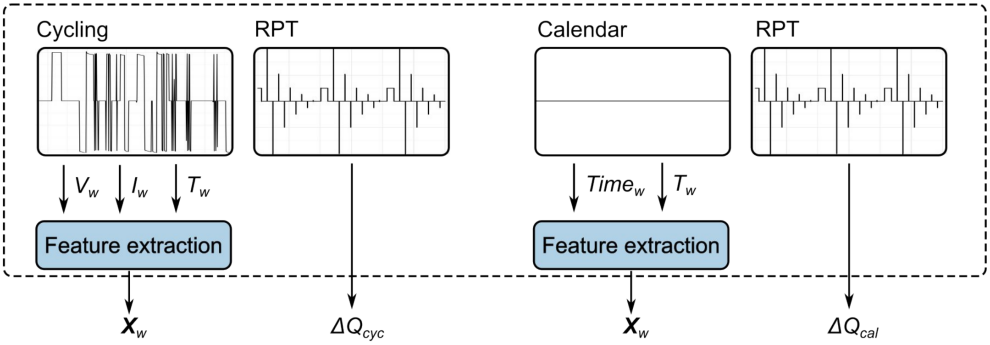


Figure from: "Transfer Learning for Adapting Battery State-of-Health Estimation From Laboratory to Field Operation", Vilsen et al., (2022).

A simple state-of-health model

Feature extraction



A simple state-of-health model

Modelling state-of-health

- We will assume that the change in capacity can be decomposed into change due to calendar and cycle ageing:

$$Q = Q_0 - \Delta Q_{cal} - \Delta Q_{cyc}.$$

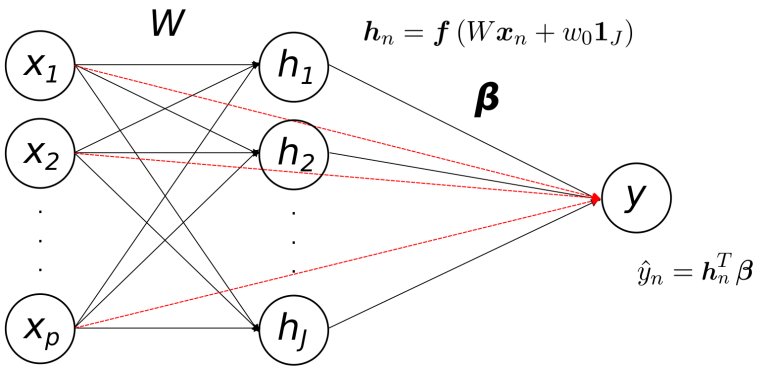
- The loss in capacity due to calendar ageing is log-linear in time, w, and temperature, T:

$$\log(\Delta Q_{cal}) = \eta_0 + \eta_1 w + \eta_2 T + \eta_3 wT.$$

- The loss in capacity due to cycle ageing will be modelled using a neural network...

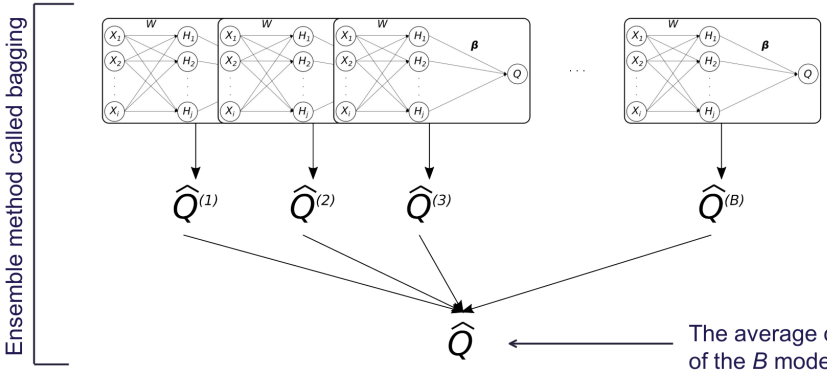
A simple state-of-health model

RWNN



A simple state-of-health model

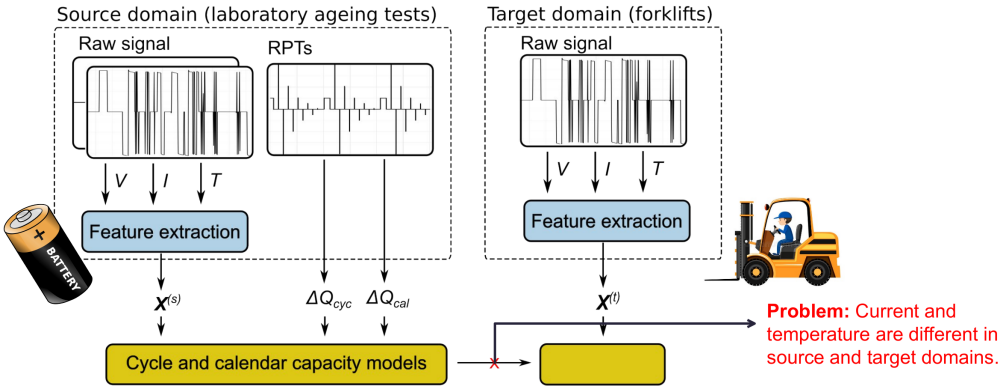
Bagging-RWNN



The average of the predictions of the *B* models.

A simple state-of-health model

Why domain adaptation?



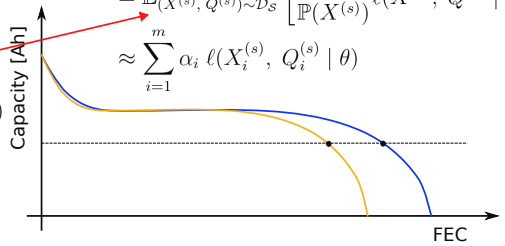
A simple state-of-health model

Domain adaptation

$$
\begin{aligned}
R_{\mathcal{T}} &= \mathbb{E}_{(X^{(t)},\, Q^{(t)})\sim\mathcal{D}_{\mathcal{T}}}\left[\ell(X^{(t)},\, Q^{(t)} \mid \theta)\right] \\
&= \mathbb{E}_{(X^{(s)},\, Q^{(s)})\sim\mathcal{D}_{\mathcal{S}}}\left[\frac{\mathbb{P}(X^{(t)},\, Q^{(t)})}{\mathbb{P}(X^{(s)},\, Q^{(s)})}\ell(X^{(s)},\, Q^{(s)} \mid \theta)\right] \\
&= \mathbb{E}_{(X^{(s)},\, Q^{(s)})\sim\mathcal{D}_{\mathcal{S}}}\left[\frac{\mathbb{P}(X^{(t)})}{\mathbb{P}(X^{(s)})}\ell(X^{(s)},\, Q^{(s)} \mid \theta)\right] \\
&\approx \sum_{i=1}^{m} \alpha_i\, \ell(X_i^{(s)},\, Q_i^{(s)} \mid \theta)
\end{aligned}
$$

Key assumption:

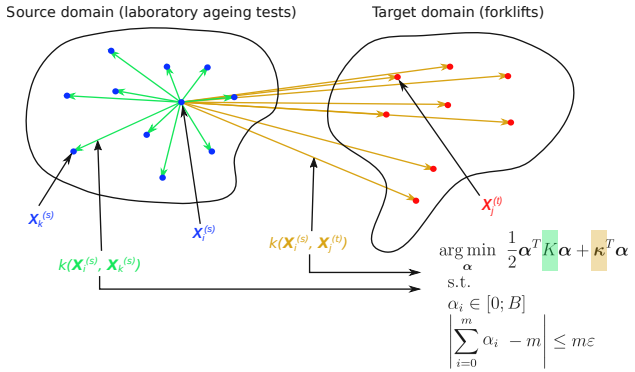
$$\mathbb{P}(Q^{(t)} \mid X^{(t)}) \approx \mathbb{P}(Q^{(s)} \mid X^{(s)})$$



"Correcting sample selection bias by unlabeled data", Huang et al., (2007).

A simple state-of-health model

Kernel mean matching



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A simple state-of-health model

Results of domain adaptation on the source domain

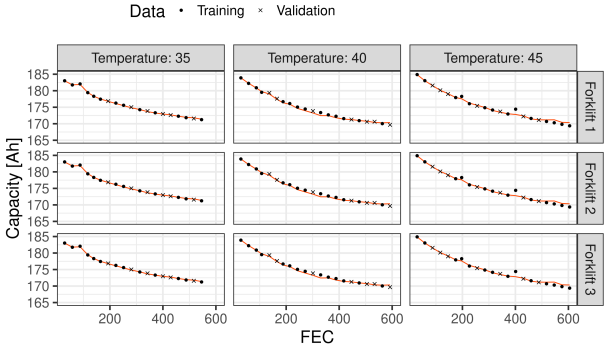
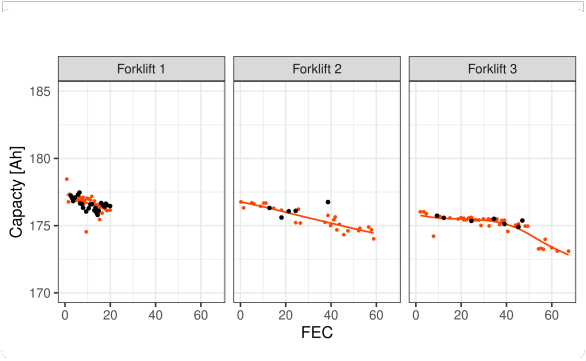


Figure from: "Transfer Learning for Adapting Battery State-of-Health Estimation From Laboratory to Field Operation", Vilsen et al., (2022).

A simple state-of-health model

Results of domain adaptation on the target domain



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THANKS FOR YOUR ATTENTION