OTTO VON GUERICKE UNIVERSITÄT MAGDEBURG

INF FAKULTÄT FÜR INFORMATIK

Transferability of Battery Cell Ageing Prediction Models

Master's Colloquium

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Agenda

- Introduction
- Research Problem
- Selected Methods
- Experiments and Results
- Conclusion and Future Work

Introduction
⇒ Motivation

- Increasing usage of electric vehicles
- Paris Agreement to reduce carbon emission by at least 40% by 2030 compared to 1990 [1]
- The battery is the heart of an electric car
- Battery life testing is expensive and long (6 months to 2 years)
- Many battery cells do not reach end of life (EoL) by the end of testing period

Introduction
⇒ Ageing factors for lithium-ion batteries

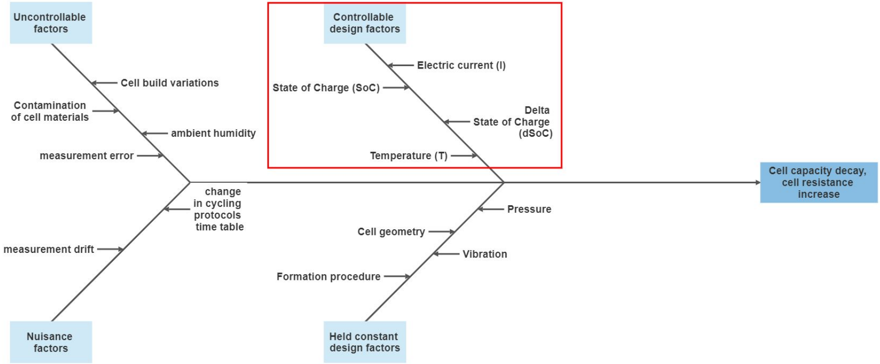
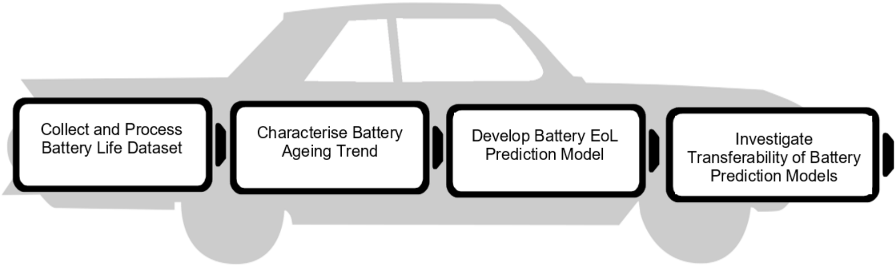


Figure: Fishbone diagram of battery ageing influence factors [2]

Research Problem

- How to build an EoL prediction model that can incorporate incomplete data points?
- Can a prediction model built on what type of battery chemistry be reused to predict the EoL for a different type of battery chemistry?

Conceptual Framework



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Collect and Process Battery Life Dataset

- Battery cell life from two chemistries - NMC and NCA
- Battery cells were tested under different parameter settings/loadpoints
- Battery capacity measurement collected in intervals
- End of life threshold set to 80%
- Dataset labelling

Characterise Battery Ageing Trend

- Dataset 1: NMC Ageing Trend

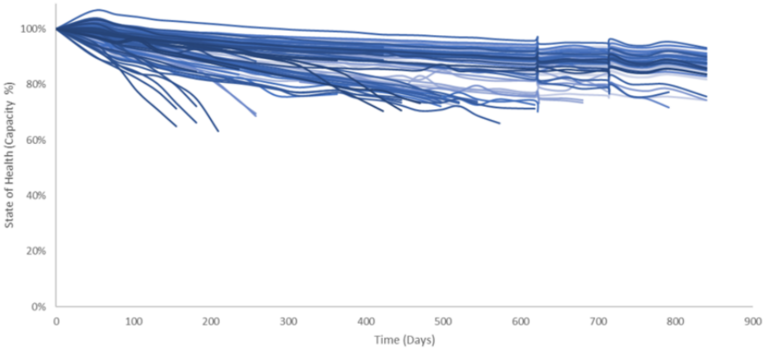


Figure: Capacity Degradation for Dataset 1

Characterise Battery Ageing Trend

- Dataset 2: NCA Ageing Trend

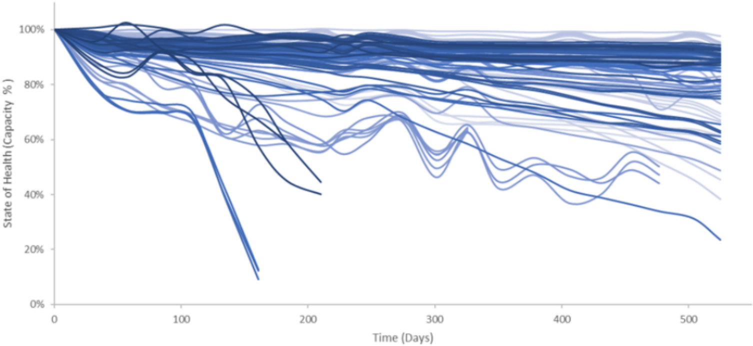


Figure: Capacity Degradation for Dataset 2

Develop Battery End of Life Prediction Model $\Rightarrow$ Selected Method

- Method: Survival analysis
  - Statistical model to estimate time to an event happening
  - Able to handle censored data
  - "1" = Event occurred, "0" = Event did not occur
- Main functions: survival function and hazard function

Develop Battery End of Life Prediction Model $\Rightarrow$ Survival Prediction Models

Model Type	Model Name	Description
Non-parametric	Kaplan-Meier	Describes the shape of the survival function Compare survival probabilities
Semi-parametric	Cox-PH	Estimate hazard ratio Allows hazard to fluctuate with time Cannot estimate survival time
Parametric	Exponential Weibull Log-normal Log-logistic	Can estimate survival time Accelerated Failure Time (AFT) Model

Develop Battery End of Life Prediction Model

Compare survival probabilities between NMC and NCA

- Kaplan-Meier Curve
- Log-rank test

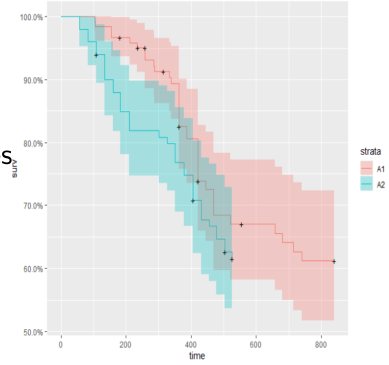
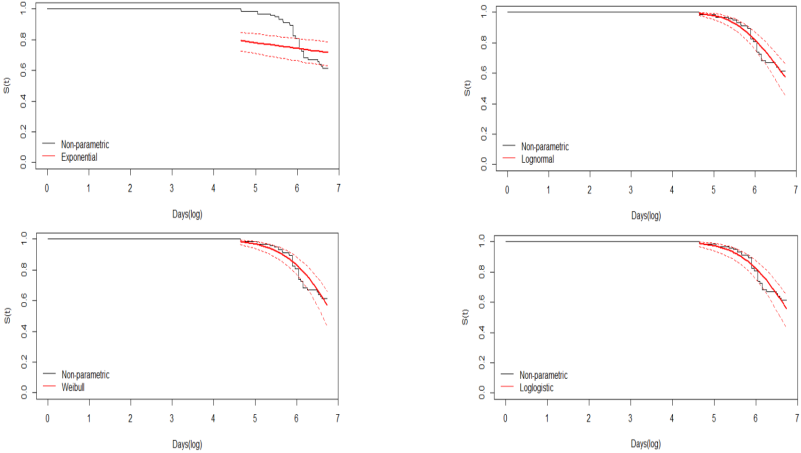


Figure: Kaplan-Meier Plot

Develop Battery End of Life Prediction Model $\Rightarrow$ Parametric Distribution Fit



Develop Battery End of Life Prediction Model $\Rightarrow$ Model Selection

Feature Selection

Exhaustive Search
Forward Selection
Backward Elimination

Model Evaluation

Akaike information criterion
Adjusted R-squared
Bayesian information criterion
Mallows Cp

model1 = Freq+SoC+Temp2+ADC2 + SoC2 + Temp:CC
+Temp:PDC+CC:PDC+CC:DSoC+Temp:SoC

model2 = Temp2+ADC2+Temp:PDC+CC:PDC+CC:DSoC
+Temp:SoC

model3 = ADC2+Temp:PDC+CC:DSoC+Temp:SoC

model4 = Temp2+ADC2+Temp:CC+Temp:PDC+CC:PDC
+CC:DSoC+SoC:DSoC+Temp:SoC+Freq:SOC

model5 = ADC2+Temp:CC+Temp:PDC+CC:DSoC+Temp:SoC

model6 = SoC+Temp2+ADC2+SoC2+Temp:PDC+CC:PDC
+CC:DSoC+Temp:SoC+Freq:SOC

model7 = Temp:SoC+Temp:PDC+CC:DSoC+ADC2+CC:PDC
+Temp2

Develop Battery End of Life Prediction Model $\Rightarrow$ Results

Model	Log-logistic	Log-normal	Weibull
model5	219.03	226.10	313.72
model3	243.59	255.72	353.45
model6	1453.80	340.12	1.35198E+18

Table: Top 3 Out of Sample Prediction Results

- The Weibull AFT model was selected based on domain application [3]
- Weibull distribution allows for the hazard to increase or decrease with time

Investigate Transferability of EoL Prediction Models $\Rightarrow$ Transfer Learning Definition

image source: creative commons

Investigate Transferability of EoL Prediction Models $\Rightarrow$ Transfer Learning Definition

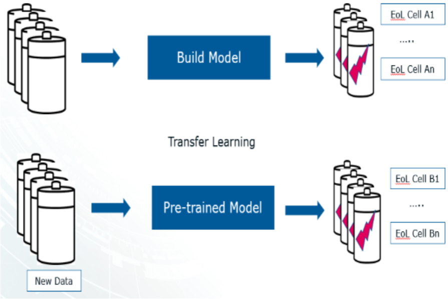
- Situation where what has been learned in one setting is exploited to improve the generalisation in another setting [4].
- **Definition:** Given a source domain D_S and learning task T_S, a target domain D_t and a learning task T_T, transfer learning aims to help improve the learning of the target predictive function $f_T(\cdot)$ in D_T using the knowledge in D_S and T_S where $D_S \neq D_T$, or $T_S \neq T_T$ [5].

Investigate Transferability of EoL Prediction Models $\Rightarrow$ Transfer Learning Guiding Questions

What to transfer?

How to transfer?

When to transfer?



Investigate Transferability of EoL Prediction Models
⇒ Transfer Learning Strategies

Learning setting

Learning Type	**Source and Target Domains**	**Source and Target Tasks**
Machine Learning	the same	the same
Inductive Transfer Learning	the same	different but related
Unsupervised Transfer Learning	the same	different but related
Transductive Transfer Learning	different but related	the same

Investigate Transferability of EoL Prediction Models $\Rightarrow$ Transfer Learning Strategies

Homogeneous Transfer Learning Strategies	
Instance Based Approach	Overlapping features Reweighting & resampling Labelled data available/not available
Feature Based Approach	Identify good feature representation Mapping to reduce feature space difference
Model Parameter Based Approach	Learned relationship between features and response variable

Investigate Transferability of EoL Prediction Models ⇒ Experiments (1-4)

Experiment 1:	Baseline model: Train and validate on target dataset
Train 100% source dataset, Train 70% on target dataset	
Experiment 2	Transfer coefficients only
Experiment 3	Transfer intercept only
Experiment 4	Transfer both coefficient and intercept
Validate on 30% of target dataset	

Investigate Transferability of EoL Prediction Models $\Rightarrow$ Experiment (5)

Calculate weighted mean for source and 70% target dataset
$w_S = n_S \,/\, n_S + n_T, \quad w_T = n_T \,/\, n_T + n_S$

$\Downarrow$

Multiply weights with covariance of source and target models
$X_T = w_S X_S + w_T X_T$

$\Downarrow$

Multiply weights with coefficients of source and target models
$\beta_T = w_S X_S + w_T X_T$

$\Downarrow$

Validate on 30% of target dataset

Investigate Transferability of EoL Prediction Models

$\Rightarrow$ Evaluation Criteria

Using Root Mean Squared Error (RMSE)

$$RMSE = \sqrt{\left(\frac{1}{n}\right)\sum_{i=1}^{n}(\hat{y}_i - y_i)^2} \tag{1}$$

Where,

n = total number of battery cells tested

i = battery cell i

$\hat{y}_i$ = predicted end of life value in days battery cell i

y_i = actual end of life value in days for battery cell i

Investigate Transferability of EoL Prediction Models ⇒ Results

Experiment Type	Data Split 70:30
Train dataset 2 and validate on dataset 2	923.30
Transfer source model coefficients only and validate on dataset 2	846.74
Transfer source model intercept only and validate on dataset 2	708.29
Transfer source model coefficients and intercept	691.49
Use weighted sum coefficient and weighted sum co-variance	550.99

Table: Experiment Results

Conclusion

- First attempt at combining AFT survival model with transfer learning
- Similarities in ageing observed between the NCA and NMC chemistry
- Parametric Weibull AFT model was selected based on domain application
- Model based parameter transfer learning showed promising results that improved prediction of the target dataset compared to baseline
- Using the weighted transfer learning approach showed the best improvement in end of life prediction for the target dataset
- Further testing beneficial with unseen data and other chemistry types

Future Work

- To seek an opinion from domain experts especially reliability engineers who can assist with validating the results and methods used.
- To acquire testing datasets from other types of battery cell chemistry to improve model robustness and further confirm the tested hypotheses.
- To acquire a larger dataset so that the trained model can be tested on purely unseen data and to allow for different splits of training, validation and testing data.

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[4] I. Goodfellow, Y. Bengio, and A. Courville, *Deep Learning*. MIT Press, 2016, *http://www.deeplearningbook.org*.

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[9] C. Bouveyron and J. Jacques, "Adaptive linear models for regression: Improving prediction when population has changed," *Pattern Recognition Letters*, vol. 31, no. 14, pp. 2237–2247, 2010, ISSN: 01678655. DOI: 10.1016/j.patrec.2010.03.021.

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[10] M. Stevenson, Lecture Notes on Introduction to Survival Analysis, Massey University, 2007.

Thank you

Appendix - Literature Review

- Predicting Battery End of Life
  - Most datasets used had complete battery life points - this often doesn't match reality in battery test labs
  - Most recent paper that made headlines by Severson et al. claims to be able to predict battery end of life within the first few cycles [6].
  - Another paper applied survival analysis on heavy fleet data and for a different type of cell chemistry [7].
  - Survival analysis combined with neural network used in [8].
  - No research found combining AFT survival model with transfer learning.

Appendix - Literature Review

- Transfer Learning
  - Most commonly use in image recognition - has a big collection of trained images that can be reused
  - Few examples available for regression tasks
  - Relevant paper by Bouveyron's et al. [9].

Appendix - Survival Models

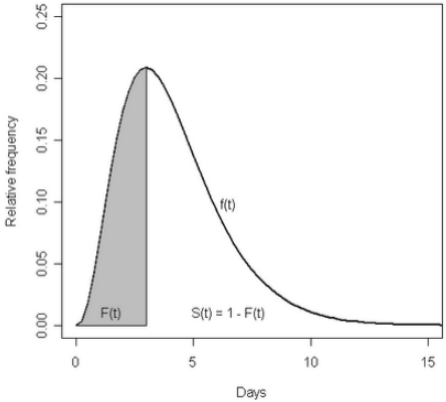

Figure: Line plot of $f(t)$ as a function of time [10]

Appendix - Survival Models

- What is the survival function?

$$S(t) = P(T \geqslant t) = 1 - F(t) \tag{2}$$

- Probability of surviving beyond time t
- If t = 8 years then what is the probability of surviving beyond 8 years.

Appendix - Survival Models

- What is the hazard function?

$$h_T(t) = Pr(t \leq T < t + \delta t \mid T \geqslant t) \tag{3}$$

- Probability of dying in the next few seconds given the cell is still more than 80% remaining capacity
- Given that the cell is still at more than 80% remaining capacity at 8 years, what is the probability of it being less than 80% remaining capacity right after 8 years.
- Rate of decrease along the K-M curve

Appendix - Survival Models

The cumulative distribution function (c.d.f) of the random variable T is given by $F(t)$ as follows:

$$F(t) = Pr(t > T) = \int_0^t f(u)du \quad \text{for} \quad T \geqslant 0 \tag{4}$$

The c.d.f gives the probability that the failure event has occurred by time, t.

Appendix - Censoring

- Right censoring: a battery cell is considered right censored if it has not experienced end of life at the end of the experiment.
- Left censoring: if a battery cell has experienced end of life prior to the start of the experiment, then the battery cell is considered left censored. As this situation is not applicable for our application, it will not be considered
- Interval censoring: this situation occurs when an event is expected to occur between two time points and the exact point of end of life is not known.

Appendix - Model Selection

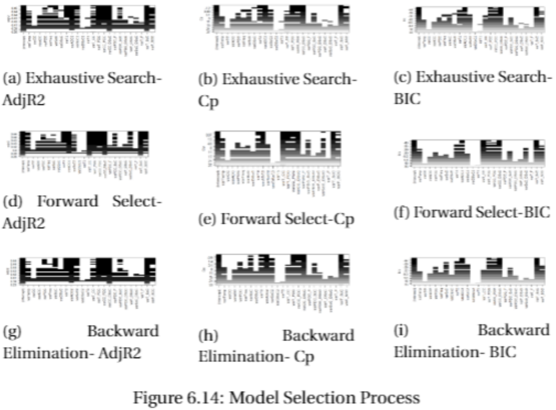

Figure: Model Selection