Li-ion Battery SoC estimation algorithm with Neural Networks and Transfer Learning using synthetic training data

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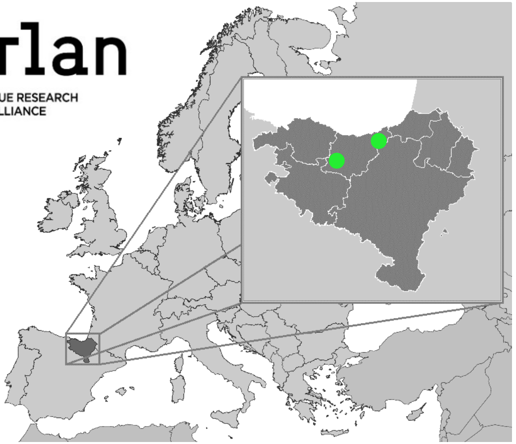

3 research focuses aligned with our 3 areas of expertise

ENERGY AND POWER ELECTRONICS

ELECTRONICS, INFORMATION, AND COMMUNICATION TECHNOLOGIES

MECHATRONIC AND AUTOMATION

> 300 people

Agenda

1. Introduction
2. SoC Estimation Algorithm
3. Dataset
4. Methodology
5. Results and Discussion
6. Conclusions and Future Work

Agenda

BMS needed for safe use of Li-ion batteries

WHY?

- Batteries will fail if they over-charge/over-discharge
- Batteries will fail if they operate outside safe temperature range
- Batteries will fail if an over-current is applied

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FUNCTIONS

- Monitoring measurable variable: V, I, T
- Monitoring non-measurable states: SoC, SoH and SoP
- Advanced functions: cell balancing, performance optimisation…

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FUNCTIONS

- Monitoring measurable variable: V, I, T
- **Monitoring non-measurable states: SoC**, SoH and SoP
- Advanced functions: cell balancing, performance optimisation…

SoC is not a measurable variable, so it must be estimated

VARIABLES INFLUENCING THE ESTIMATION

- Battery Voltage
- Temperature
- C-rate (Charge/Discharge)
- SoH

CREATING A SoC ESTIMATION ALGORITHM

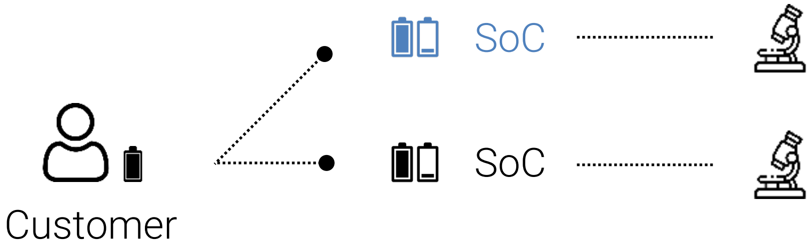
Laboratory tests

- Voltages
- Temperatures
- C-rates (Charge/Discharge)
- SoCs / SoHs

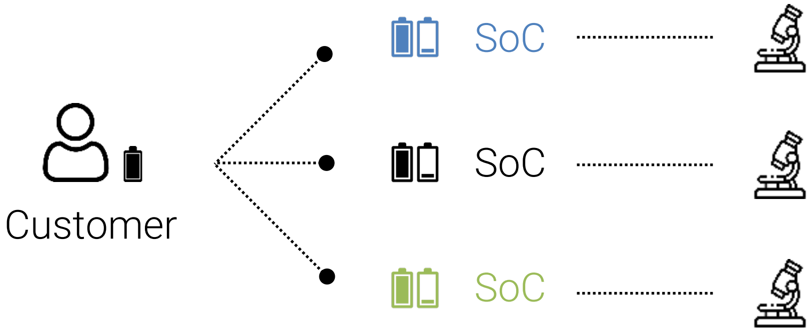
To create one SoC
algorithm for one battery

CREATING A SoC ESTIMATION ALGORITHM

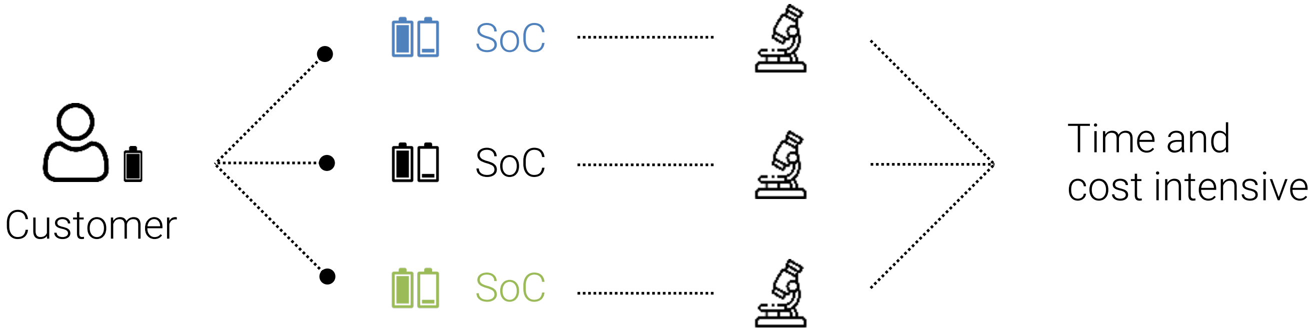
CREATING A SoC ESTIMATION ALGORITHM



CREATING A SoC ESTIMATION ALGORITHM



CREATING A SoC ESTIMATION ALGORITHM



CREATING A SoC ESTIMATION ALGORITHM

CREATING A SoC ESTIMATION ALGORITHM

Can the required number of tests be reduced? How?

CREATING A SoC ESTIMATION ALGORITHM

Can the required number of tests be reduced? How?

↓

Learning from in-field data, adaptability

GOAL

To **develop and validate** a **SoC estimator** that has the **ability to adapt** to new lithium-ion battery **chemistries**, thus **minimising the cost and time required** compared to developing analogous algorithms from scratch.

> Using as much knowledge or data generated from other batteries and applications to improve the state estimator while achieving more robust estimator.

1 Introduction

2 **SoC Estimation Algorithm**

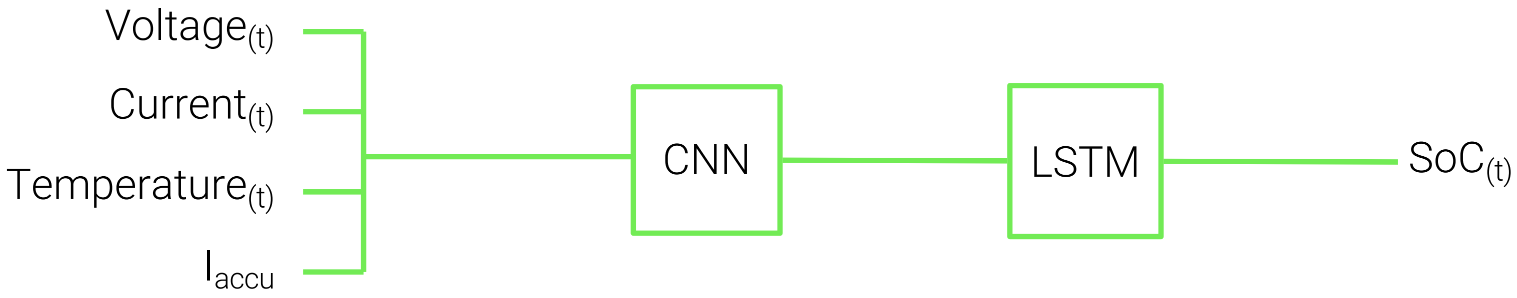
3 Dataset

4 Methodology

5 Results and Discussion

6 Conclusions and Future Work

SoC ESTIMATION ALGORITHM BASED ON:



CNN

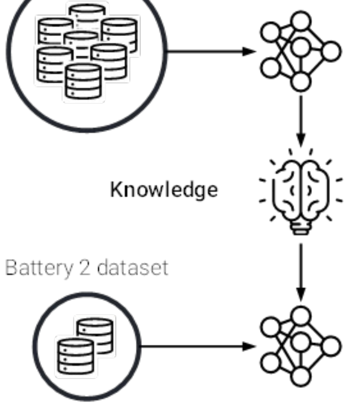
Capacity to automatically detect the important features

LSTM

- Particularly adequate for time-series data
- Extract the temporal relationships of the timeseries that make up both the input and output data

SoC ESTIMATION ALGORITHM BASED ON:

Transfer Learning (TL)



TL takes advantage of the data and prior knowledge generated from previously tested or deployed cell references

1. Train the algorithm with data obtained from a previously tested and/or deployed cell reference

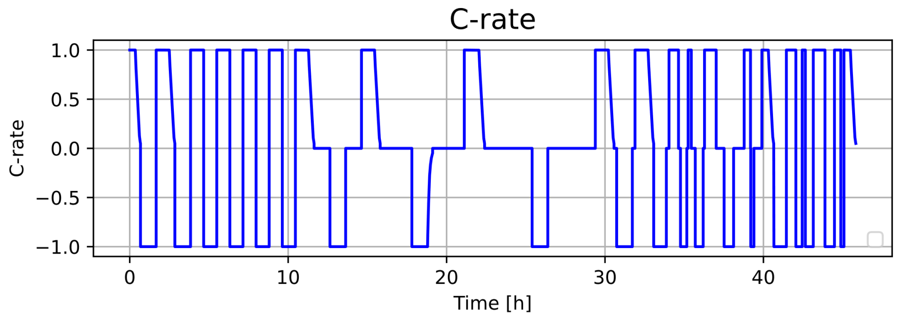
2. Retrain the ANN using a reduced amount of data from the new cell reference

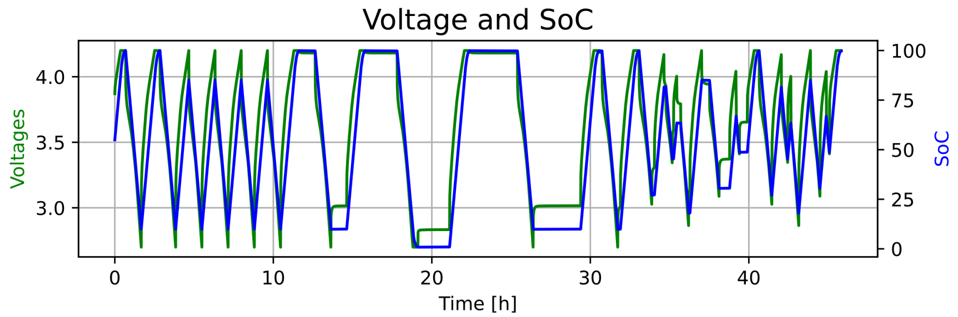
Agenda

DOYLE CELL DATASET

Electrochemical model

Temperature	C-rate DCH	C-rate CHA
45 ºC	0.5 – 1 – 2 – 4	0.5 - 1
25 ºC		
10 ºC		
0 ºC		





NMC 58Ah CELL DATASET

Test*	CHA C-rate	DCH C-rate	Temperatures
Capacity	1C	1C	10 – 25 – 45 ˚C
HPPC	0.5C – 3C	0.5C – 3C	10 – 25 – 45 ˚C
Quasi-OCV	0.05C	0.05C	10 – 25 – 45 ˚C
Designed profile + WLTC	0.5C – 3C	0.5C – 3C	25 ˚C

* Three different cells tested in each condition to ensure the repeatability of the results

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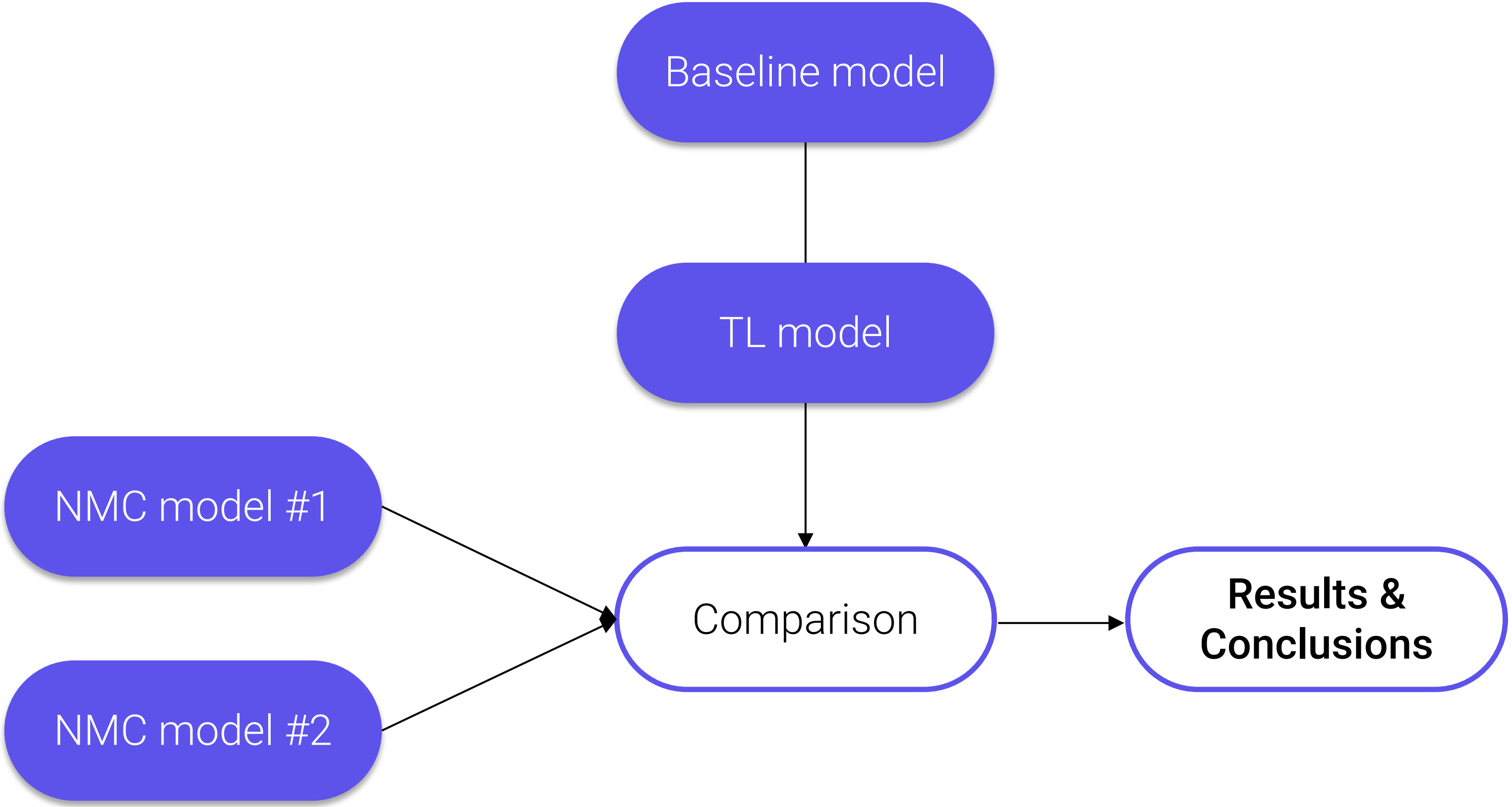
Methodology



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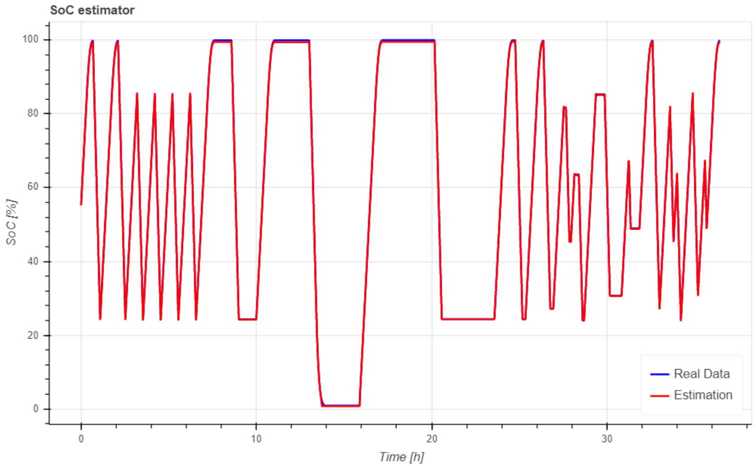
BASELINE MODEL

Trained with Doyle cell dataset

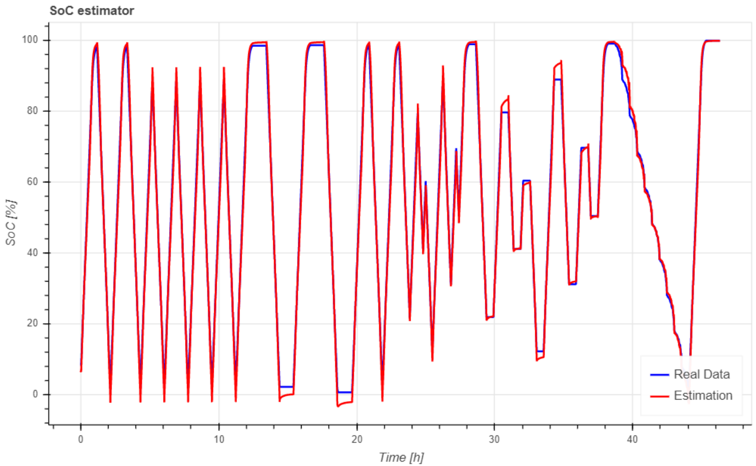
Dataset	Conditions
Training data	0 ºC - 0.5C CHA - 0.5C DCH 10 ºC - 0.5C CHA - 0.5C DCH 10 ºC - 1C CHA - 4C DCH 25 ºC - 0.5C CHA - 0.5C DCH 25 ºC - 1C CHA - 1C DCH 25 ºC - 1C CHA - 4C DCH 45 ºC - 1C CHA - 4C DCH
Validation data	0 ºC - 1C CHA - 2C DCH 10 ºC - 1C CHA - 1C DCH
Test data	0 ºC - 1C CHA - 1C DCH 10 ºC - 1C CHA - 2C DCH 25 ºC - 1C CHA - 2C DCH 45 ºC - 1C CHA - 2C DCH



Dataset	Mean Absolut Error (MAE)	Maximum Error
Training data	0.113%	1.435%
Validation data	0.097%	1.512%
Test data	0.077%	1.459%

NMC 58Ah CELL MODEL #1

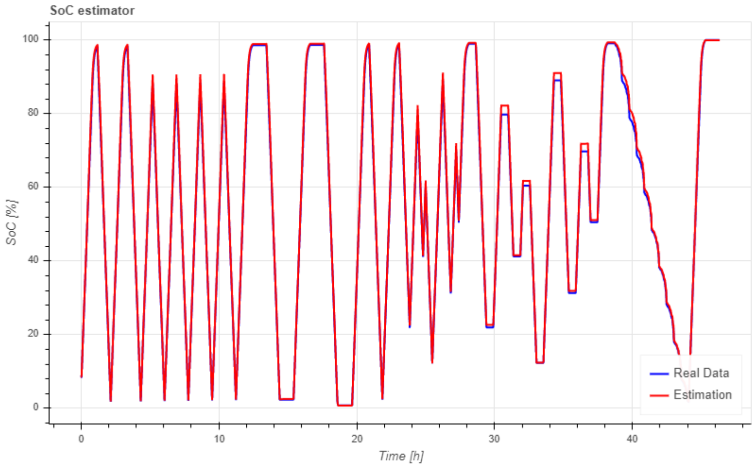
Dataset	Conditions	Tests
Training data	CELL1: 25 ºC	Capacity Quasi-OCV HPPC
Validation data	CELL2: 10 ºC CELL3: 25 ºC CELL4: 45 ºC	
Test data	CELL5: 10 ºC CELL6: 10 ºC CELL7: 25 ºC CELL8: 45 ºC CELL9: 45 ºC	
	CELL10: 25 ºC	Designed profile



Dataset	Mean Absolut Error (MAE)	Maximum Error
Training data	1.497%	16.787%
Validation data	2.653%	17.458%
Test data	3.168%	18.369%

NMC 58Ah CELL MODEL #2

Dataset	Conditions	Tests
Training data	CELL1: 25 ºC **CELL5: 10 ºC** **CELL8: 45 ºC**	Capacity Quasi-OCV HPPC
Validation data	CELL2: 10 ºC CELL3: 25 ºC CELL4: 45 ºC	
Test data	CELL6: 10 ºC CELL7: 25 ºC CELL9: 45 ºC	
	CELL10: 25 ºC	Designed profile

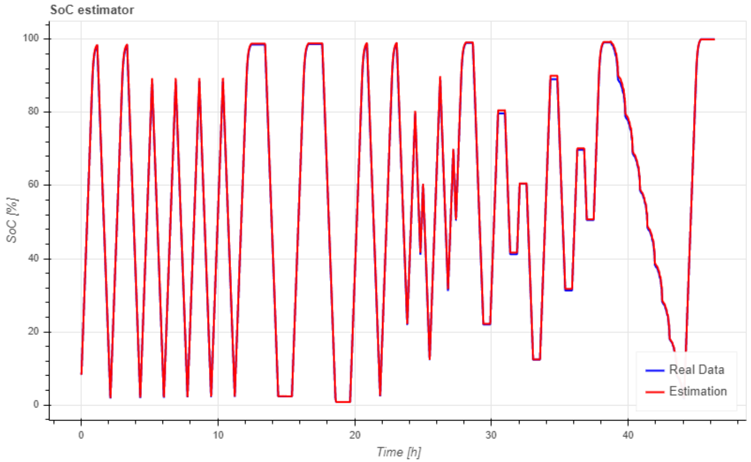


Dataset	Mean Absolut Error (MAE)	Maximum Error
Training data	0.487%	2.083%
Validation data	0.486%	2.102%
Test data	0.494%	2.504%

Results and Discussion

TL MODEL

Dataset	Conditions	Tests
Training data	CELL1: 25 ºC	Capacity Quasi-OCV HPPC
Validation data	CELL2: 10 ºC CELL3: 25 ºC CELL4: 45 ºC	
Test data	CELL5: 10 ºC CELL6: 10 ºC CELL7: 25 ºC CELL8: 45 ºC CELL9: 45 ºC	
	CELL10: 25 ºC	Designed profile



Dataset	Mean Absolut Error (MAE)	Maximum Error
Training data	0.251%	4.045%
Validation data	0.243%	4.086%
Test data	0.243%	3.411%

COMPARISON OF THE RESULTS

Model	Dataset	Mean Absolut Error (MAE)	Maximum Error
Model trained with reduced training data (NMC model #1)	Train	1.497%	16.787%
	Validation	2.653%	17.458%
	Test	3.168%	18.369%
Model trained with increased training data (NMC model #2)	Train	0.487%	**2.083%**
	Validation	0.486%	**2.102%**
	Test	0.494%	**2.504%**
TL model	Train	**0.251%**	4.045%
	Validation	**0.243%**	4.086%
	Test	**0.243%**	3.411%

Agenda

Conclusions and Future Work

- SoC estimation algorithm was developed using a neural network composed of a **CNN layer** and a **LSTM layer**. Network was trained with **four different training datasets**, leading to **four different models**

- **Benefits** of the proposed TL-based approach were highlighted:
  - Needed data to train the algorithm significantly reduced
  - Accuracy improved
  - Compared to analogue algorithm developed from scratch error reduced in 50% and required laboratory data reduced by 40%

- Degradation of the cell not taken into account

- Analysis of the behaviour of the algorithm with different chemistries as LFP to be done

THANK YOU

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