

# Notes FYP

George W. Kirby

*200328186*

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**Supervisor:** Dr. Ross Drummond

# 1 Constraining the research

Spent a fair amount of time learning about the basic machine learning techniques, then NN methods, then applying with pytorch. Managed to get a basic raw NN to work for fashion sets, then began looking at CNNS and LSTMS for learning data, in the hopes it could predict battery degredation over time. However, given the sheer data needed, as well as a very large possible set of outputs and too many inputs to consider, it did not look feasable to continue down this route. Atleast for a black box approach, to parameterise the current state of health, perhaps this could be used to live tune the current profile.

It was also found [1] that differences of only 2% can have large effects in the degredation states over time, meaning the ability for a NN to generalise well enough and capture these differences would be hard and more specifically, beyond the ability of the autor of this paper.

Instead of a *black box battery* model, the goal is now to focus on the actuall optimal charging method themselfs, to reduce degredation. Specifically the constant current stage of the charging cycle, as this is where most of the heat is generated, research shows this to be a large factor of degredatdion alongside instantatious applied voltages.

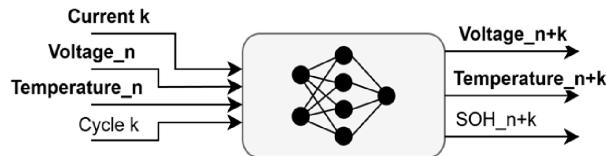


Figure 1: Original end objective: Black Box Battery to allow for discorvery & testing of optimal charging profiles

# 2 Data Analysis on Dans Data

Gave a good insight to the degredation patterns on an array of lithium batterys, data was analysed and plotted on jypter notebook. Despite not complete draining ect, resting points, internal resistance and *importantly* temperature were able to be extracted from the data too

### 3 Lithium Battery Modelling

Starting off, only knowing the basics of batteries, i.e the resistance increases over time, capacity drops ect. I'm continuing learning the various battery models, behaviours ect.

- For the most part, atleast within the context of the problem, the dynamics of the battery can be modelled with an equivalent circuit model (ECM). Subject to vary between cycles
- Looking at dans data, parameters will be different between cells, as well as cycle degredation, but if the degredation can be modelled based off initial parameters, then an optimal charging method can be found for a given battery at a given time.
- Degredation causes:

- SEI layer growth via pores  $\approx$  not really solvable, grows square root over time and cycle number
- Lithium plating

Causes increased ageing and seftey risks, its the deposition of metallic lithium on the anote surface, happens at high charging currents and low temperature. Since during charging, the lithium ions move , through the sei into the anode, if the ions cannot intercalate fast enough, they deposit and can become metallic lithium. Especially ehrn chargis is forces, local overpotential can causes the lithium plating, can cause dentrites **this is one of the main constraints for the chargings profile**

- Active material loss (from parts mentiones above)
- SEI Brakeages

Charging too **high** of a temperatures causes mechanical stress on the sei layer, causing it to crack and reform, consuming more lithium ions in the process. Loose sei material can also float in the electrolyte, causing further issues.

- Electrolyte decomposition

Superlinear battery degredadion known as "Knee" is where degredation drops rappidly over later cycles.

Appears the multistage cc is advantaguous for keeping charge time down, yet reducing degredation by ensuring most of the current is applied at lower states of charge, where the battery is less prone to lithium plating and high internal resistance heating.

## 4 Current work and Results

Looking at the paper on CLO, large question about the early predictor aoutcome, mentions its a linear mechanism, how are they confimring what the characteristics are after atleast the knee point?

## 5 Current plan

- Look at existing charging methods, including the complex ones and continous ones (explain complexity and non generalisability).
- Look at the different SOC estimation methods, since the cc high current section works good for 20-60 % soc [2] This could, and hopefully so, be a chance to use NN to predict soc quickly and something that can be implamented on hardware. Could also give chace to be compared against paings offline parameterisation solver
- If this is adaptive over the ageing, since R and C values change, need to look at maybe live cc tuning methods, maybe a form of MPC? , see the feasability of implamenting on actual hardware, explicit MPC could be a possability, but not sure yet how recomputing QP (or probably nonlinear) with changing dynamics is done
- Run the experiment against standard cc-cv methods, look at temp, internal resistance and capacity over time.

Baseline batteries with fixed CC CV (need to look at the CC used)

Idea: Use ICLOCS2, paintings model to extract features and the ECM parameters. Use this in a NN, possibly LSTM and NN to then allow for prediction of future features

CC stages - follow roughly what Georges Paper utilised to minimise the constraints, maybe change the cost functions

Adaptive, id like to be able to

## 6 Questions

- Deciding on the constraints, besides the total charge volume, does the charge time need to be minimised also? Or keeping that constant and purely investigating the degradation effects compared to standard CC-CV method
- Enquire about the temperature control side, is the ambient area controlled, can the temp be controlled?
- General guidance on the control method, is this entire plan okay, any suggested reading? Some of the heavy matrices are a bit over my head. (Happy with the idea of matrices transforming vectors, some basic forms of matrices w properties etc)

## 7 Progress Log

Entry 1: Terrible, a such fruitfull datasheet has made extracting parameters a breeze, infact, its taken such small amount of time, i have been free to complete all my other modules, its so nice not to have to do anything

I definitely did not need to spend hours getting nowhere

Going to try to find a OCV curve to help with the ICLOCS2 model, iterative type method. I also know  $R_1 + R_0$ . Okay, so some okay progress been made, was really struggling with

nopthing giving to it, hard part is the graph isnt even complete! So using this ocv curvce with a poly count of 10 seemed okay and a setting of 120

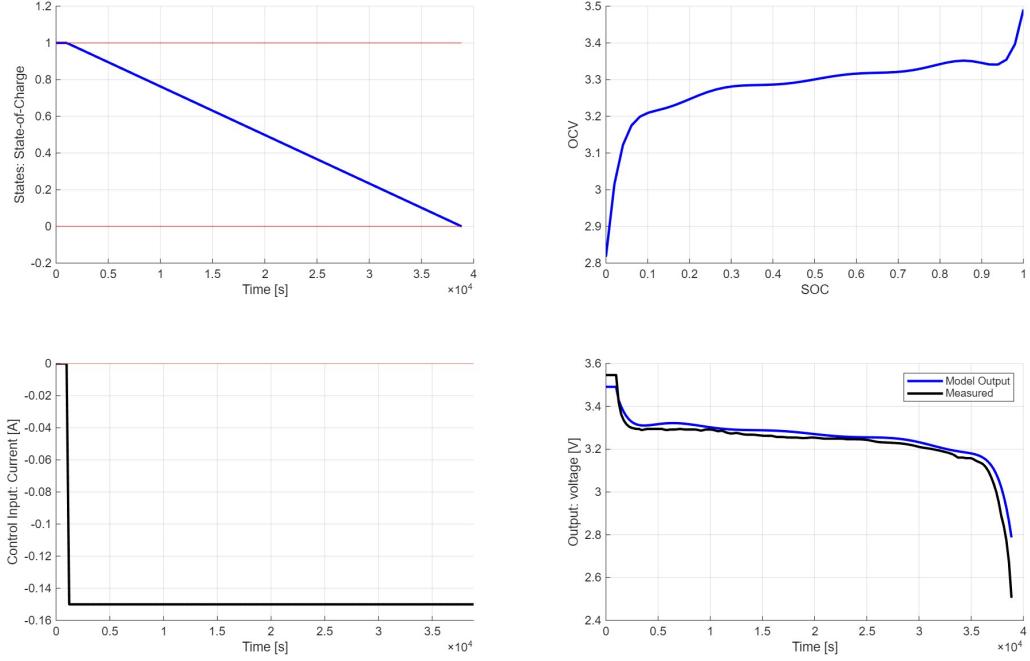


Figure 2: Fixed OCV curve from paper ...

On the thermal note, maybe see if it does affect a single cycle path for even more accuracy. From paper ... it shows that temperture dosent really affect the ocv cuve, mainly the internal resistance and maybe the ecm capaicotr. Its a misconception that the charge (capaicty) changes with temperature, its the ability to deliver that changes, i.e energy extraction, directly related to internal resistance increase and limitls on max current draw for sei for the cold temperatures too. (Cold temperatures are not looked at in this scope, mainly high temp effects during charge)

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Case	<b>Q (As)</b>	<b>C (F)</b>	<b>R<sub>0</sub> (Ω)</b>	<b>R<sub>1</sub> (Ω)</b>	<b>MSE</b>
Baseline	5400	900	0.008	0.004	0.2
Cold Test	5200	1100	0.010	0.006	
High Load	4800	700	0.012	0.008	
Optimized Fit	5500	950	0.007	0.003	

Table 1: Parameter values

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