Notes FYP

George W. Kirby

200328186

December 18, 2025

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.

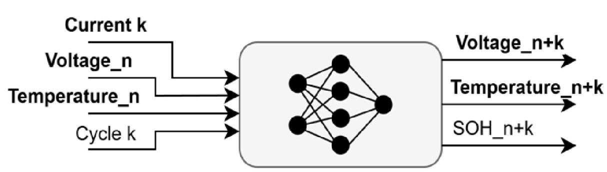

Figure 1: Original end objective: Black Box Battery to allow for discorvery & testing of optimal charging profiles

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 ≈ not really solvable, grows square root over time and cycle number
  - Lithium plating

    Causes increased ageing and seftey risks, its the deposition of metallic lithoum 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.

Baselinse batterys with fixed cc cv (need to look at the cc used)

Idea: Use ICLOCS2, paings model to extract features and the ECM parameters Use this in a NN , possibly LSTM and NN to then allow for redicitoikn of furutre features

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

Adapdtive, 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 purrley investigating the degredation effects compared to standard cc-cv method
- Enquire about dans temperature controll side, is the abient area controlled, can the temp be controlled?
- General guidance on the controll 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 matracies transforming vectors, some basic forms of matrices w properties ect)

7 Porgress 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 definitley did not need to spend hours getting nowhere

Going to try to find a ocv cuve to help with the ICLOCS2 model, ittertive type method. I also know R1+R0. Okay, so some okay progress been made, was really stuggling with nopthing giving to it, hard part is the graph isnt even complete! So using this ocv curvce with a poly count of 12 seemed okay and a setting of 130

The problem risided in the Resistance chosen, since ICLOCS is wanting to match the output, since the output during the middle of the SOC can only be modified by the resistances (since the OCV curve is only generic, a large R was calculated to try fit). This meant that when the resistance was unbound, it made it look as if the parametes allowed a nice fit, but they were fitting an incorrect ocv curve. Thus, one apprach was to atleast bound one resistance by being a function of the sumed resistance. This was possible since the datasheet gave a discharge curve for various currents, thus,

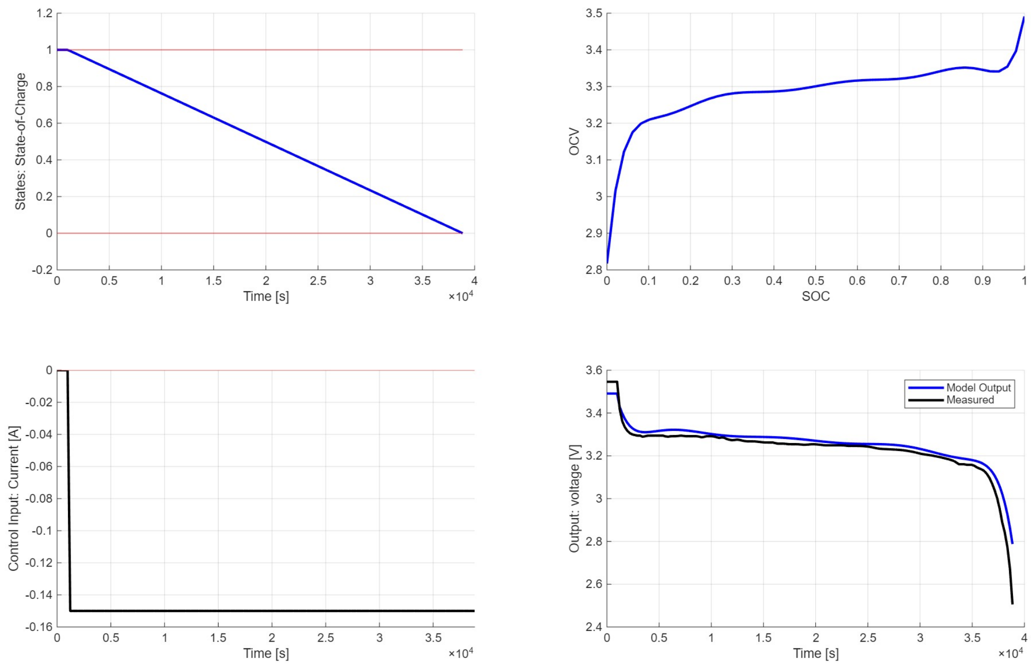

Figure 2: Fixed OCV curve from paper ...

for the center soc section (where the graph wasnt cut off), the difference between the curves should equal to the the resistiver drop across R1+R0. This allowed a decent estimate of R1+R0, and then R0 was bounded to be less than this value.

Between 0.1C and 3C dishcarge (at SOC 50%), the voltage difference was 0.287, thus R1+R0 = 0.287/ (2.9C rate current) = 0.287/ (2.9*1.5A) = 0.066 Ohms. Thus $R0 + R1 < 0.066\Omega$. The initial drop in voltage would have allowed R1 to be estimated, however the graph is cut off too early to see this, when taking the litteral values from the table, R1 is shown to be 0.09Ω which is not possible since R1 + R0 must be less than 0.066 Ohms.

Thus, the next approach was to parametrise only R0, and set R1 to be 0.066 - R0. Before attempting this, its expected a fair offset from the actual oputput given the ocv curve discrepencies. Nevertheless, this was attempted. In order to implament this in iclocs, R1 was taken out of the parameterisation and refomrulated as 0.066 - R0. It was discovered that then applying bounds on R0 caused larghe changes in the capaicty values, i.e a 10Ω change in R0 caused a near $1000F$ change in capaicty - its assumed this is due to the small available transients in the limited data, so a sensible bound of 0.01 to 0.04 Ohms was chosen, based on most ECM's showing similar R0 &

R1 values. From this, atleast a Capaictance can be narrowred to a true value of 1500F +- 500F.

Now, the bounds sensiblys taken from the above results should hopefuuly allow the true ocv curve to be estimated, a 10th order polynomial was chosen to give enough flexability.

Case	**Q (As)**	**C (F)**	$\mathbf{R_0}$ **(Ω)**	$\mathbf{R_1}$ **(Ω)**	**MSE**
Fixed_OCV_0.1	5675	min bound	0.1	0.1	0.2
Fixed_OCV_Unbound	5684	6085	0.24	0.133	d
Fixed_OCV_R0_Fix	4800	1024	0.012	0.008	d
Fixed_OCV_R1_Fix	5684	2841	0.007	0.003	d
Fixed_OCV_Symetric	5685	1561	0.026	0.04	d

Table 1: Parameter values for different estimation configurations.

Very much sturggling, always seems to be fitting it to the ocv curtve, capaictance is just reallyt stuggling. Nex step, run it through dans currnet and simulate on ode45

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 misconeption 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 limilts 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). Infact, this phenominan can be shoiwn on the discharge graph for the LiPo datasheet, higher current draw is causing a larger voltage drop, thus without risking damage to the cell, the 2.6V limit is reached sooner, showing less capacity effecitively drained.

NOTE: The ocv curve does indeded change during degredation and has been reported to significantly change esitmation models [3], will mean unfortunatley this cant be fixed (but we can atleast try)

So, next step is to just get the parameterised model to run better duriing current inputs via ode45 first.

7.1 Thermal

Since BIOT number is very small, we can assume the temp within the cell is uniform, thus a lumped model can be used [4]. Heat itself if formed by the following:

$$Q_{gen} = I^2 R + I \left(\frac{\partial U}{\partial T} \right)_{soc} \tag{1}$$

$$Q_{gen} = I(Uoc - V) - I \left(T \frac{dUoc}{dT} \right) \tag{2}$$

- Joule Heating: $I^2 R$: Resistive heating from internal resistance
- Entropc (reversable) heating: $I \left(\frac{\partial U}{\partial T} \right)_{soc}$: Caused by the entropy change during the electrochemical reactions,
-

Yya, got those styuff done, will preobs auytmate on all dans to get cp, l values

Anyways, for the cyurrent sims, before the mpc which im still stuffed for, i can discriteise mysen and ill run it thru a 3 part soc charge too so im gonna make a (profile maker) function

Points for next meeting:

Concern on the simulation: Capacity valueus and OCV curve accuracy (shouw variations with pinning SOC(0) voltage, forced capacity, and free rein) Show current sim results Show stages of charging simed ode45 Discriticisation (Explain working on mpc)

$$\frac{\partial U}{\partial T} \approx f(SoC) = f(z) \tag{3}$$

$$mCp \frac{dT}{dt} = I^2 R_{ecm} - ITf(z) - hAT \tag{4}$$

$$f(z, z_0) \sim c_0 + zc_1 + z^2 c_2 + z^3 c_3 + z^4 c_4 \tag{5}$$

$$mCp \frac{dT}{dt} = I^2 R_0 + IV_1 - IT(c_0 + zc_1 + z^2 c_2 + z^3 c_3 + z^4 c_4) - hAT \tag{6}$$

$$\begin{bmatrix} \dot{T} \\ \dot{z} \\ \dot{V_1} \end{bmatrix} = \begin{bmatrix} I^2 R_0 + IV_1 - IT \frac{1}{mCp}(c_0 + zc_1 + z^2 c_2 + z^3 c_3 + z^4 c_4) - hAT \frac{1}{mCp} \\ I/Q \\ I/C - V_1/R_1 C \end{bmatrix} \tag{7}$$

B01Charac R0 R1 points : 84586 - 84989, 120362 - 120713, 251964 - 252328, 240052 - 240374

B02Charac R0 R1 points : 85540 - 85940, 109372 - 109834, 205557 - 205973, 241438 - 241816 35134

7.2 Normalising attia current profile

The battery chosen is different to the one from attia, and has a higher resistance and lower charging capaicity, therefore, the limits and most optimal profile for the attia has to be normalised to the battery we have. This isnt trivial, since there are many variables that are set in the attia framework and as many as possible should be approprately matched. The framework from attia is as follows the charging is broken into 5 segments, with the lower 4 been CC style, and the 4th as a CC-CV section. Each section is seperated by the SoC of which the charge value occupiys, each section takes up 20% SoC, therfore the CC section values can be denoted as **CC1**, **CC2**, **CC3** and **CC4**.

CC1, **CC2**and **CC3** are variables which can be directly optimised and controlled, subject to their respective upper bound which is limited in the attia case to not reach the batteries upper OCV voltage during the charging stages (in attia case this is 3.6V), and their is a constant lower bound for these three sections also. **CC4** has the same upper bound constraint definition, yet its defined value depends only on the given values for **CC1**, **CC2** and **CC3**. This allows the charge duration from SoC 0-80% to be fixed whilst allowing the charging current during the SoC ranges to be modified. The equality that must be held (before variable constraints), given in attia, is given as ...

$$t_{0-80\%} = 0.2\left(\frac{1}{CC1} + \frac{1}{CC2} + \frac{1}{CC3} + \frac{1}{CC4}\right)$$

To provide inequalities to help decide values, two cases were considered to help to help reduce descisions, since all $\mathbf{CC}_i$ sections have there maximum value limited ($\mathbf{CC}_{i,\max}$) physically, these can be calculated to help define the minimum bounds and $t_{0-80\%}$.

The first case considered is when $\mathbf{CC}_i$, $i = 1, 2, 3$, are at their maximum, since all currents are posotive values, the equality given above must mean that $\mathbf{CC}_4$ is at its minimum. This inequality narrows descision variables to only 2, with the equality given as

$$\mathbf{CC}_{4,\min} \times \left(t_{0-80\%} - 0.2\sum_{i=1}^{3}\frac{1}{CC_i, max}\right) = 0.2$$

. The maximum permissable current values can be worked out by finding for each stage along a charging profile, the current that can be applied to bring the OCV voltage to the upper bound (difference is just IR_{0+1}), using the OCV curve obtained gives the graph below, the values were obtained in C units: $\mathbf{CC}_{1,\text{max}} = 3.4$, $\mathbf{CC}_{2,\text{max}} = 2.9$, $\mathbf{CC}_{3,\text{max}} = 2.8$ and $\mathbf{CC}_{4,\text{max}} = 2.5$. Thus the equation has only two variables and can be written as $\mathbf{CC}_{4,\text{min}} = \frac{0.2}{t_{0-80\%}-0.279}$

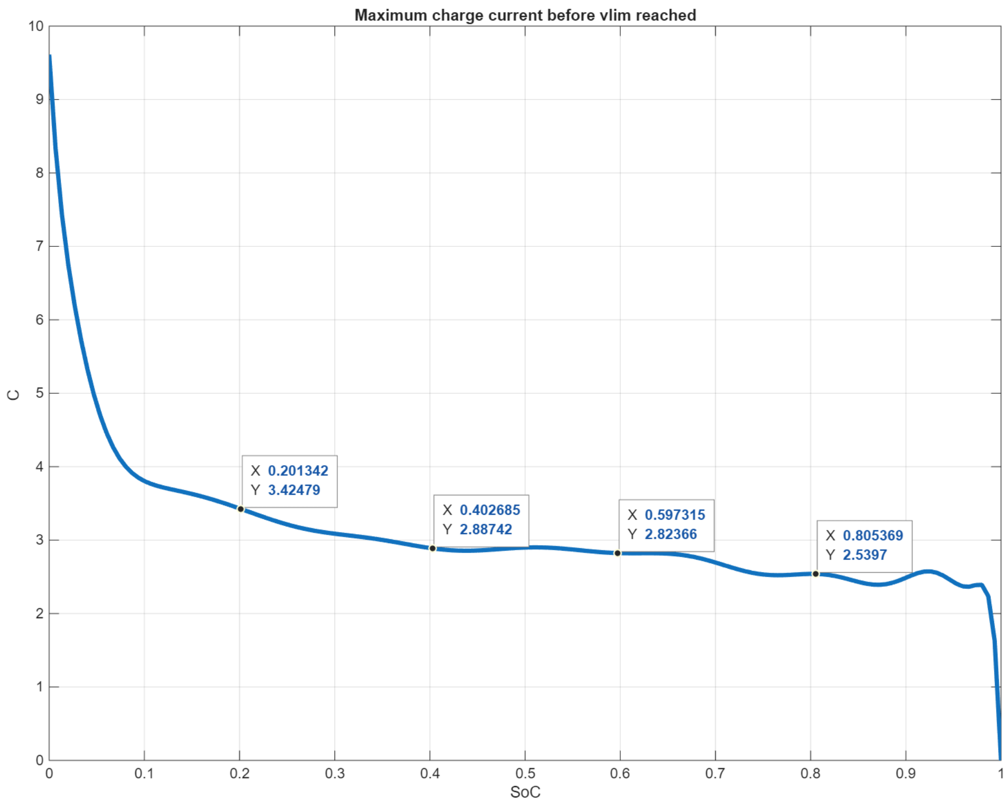

Figure 3: RS battery (our battery) C limits

In the second case, supose there is a current profile which is lowest for all $\mathbf{CC}_i$, $i = 1, 2, 3$ (which as mentioned is the same for those segments, thus is denoted as $\mathbf{CC}_{1:3,min}$), again due to the posotive nature of the currents, must mean $\mathbf{CC}_4$ is at its maximum. Since as before $\mathbf{CC}_{4,max}$ is known, a similar equation as before is calculated as $\mathbf{CC}_{1:3,min} = \frac{0.2\times3}{t_{0-80\%}-\frac{0.2}{\mathbf{CC}_{4,max}}} = \frac{0.6}{t_{0-80\%}-0.08}$. These two equations can now be plotted to help decide values based on $t_{0-80\%}$.

This shows that if the charging duration is increase, it allows for a greater range of the available currents at different SoC ranges which is advantaguous to find the optimal protocols, however this does increase charge time and lab time is of priority given the FYP time.

The above work shows how the minimum ranges for the segments can be derived, clearley, however

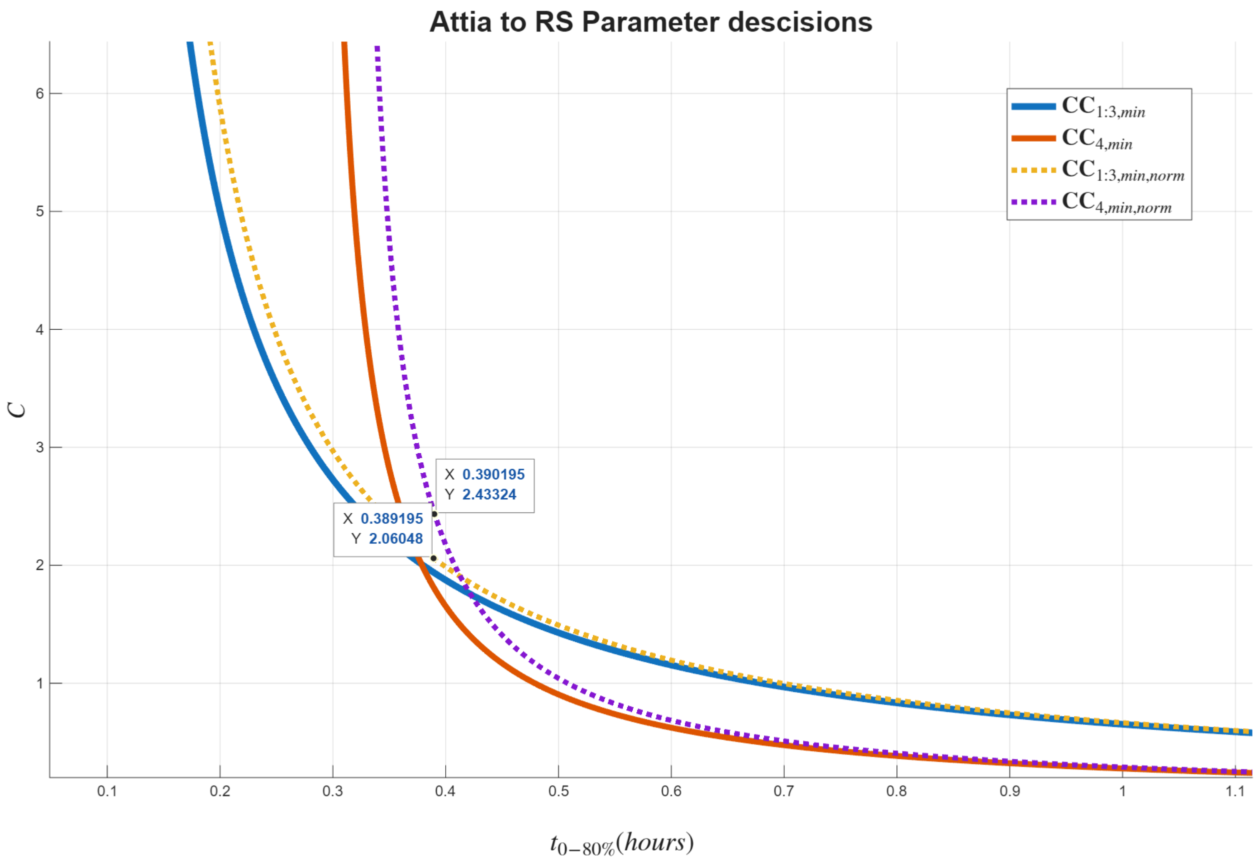

Figure 4: Ffes

these upper and lower bounds and times do not equate to Attias values - they only provide values in the same matter Attia derived theirs, and time still needs finding. A descision is now made on how to scale the charge protocols provided by attia, if the CC upper segments are scaled by the ratio of $\mathbf{CC}_{1,attia,max}/\mathbf{CC}_{1,RS,max}$, since both batteries are of similar chemistry, the ratio of upper CC limits nearly coicide with the RS battery. A table is shown below to highlights this. Only $\mathbf{CC}_2$ is slighly over the limit.

CC_max values	$\mathbf{CC}_{1,\text{max}}$	$\mathbf{CC}_{2,\text{max}}$	$\mathbf{CC}_{3,\text{max}}$	$\mathbf{CC}_{4,\text{max}}$
CC_{rsmax} Actual	3.4	2.9	2.8	2.5
$CC_{1,\text{attia,max}}/CC_{1,\text{rs,max}}$ Norm	3.4	2.97	2.38	2.04

Table 2: Parameter values for different estimation configurations.

The duration of $t_{0-80\%}$ in Attia is 10 minuets, looking at figure x, this clearley can not be achived, if, the scaling used in table Cs row 2 is used as the upper limits are slightly reduced futher, yeilding ever worse achivability. However by scaling the CC_max that way, the CC values obtained by Attia can be siply each devided by the same scaling factor (2.35 in this case). This then forces the $t_{0-80\%}$ to be 23.5 minuets. For example, the best CC segments from attia are 5.2C-5.2C-4.8C-4.16C, since the scaling of CC_max is 2.35, the CC segments for out battery can be 2.2C-2.2C-2C-1.3C at takes 23.5 minuets. This is acceptable, however, 23.5 minuets limits the lower bounds on the CC segments, thus reducing the possible combinations to try optimising. To show this, the dashed lines are added to figure x which use the normalised CC_max values in table C, and at $t_{0-80\%} = 0.39$ would give the lower limits of $\mathbf{CC}_{1;3min}$ (2.43C) and $\mathbf{CC}_{4min}$ (2.06C). This is a problem straight away, this gives 0 variance to $\mathbf{CC}_4$. This poses a problem in translating the Attia framework, the cycles could be futher reduced in current by a scale factor greater than that which can scale the CC_max, but these optimum values were obtained with these limits in place. It is therefore a balance between matching the trend of the attia protocols, and current ranges to allow more variation.

An idea is to subjectivley choose $t_{0-80\%}$ from figure x, and for the attia protocols, scale the $\mathbf{CC}_{1;3}$ segments by a factor which causes $\mathbf{CC}_{1;4}$ to be as close as possible in ratio to that of $CC_{1,\text{attia,max}}/CC_{1,\text{rs,max}}$, the $\mathbf{CC}_4$ value is to be calculated inline with methods before and attia - constrained to meet 80% SoC, in $t_{0-80\%}$ time. This can very simply represented at $t_{0-80\%} = 0.2/x_{scale} \times (\left(\sum_{i=1}^{3} \mathbf{CC}_i^{-1}\right) + \mathbf{CC}_4^{-1})$, which can be written in a graphical form as

$$\mathbf{CC}_4 = 0.2/(x_{scale} t_{0-80\%} - 0.2\left(\sum_{i=1}^{3} \mathbf{CC}_i^{-1}\right))$$

. The right hand side can be plotted and yeilds the following (Y value is $t_{0-80\%}$), the optimised choice is such that the scalar value in the feild is as close to $\mathbf{CC}_4$ of the chosen Attia profile (the most optimal version they found for example), so $\mathbf{CC}_4 = 4.16$ in the chosen protocol, alongside the respective $\mathbf{CC}_{1;3}$ values, the point which is scaled given in the previous pharagraph is shown in red, but as mentioned it limits the potential currents for more optimisations and is too short of a charge time. The point decided keeps the scaling of $\mathbf{CC}_4$ almost identical to that of the other segments, thus keeping the pattern correct, whilst choosing a scaling factor as close as possible to that in the previous pharagraph without been to short of charging. A balance was thus decided, with a $t_{0-80\%}$ of 0.55 chosen, this, refering back to the previous graph still allows for a large range of current choices with a low enough C_min set of values. Thus, for the Attia optimal protocol, the

CC values are **1.73-1.73-1.6-1.39**.

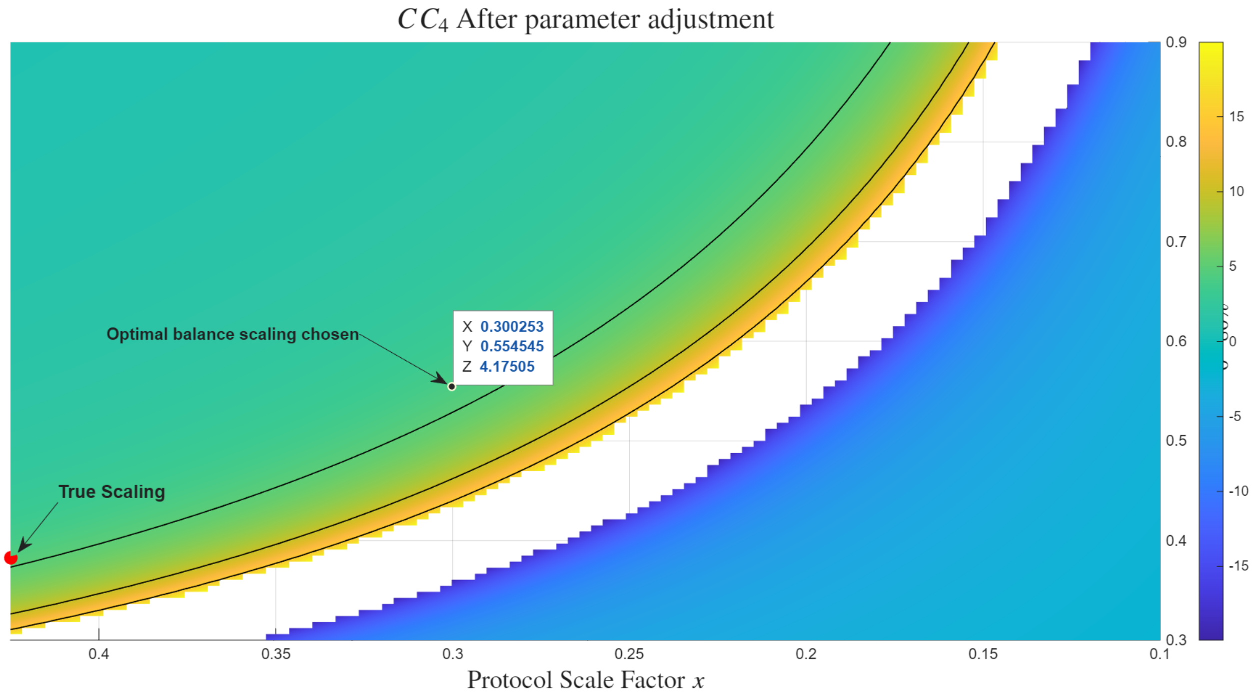

Figure 5: Ffes

Lastly the final CV section is to be chosen, this could have been scaled with more reasoning, but for now a value of 0.5C (half of the Attia value was chosen for now to balance total charge duration and the scaling of the previous segments), Attia value was fixed to 1C.

References

[1] P. R. Chinnam, A. M. Colclasure, B.-R. Chen, T. R. Tanim, E. J. Dufek, K. Smith, M. C. Evans, A. R. Dunlop, S. E. Trask, B. J. Polzin, and A. N. Jansen, “Fast-Charging Aging Considerations: Incorporation and Alignment of Cell Design and Material Degradation Pathways,” *ACS Applied Energy Materials*, vol. 4, no. 9, pp. 9133–9143, Sep. 2021, publisher: American Chemical Society. [Online]. Available: https://doi.org/10.1021/acsaem.1c01398

[2] A. B. Khan, V.-L. Pham, T.-T. Nguyen, and W. Choi, “Multistage constant-current charging method for Li-Ion batteries,” in *2016 IEEE Transportation Electrification Conference and Expo, Asia-Pacific (ITEC Asia-Pacific)*, Jun. 2016, pp. 381–385. [Online]. Available: https://ieeexplore.ieee.org/document/7512982

[3] J. Schmitt, M. Rehm, A. Karger, and A. Jossen, “Capacity and degradation mode estimation for lithium-ion batteries based on partial charging curves at different current rates,” *Journal of Energy Storage*, vol. 59, p. 106517, Mar. 2023. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2352152X22025063

[4] Q. Wang, B. Jiang, B. Li, and Y. Yan, “A critical review of thermal management models and solutions of lithium-ion batteries for the development of pure electric vehicles,” *Renewable and Sustainable Energy Reviews*, vol. 64, pp. 106–128, Oct. 2016. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1364032116301435

[5] M.-K. Tran, M. Mathew, S. Janhunen, S. Panchal, K. Raahemifar, R. Fraser, and M. Fowler, “A comprehensive equivalent circuit model for lithium-ion batteries, incorporating the effects of state of health, state of charge, and temperature on model parameters,” *Journal of Energy Storage*, vol. 43, p. 103252, Nov. 2021. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2352152X2100949X

[6] T. Kalogiannis, M. S. Hosen, M. A. Sokkeh, S. Goutam, J. Jaguemont, L. Jin, G. Qiao, M. Berecibar, and J. Van Mierlo, “Comparative Study on Parameter Identification Methods for Dual-Polarization Lithium-Ion Equivalent Circuit Model,” *Energies*, vol. 12, no. 21, p. 4031, Jan. 2019, publisher: Multidisciplinary Digital Publishing Institute. [Online]. Available: https://www.mdpi.com/1996-1073/12/21/4031

[7] J. Tebbe, A. Hartwig, A. Jamali, H. Senobar, A. Wahab, M. Kabak, H. Kemper, and H. Khayyam, "Innovations and prognostics in battery degradation and longevity for energy storage systems," *Journal of Energy Storage*, vol. 114, p. 115724, Apr. 2025. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2352152X25004372

[8] L. Chen, C. Chang, X. Liu, J. Jiang, Y. Jiang, and A. Tian, "Physics-informed neural networks for small sample state of health estimation of lithium-ion batteries," *Journal of Energy Storage*, vol. 122, p. 116559, Jun. 2025. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2352152X25012721

[9] Y. Li, W. Guo, D.-I. Stroe, H. Zhao, P. Kjær Kristensen, L. Rosgaard Jensen, K. Pedersen, and L. Gurevich, "Evolution of aging mechanisms and performance degradation of lithium-ion battery from moderate to severe capacity loss scenarios," *Chemical Engineering Journal*, vol. 498, p. 155588, Oct. 2024. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1385894724070797

[10] M. Lucu, E. Martinez-Laserna, I. Gandiaga, K. Liu, H. Camblong, W. Widanage, and J. Marco, "Data-driven nonparametric Li-ion battery ageing model aiming at learning from real operation data – Part A: Storage operation," *Journal of Energy Storage*, vol. 30, p. 101409, Aug. 2020.

[11] Q. Guo, S. Liu, J. Zhang, Z. Huang, and D. Han, "Effects of charging rates on heat and gas generation in lithium-ion battery thermal runaway triggered by high temperature coupled with overcharge," *Journal of Power Sources*, vol. 600, p. 234237, Apr. 2024. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S0378775324001885

[12] X. Lin, H. E. Perez, S. Mohan, J. B. Siegel, A. G. Stefanopoulou, Y. Ding, and M. P. Castanier, "A lumped-parameter electro-thermal model for cylindrical batteries," *Journal of Power Sources*, vol. 257, pp. 1–11, Jul. 2014. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0378775314001244

[13] M. Usman Tahir, A. Sangwongwanich, D.-I. Stroe, and F. Blaabjerg, "Overview of multi-stage charging strategies for Li-ion batteries," *Journal of Energy Chemistry*, vol. 84, pp. 228–241, Sep. 2023. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2095495623003091

[14] P. Keil and A. Jossen, “Charging protocols for lithium-ion batteries and their impact on cycle life—An experimental study with different 18650 high-power cells,” *Journal of Energy Storage*, vol. 6, pp. 125–141, May 2016. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2352152X16300147

[15] “How Do I Make an LSTM Model with Multiple Inputs?” [Online]. Available: https://datasciencedojo.com/blog/how-do-i-make-an-lstm-model-with-multiple-inputs/

[16] K. A. Severson, P. M. Attia, N. Jin, N. Perkins, B. Jiang, Z. Yang, M. H. Chen, M. Aykol, P. K. Herring, D. Fraggedakis, M. Z. Bazant, S. J. Harris, W. C. Chueh, and R. D. Braatz, “Data-driven prediction of battery cycle life before capacity degradation,” *Nature Energy*, vol. 4, no. 5, pp. 383–391, May 2019, publisher: Nature Publishing Group. [Online]. Available: https://www.nature.com/articles/s41560-019-0356-8

[17] P. M. Attia, A. Grover, N. Jin, K. A. Severson, T. M. Markov, Y.-H. Liao, M. H. Chen, B. Cheong, N. Perkins, Z. Yang, P. K. Herring, M. Aykol, S. J. Harris, R. D. Braatz, S. Ermon, and W. C. Chueh, “Closed-loop optimization of fast-charging protocols for batteries with machine learning,” *Nature*, vol. 578, no. 7795, pp. 397–402, Feb. 2020, publisher: Nature Publishing Group. [Online]. Available: https://www.nature.com/articles/s41586-020-1994-5

[18] P. Kollmeyer, C. Vidal, M. Naguib, and M. Skells, “LG 18650HG2 Li-ion Battery Data and Example Deep Neural Network xEV SOC Estimator Script,” vol. 3, Mar. 2020, publisher: Mendeley Data. [Online]. Available: https://data.mendeley.com/datasets/cp3473x7xv/3

[19] M. M. Hasan, R. Haque, M. I. Jahirul, M. G. Rasul, I. M. R. Fattah, N. M. S. Hassan, and M. Mofijur, “Advancing energy storage: The future trajectory of lithium-ion battery technologies,” *Journal of Energy Storage*, vol. 120, p. 116511, Jun. 2025. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2352152X25012241

[20] H. Ritchie, P. Rosado, and M. Roser, “Access to Energy,” *Our World in Data*, Sep. 2019. [Online]. Available: https://ourworldindata.org/energy-access

[21] “Global Electricity Review 2024.” [Online]. Available: https://ember-energy.org/latest-insights/global-electricity-review-2024

[22] H. Ritchie and P. Rosado, “Energy Mix,” *Our World in Data*, Jul. 2020. [Online]. Available: https://ourworldindata.org/energy-mix

[23] A. S. Brouwer, M. van den Broek, A. Seebregts, and A. Faaij, "Impacts of large-scale Intermittent Renewable Energy Sources on electricity systems, and how these can be modeled," *Renewable and Sustainable Energy Reviews*, vol. 33, pp. 443–466, May 2014. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1364032114000987

[24] "Trends in the electric car industry – Global EV Outlook 2025 – Analysis." [Online]. Available: https://www.iea.org/reports/global-ev-outlook-2025/trends-in-the-electric-car-industry-3

[25] "Executive summary – Batteries and Secure Energy Transitions – Analysis." [Online]. Available: https://www.iea.org/reports/batteries-and-secure-energy-transitions/executive-summary

[26] N. Omar, M. A. Monem, Y. Firouz, J. Salminen, J. Smekens, O. Hegazy, H. Gaulous, G. Mulder, P. Van den Bossche, T. Coosemans, and J. Van Mierlo, "Lithium iron phosphate based battery – Assessment of the aging parameters and development of cycle life model," *Applied Energy*, vol. 113, pp. 1575–1585, Jan. 2014. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0306261913007393

[27] L. Mattia, H. Beiranvand, W. Zamboni, and M. Liserre, "Lithium-ion battery thermal modelling and characterisation: A comprehensive review," *Journal of Energy Storage*, vol. 129, p. 117114, Sep. 2025. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2352152X25018274

[28] S. Guo, R. Xiong, K. Wang, and F. Sun, "A novel echelon internal heating strategy of cold batteries for all-climate electric vehicles application," *Applied Energy*, vol. 219, pp. 256–263, Jun. 2018. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0306261918303817

[29] Q. Lin, J. Wang, R. Xiong, W. Shen, and H. He, "Towards a smarter battery management system: A critical review on optimal charging methods of lithium ion batteries," *Energy*, vol. 183, pp. 220–234, Sep. 2019. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0360544219312605

[30] M. R. Palacín and A. de Guibert, "Why do batteries fail?" *Science*, vol. 351, no. 6273, p. 1253292, Feb. 2016, publisher: American Association for the Advancement of Science. [Online]. Available: https://www.science.org/doi/abs/10.1126/science.1253292

[31] "Trends in electric vehicle batteries – Global EV Outlook 2024 – Analysis." [Online]. Available: https://www.iea.org/reports/global-ev-outlook-2024/trends-in-electric-vehicle-batteries

[32] E. Yoo, U. Lee, J. C. Kelly, and M. Wang, "Life-cycle analysis of battery metal recycling with lithium recovery from a spent lithium-ion battery," *Resources, Conservation and Recycling*, vol. 196, p. 107040, Sep. 2023. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0921344923001763

[33] L. Gaines, K. Richa, and J. Spangenberger, "Key issues for Li-ion battery recycling," *MRS Energy & Sustainability*, vol. 5, p. E14, Jan. 2018. [Online]. Available: https://www.cambridge.org/core/journals/mrs-energy-and-sustainability/article/key-issues-for-liion-battery-recycling/F37D3914A1F5A8FD0ED3EF901664D126

[34] L. Sheng, L. Su, and H. Zhang, "Experimental determination on thermal parameters of prismatic lithium ion battery cells," *International Journal of Heat and Mass Transfer*, vol. 139, pp. 231–239, Aug. 2019. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0017931019314358

[35] H. Ritchie, "Tracking global data on electric vehicles," *Our World in Data*, Feb. 2024. [Online]. Available: https://ourworldindata.org/electric-car-sales

[36] "Energy Consumption in the UK 2024."

[37] "New report: European battery storage grows 15% in 2024, EU energy storage action plan needed - SolarPower Europe." [Online]. Available: https://www.solarpowereurope.org/press-releases/new-report-european-battery-storage-grows-15-in-2024-eu-energy-storage-action-plan-needed

[38] S. Wang, R. Zhou, Y. Ren, M. Jiao, H. Liu, and C. Lian, "Advanced data-driven techniques in AI for predicting lithium-ion battery remaining useful life: a comprehensive review," *Green Chemical Engineering*, vol. 6, no. 2, pp. 139–153, Jun. 2025. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2666952824000645

[39] M. J. Lain and E. Kendrick, "Understanding the limitations of lithium ion batteries at high rates," *Journal of Power Sources*, vol. 493, p. 229690, May 2021. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0378775321002330

[40] A. K. Koech, G. Mwandila, F. Mulolani, and P. Mwaanga, "Lithium-ion battery fundamentals and exploration of cathode materials: A review," *South African Journal of Chemical Engineering*, vol. 50, pp. 321–339, Oct. 2024. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1026918524001100

[41] A. Mauger, C. Julien, and H. Xie, "Composite anodes for lithium-ion batteries: Status and trends," *AIMS Materials Science*, vol. 3, pp. 1054–1106, Jul. 2016.

[42] Z. Chen, D. L. Danilov, L. H. J. Raijmakers, K. Chayambuka, M. Jiang, L. Zhou, J. Zhou, R.-A. Eichel, and P. H. L. Notten, "Overpotential analysis of graphite-based Li-ion batteries seen from a porous electrode modeling perspective," *Journal of Power Sources*, vol. 509, p. 230345, Oct. 2021. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0378775321008570

[43] Z. Li, J. Huang, B. Yann Liaw, V. Metzler, and J. Zhang, "A review of lithium deposition in lithium-ion and lithium metal secondary batteries," *Journal of Power Sources*, vol. 254, pp. 168–182, May 2014. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0378775313020880

[44] Y. Li, M. Vilathgamuwa, T. Farrell, S. S. Choi, N. T. Tran, and J. Teague, "A physics-based distributed-parameter equivalent circuit model for lithium-ion batteries," *Electrochimica Acta*, vol. 299, pp. 451–469, Mar. 2019. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0013468618328883

[45] S. J. Moura, F. B. Argomedo, R. Klein, A. Mirtabatabaei, and M. Krstic, "Battery State Estimation for a Single Particle Model With Electrolyte Dynamics," *IEEE Transactions on Control Systems Technology*, vol. 25, no. 2, pp. 453–468, Mar. 2017. [Online]. Available: http://ieeexplore.ieee.org/document/7489035/

[46] J. M. Reniers, G. Mulder, and D. A. Howey, "Review and Performance Comparison of Mechanical-Chemical Degradation Models for Lithium-Ion Batteries," *Journal of The Electrochemical Society*, vol. 166, no. 14, p. A3189, Sep. 2019, publisher: IOP Publishing. [Online]. Available: https://iopscience.iop.org/article/10.1149/2.0281914jes/meta

[47] S. Yang, X. Gao, Y. Li, W. Xie, B. Guo, L. Zhang, and X. Liu, "Minimum lithium plating overpotential control based charging strategy for parallel battery module prevents

side reactions," *Journal of Power Sources*, vol. 494, p. 229772, May 2021. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S037877532100313X

[48] L. Li, Y. Ren, K. O'Regan, U. R. Koleti, E. Kendrick, W. D. Widanage, and J. Marco, "Lithium-ion battery cathode and anode potential observer based on reduced-order electrochemical single particle model," *Journal of Energy Storage*, vol. 44, p. 103324, Dec. 2021. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2352152X21010161

[49] J. Xu, K. Xiong, T. Tang, Y. Chen, D. Hu, D. Hou, M. Yu, and J. Ding, "Precise Determination of the Continuous Entropic Coefficient Profile of Lithium-Ion Batteries Using Frequency-Domain Method," Rochester, NY, Apr. 2024. [Online]. Available: https://papers.ssrn.com/abstract=4803435

[50] S. E. J. O'Kane, W. Ai, G. Madabattula, D. Alonso-Alvarez, R. Timms, V. Sulzer, J. Sophie Edge, B. Wu, G. J. Offer, and M. Marinescu, "Lithium-ion battery degradation: how to model it," *Physical Chemistry Chemical Physics*, vol. 24, no. 13, pp. 7909–7922, 2022, publisher: Royal Society of Chemistry. [Online]. Available: https://pubs.rsc.org/en/content/articlelanding/2022/cp/d2cp00417h

[51] M. D. Bouguern, A. K. M r, and K. Zaghib, "The critical role of interfaces in advanced Li-ion battery technology: A comprehensive review," *Journal of Power Sources*, vol. 623, p. 235457, Dec. 2024. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0378775324014095

[52] V. A. Agubra, J. W. Fergus, R. Fu, and S.-Y. Choe, "Analysis of effects of the state of charge on the formation and growth of the deposit layer on graphite electrode of pouch type lithium ion polymer batteries," *Journal of Power Sources*, vol. 270, pp. 213–220, Dec. 2014. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S037877531401180X

[53] F. Wang, Z. Zhai, Z. Zhao, Y. Di, and X. Chen, "Physics-informed neural network for lithium-ion battery degradation stable modeling and prognosis," *Nature Communications*, vol. 15, no. 1, p. 4332, May 2024, publisher: Nature Publishing Group. [Online]. Available: https://www.nature.com/articles/s41467-024-48779-z

[54] M. Aykol, C. B. Gopal, A. Anapolsky, P. K. Herring, B. van Vlijmen, M. D. Berliner, M. Z. Bazant, R. D. Braatz, W. C. Chueh, and B. D. Storey, "Perspective—Combining

Physics and Machine Learning to Predict Battery Lifetime," *Journal of The Electrochemical Society*, vol. 168, no. 3, p. 030525, Mar. 2021, publisher: IOP Publishing. [Online]. Available: https://doi.org/10.1149/1945-7111/abec55

[55] N. Kamyab, J. Weidner, and R. White, "Mixed Mode Growth Model for the Solid Electrolyte Interface (SEI)," *Journal of The Electrochemical Society*, vol. 166, pp. A334–A341, Jan. 2019.

[56] J. A. Kuzhiyil, T. Damoulas, F. B. Planella, and W. D. Widanage, "Lithium-ion battery degradation modelling using universal differential equations: Development of a cost-effective parameterisation methodology," *Applied Energy*, vol. 382, p. 125221, Mar. 2025. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0306261924026059

[57] Y. Liu, X. Xu, M. Sadd, O. O. Kapitanova, V. A. Krivchenko, J. Ban, J. Wang, X. Jiao, Z. Song, J. Song, S. Xiong, and A. Matic, "Insight into the Critical Role of Exchange Current Density on Electrodeposition Behavior of Lithium Metal," *Advanced Science*, vol. 8, no. 5, p. 2003301, 2021, _eprint: https://advanced.onlinelibrary.wiley.com/doi/pdf/10.1002/advs.202003301. [Online]. Available: https://onlinelibrary.wiley.com/doi/abs/10.1002/advs.202003301

[58] "Doyle-Fuller-Newman Model (DFN) — PyBaMM v25.10.1 Manual." [Online]. Available: https://docs.pybamm.org/en/stable/source/examples/notebooks/models/DFN.html

[59] W. Guo, Z. Sun, S. B. Vilsen, J. Meng, and D. I. Stroe, "Review of "grey box" lifetime modeling for lithium-ion battery: Combining physics and data-driven methods," *Journal of Energy Storage*, vol. 56, p. 105992, Dec. 2022. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2352152X22019806

[60] G. Xu, J. Xu, and Y. Zhu, "LSTM-based estimation of lithium-ion battery SOH using data characteristics and spatio-temporal attention," *PLOS ONE*, vol. 19, no. 12, p. e0312856, Dec. 2024, publisher: Public Library of Science. [Online]. Available: https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0312856

[61] H. Liu, I. H. Naqvi, F. Li, C. Liu, N. Shafiei, Y. Li, and M. Pecht, "An analytical model for the CC-CV charge of Li-ion batteries with application to degradation analysis," *Journal of Energy Storage*, vol. 29, p. 101342, Jun. 2020. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2352152X20300517

[62] B. Y. Liaw, R. G. Jungst, A. Urbina, and T. L. Paez, "Modeling of Battery Life I. The Equivalent Circuit Model (ECM) Approach."

[63] A. Farmann and D. U. Sauer, "A study on the dependency of the open-circuit voltage on temperature and actual aging state of lithium-ion batteries," *Journal of Power Sources*, vol. 347, pp. 1–13, Apr. 2017. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0378775317301088

[64] "Choosing an appropriate model · JuliaSimBatteries." [Online]. Available: https://help.juliahub.com/batteries/stable/model_options/

[65] "Doyle Fuller Newman Battery Model," Nov. 2025. [Online]. Available: https://www.batterydesign.net/modelling/doyle-fuller-newman-battery-model/

[66] V. Sulzer, S. Marquis, R. Timms, M. Robinson, and S. Chapman, *Python Battery Mathematical Modelling (PyBaMM)*, Feb. 2020.

[67] M. Auch, T. Kuthada, S. Giese, and A. Wagner, "Influence of Lithium-Ion-Battery Equivalent Circuit Model Parameter Dependencies and Architectures on the Predicted Heat Generation in Real-Life Drive Cycles," *Batteries*, vol. 9, no. 5, p. 274, May 2023, publisher: Multidisciplinary Digital Publishing Institute. [Online]. Available: https://www.mdpi.com/2313-0105/9/5/274

[68] "ICLOCS2: A MATLAB Toolbox for Optimization Based Control." [Online]. Available: http://www.ee.ic.ac.uk/ICLOCS/default.htm

[69] J. S. Edge, S. O'Kane, R. Prosser, N. D. Kirkaldy, A. N. Patel, A. Hales, A. Ghosh, W. Ai, J. Chen, J. Yang, S. Li, M.-C. Pang, L. B. Diaz, A. Tomaszewska, M. W. Marzook, K. N. Radhakrishnan, H. Wang, Y. Patel, B. Wu, and G. J. Offer, "Lithium ion battery degradation: what you need to know," *Physical Chemistry Chemical Physics*, vol. 23, no. 14, pp. 8200–8221, Apr. 2021, publisher: The Royal Society of Chemistry. [Online]. Available: https://pubs.rsc.org/en/content/articlelanding/2021/cp/d1cp00359c

[70] M. A. A. Mohamed, T. F. Yu, G. Ramsden, J. Marco, and T. Grandjean, "Advancements in parameter estimation techniques for 1RC and 2RC equivalent circuit models of lithium-ion batteries: A comprehensive review," *Journal of Energy Storage*, vol. 113, p. 115581, Mar. 2025. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2352152X25002944

[71] S. Gifford, “Lithium, Cobalt and Nickel: The Gold Rush of the 21st Century,” no. 6.

[72] S. W. Boettcher, S. Z. Oener, M. C. Lonergan, Y. Surendranath, S. Ardo, C. Brozek, and P. A. Kempler, “Potentially Confusing: Potentials in Electrochemistry,” *ACS Energy Letters*, vol. 6, no. 1, pp. 261–266, Jan. 2021, publisher: American Chemical Society. [Online]. Available: https://doi.org/10.1021/acsenergylett.0c02443

[73] “Battery Metals Report 2023/03 - Everything you need to know about the battery metals lithium, nickel, cobalt and copper!” Mar. 2023. [Online]. Available: https://www.resource-capital.ch/en/reports/view/battery-metals-report-2023-03/

[74] W. A. Appiah, L. H. Rieger, E. Flores, T. Vegge, and A. Bhowmik, “Unravelling degradation mechanisms and overpotential sources in aged and non-aged batteries: A non-invasive diagnosis,” *Journal of Energy Storage*, vol. 84, p. 111000, Apr. 2024. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2352152X2400584X

[75] “ARTECH HOUSE U.K.: Battery Management Systems, Volume III: Physics-Based Methods.” [Online]. Available: https://uk.artechhouse.com/Battery-Management-Systems-Volume-III-Physics-Based-Methods-P2201.aspx

[76] “Battery Management Systems, Volume 1: Battery Modeling.” [Online]. Available: http://mocha-java.uccs.edu/BMS1/

[77] “Bayesian Optimization Algorithm - MATLAB & Simulink.” [Online]. Available: https://uk.mathworks.com/help/stats/bayesian-optimization-algorithm.html

[78] J. Xu, K. Xiong, T. Tang, Y. Chen, D. Hu, D. Hou, M. Yu, and J. Ding, “Precise determination of the continuous entropic coefficient profile of lithium-ion batteries using frequency-domain method,” *Measurement*, vol. 240, p. 115578, Jan. 2025. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0263224124014635

[79] G. Tucker, R. Drummond, and S. R. Duncan, “Optimal fast charging of lithium ion batteries: between model-based and data-driven methods,” *Journal of The Electrochemical Society*, vol. 170, no. 12, Dec. 2023, publisher: The Electrochemical Society. [Online]. Available: https://eprints.whiterose.ac.uk/id/eprint/209066/

[80] “Renewable electricity – Renewables 2025 – Analysis.” [Online]. Available: https://www.iea.org/reports/renewables-2025/renewable-electricity

[81] P. Das, K. Hewage, R. Kotagodahetti, S. Wanniarachchi, and R. Sadiq, “Lithium-ion battery recycling: a critical review of techno-economical and socio-environmental impacts,” *Separation and Purification Technology*, vol. 382, p. 135847, Feb. 2026. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1383586625044442

[82] W. Wang and Y. Wu, “An overview of recycling and treatment of spent LiFePO4 batteries in China,” *Resources, Conservation and Recycling*, vol. 127, pp. 233–243, Dec. 2017. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0921344917302677

[83] “Energy consumption in the UK 2024.” [Online]. Available: https://www.gov.uk/government/statistics/energy-consumption-in-the-uk-2024

[84] “Trends in electric car markets – Global EV Outlook 2025 – Analysis.” [Online]. Available: https://www.iea.org/reports/global-ev-outlook-2025/trends-in-electric-car-markets-2

[85] C. R. Birkl, M. R. Roberts, E. McTurk, P. G. Bruce, and D. A. Howey, “Degradation diagnostics for lithium ion cells,” *Journal of Power Sources*, vol. 341, pp. 373–386, Feb. 2017. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0378775316316998

[86] M. Doyle, T. F. Fuller, and J. Newman, “Modeling of Galvanostatic Charge and Discharge of the Lithium/Polymer/Insertion Cell,” *Journal of The Electrochemical Society*, vol. 140, no. 6, p. 1526, Jun. 1993, publisher: IOP Publishing. [Online]. Available: https://iopscience.iop.org/article/10.1149/1.2221597/meta