

Notes FYP

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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 degradation 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 feasible 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 degradation 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 actual optimal charging method themselves, to reduce degradation. 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 degradation alongside instantaneous applied voltages.

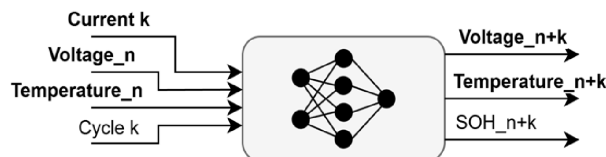


Figure 1: Original end objective: Black Box Battery to allow for discovery & testing of optimal charging profiles

2 Data Analysis on Dans Data

Gave a good insight to the degradation patterns on an array of lithium batteries, data was analysed and plotted on jupyter 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 degradation, but if the degradation 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 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 dendrites

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 degradation drops rappidly over later cycles.

Appears the multistage cc is advantageous for keeping charge time down, yet reducing degradation 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 outcome, mentions its a linear mechanism, how are they confirming what the characteristics are after atleast the knee point?

5 Current plan

- Look at existing charging methods, including the complex ones and continuous 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 implemented on hardware. Could also give chance 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 feasibility of implementing on actual hardware, explicit MPC could be a possibility, 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 battery 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 future features

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

Adaptdtive, 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 degradation 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,

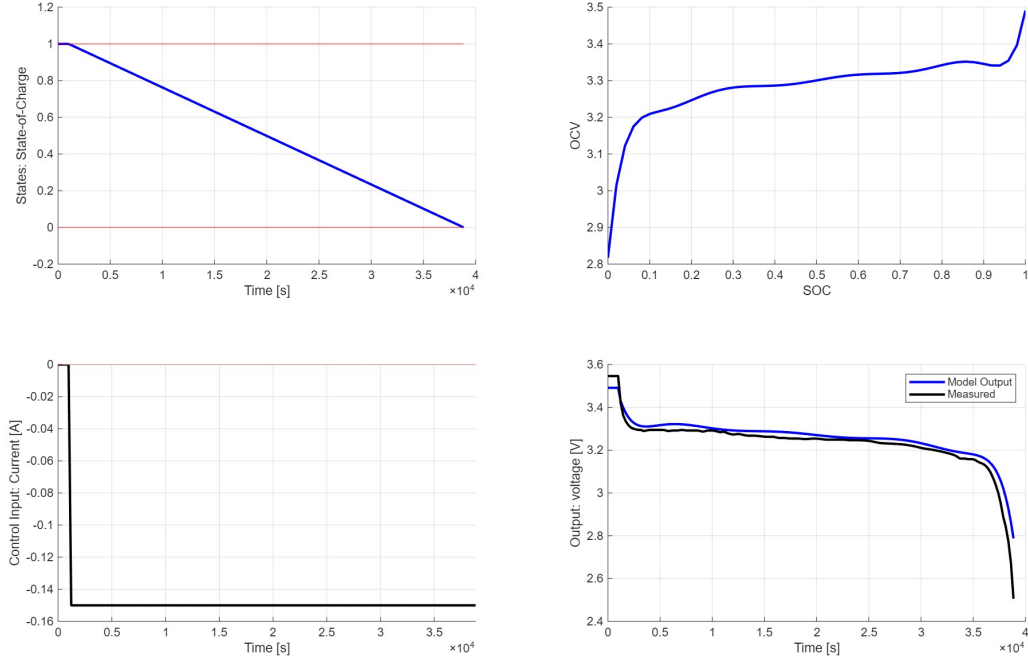


Figure 2: Fixed OCV curve from paper ...

for the center soc section (where the graph wasnt cut off), the difference between the curves should equal to the the resistive drop across $R_1 + R_0$. This allowed a decent estimate of $R_1 + R_0$, and then R_0 was bounded to be less than this value.

Between 0.1C and 3C discharge (at SOC 50%), the voltage difference was 0.287, thus $R_1 + R_0 = 0.287 / (2.9C \text{ rate current}) = 0.287 / (2.9 * 1.5A) = 0.066 \text{ Ohms}$. Thus $R_0 + R_1 < 0.066 \Omega$. The initial drop in voltage would have allowed R_1 to be estimated, however the graph is cut off too early to see this, when taking the literal values from the table, R_1 is shown to be 0.09Ω which is not possible since $R_1 + R_0$ must be less than 0.066 Ohms .

Thus, the next approach was to parametrise only R_0 , and set R_1 to be $0.066 - R_0$. Before attempting this, its expected a fair offset from the actual output given the ocv curve discrepancies. Nevertheless, this was attempted. In order to implament this in iclcs, R_1 was taken out of the parameterisation and reformulated as $0.066 - R_0$. It was discovered that then applying bounds on R_0 caused larghe changes in the capaicty values, i.e a 10Ω change in R_0 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 R_0 &

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 flexibility.

Case	Q (As)	C (F)	R ₀ (Ω)	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 capaicoctr. 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 signifi- cantly change esitimation 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 is formed by the following:

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

$$Q_{gen} = I(U_{oc} - V) - I \left(T \frac{dU_{oc}}{dT} \right) \quad (2)$$

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

Yya, got those stuff done, will probs auytmate on all dans to get cp, l values

Anyways, for the current sims, before the mpc which im still stuffed for, i can discretise 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 values and OCV curve accuracy (show variations with pinning SOC(0) voltage, forced capacity, and free rein) Show current sim results Show stages of charging simed ode45 Discretisation (Explain working on mpc)

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

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

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

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

$$\begin{bmatrix} \dot{T} \\ \dot{z} \\ \dot{V}_1 \end{bmatrix} = \begin{bmatrix} I^2 R_0 + IV_1 - IT \frac{1}{mCp} (c_0 + zc_1 + z^2 c_2 + z^3 c_3 + z^4 c_4) - hAT \frac{1}{mCp} \\ I/Q \\ I/C - V_1/R_1 C \end{bmatrix} \quad (7)$$

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 capacity, 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 appropriately 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, therefore 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 **CC_i** sections have there maximum value limited (**CC_{i,max}**) physically, these can be calculated to help define the minimum bounds and $t_{0-80\%}$.

The first case considered is when **CC_i**, $i = 1, 2, 3$, are at their maximum, since all currents are posotive values, the equality given above must mean that **CC₄** is at its minimum. This inequality narrows descision variables to only 2, with the equality given as

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

. The maximum permissible 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: $CC_{1,max} = 3.4$, $CC_{2,max} = 2.9$, $CC_{3,max} = 2.8$ and $CC_{4,max} = 2.5$. Thus the equation has only two variables and can be written as $CC_{4,min} = \frac{0.2}{t_{0-80\%}-0.279}$

In the second case, suppose there is a current profile which is lowest for all CC_i , $i = 1, 2, 3$ (which as mentioned is the same for those segments, thus is denoted as $CC_{1:3,min}$), again due to the positive nature of the currents, must mean CC_4 is at its maximum. Since as before $CC_{4,max}$ is known, a similar equation as before is calculated as $CC_{1:3,min} = \frac{0.2 \times 3}{t_{0-80\%} - \frac{0.2}{CC_{4,max}}} = \frac{0.6}{t_{0-80\%} - 0.08}$. These two equations can now be plotted to help decide values based on $t_{0-80\%}$.

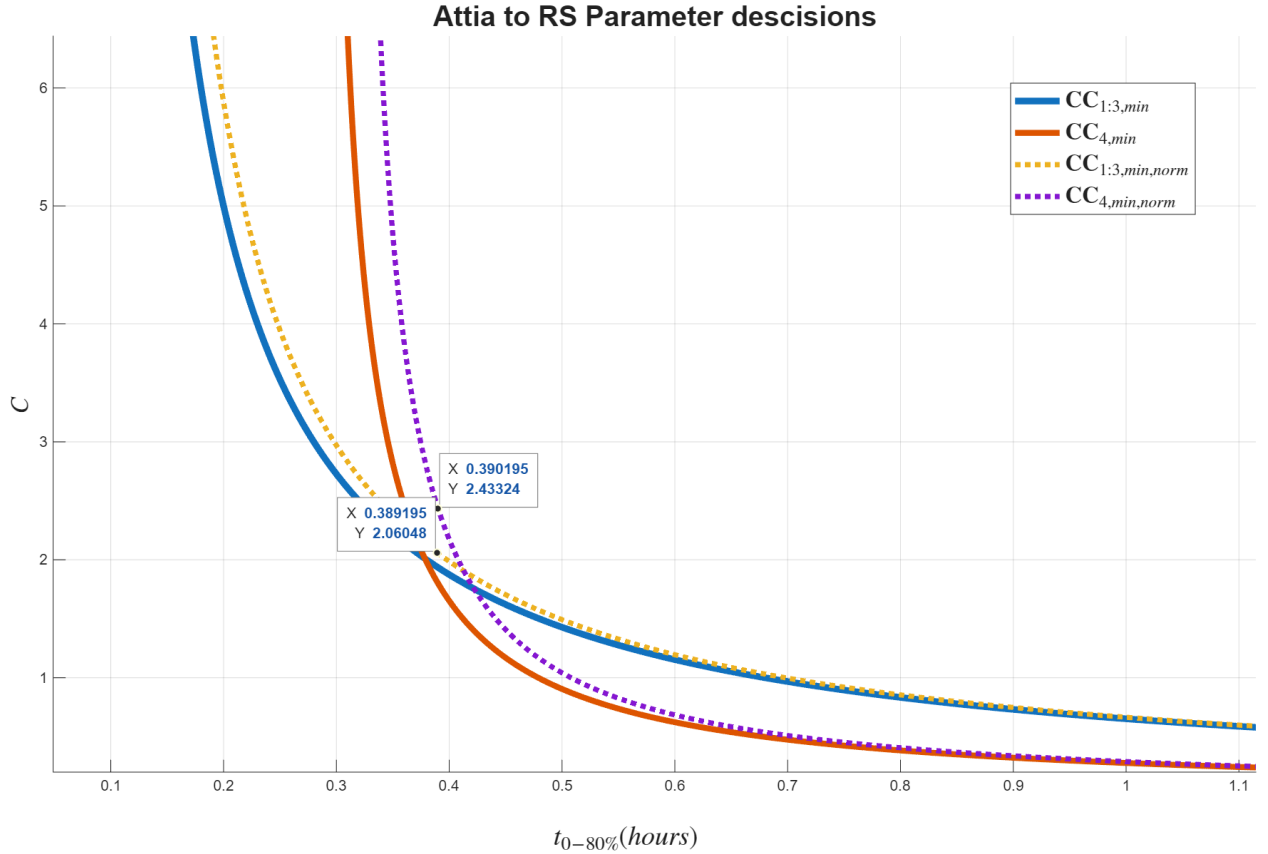


Figure 3: Ffes

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, clearly, however 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 coincide with the RS battery. A table is shown below to highlights this. Only \mathbf{CC}_2 is slightly over the limit.

CC_max values	$\mathbf{CC}_{1,max}$	$\mathbf{CC}_{2,max}$	$\mathbf{CC}_{3,max}$	$\mathbf{CC}_{4,max}$
CC_{rsmax} Actual	3.4	2.9	2.8	2.5
$CC_{1,attia,max}/CC_{1,rs,max}$ 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 clearly 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 $CC_{1,attia,max}/CC_{1,rs,max}$, 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 be represented as $t_{0-80\%} = 0.2/x_{scale} \times ((\sum_{i=1}^3 \mathbf{C}\mathbf{C}_i^{-1}) + \mathbf{C}\mathbf{C}_4^{-1})$, which can be written in a graphical form as

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

. The right hand side can be plotted and yields the following (Y value is $t_{0-80\%}$), the optimised choice is such that the scalar value in the field is as close to $\mathbf{C}\mathbf{C}_4$ of the chosen Attia profile (the most optimal version they found for example), alongside the respective $\mathbf{C}\mathbf{C}_{1;3}$ values, the point which is scaled given in the previous paragraph 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 $\mathbf{C}\mathbf{C}_4$ 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 paragraph without been too short of charging. A balance was thus decided, with a $t_{0-80\%}$ of 0.55 chosen, this, referring 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**

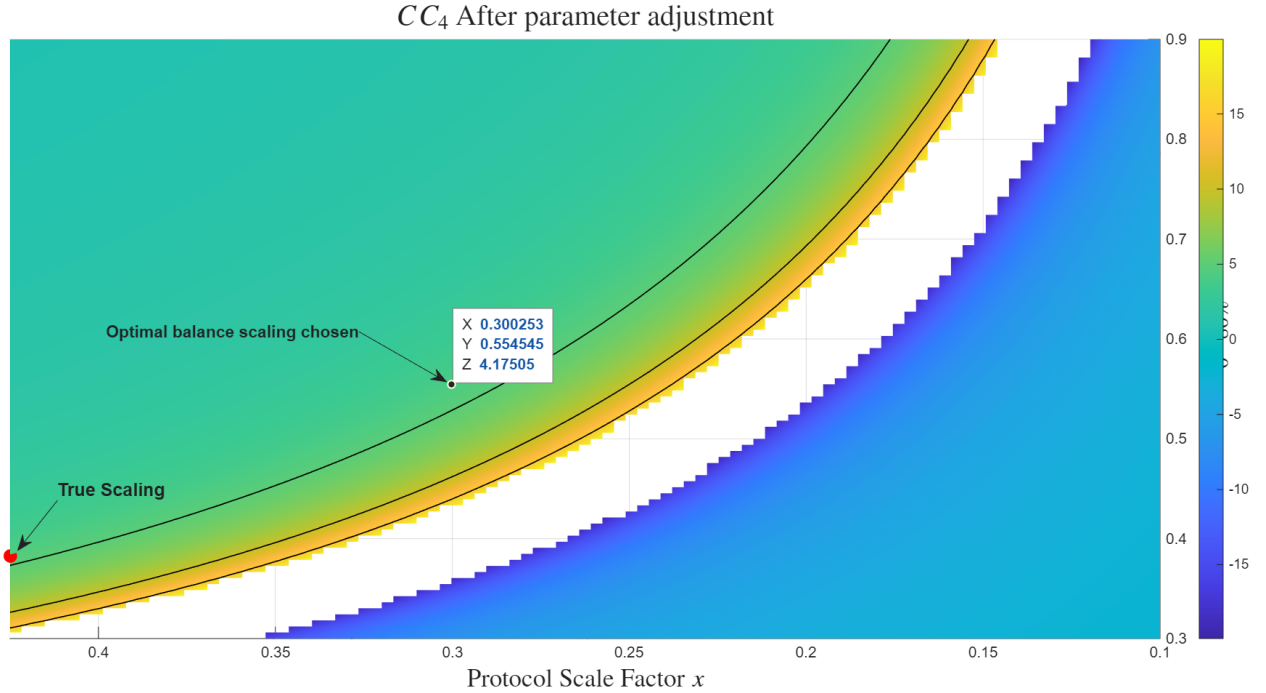


Figure 4: Ffes

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