

Understanding the problem



**University of  
Sheffield**

**Finding Machine learning methods to model the  
degradation of lithium based batteries under  
multi-stage CC charging**

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# 1 Introduction

There are currently over 7 billion people with access to electricity [1], the global consumption of energy is rising by  $4.5 \times 10^{16}$  Joules every year; 77% of which is from utilising non-renewable sources. With the affects of non-renewables on the environment still not fully realised, coupled with the concern of their finite-life nature, poses a constant need to increase usage of renewable sources. However, a large set of renewable generation methods fall under the category of variable renewable energy (VRE) sources [2], thus requiring a robust form of energy storage to solve the intermittent availability - methods of storage do exist and suitable solutions depend on the specifics and locations; as battery technology increases, the use of battery as a storage medium for the energy sector are ever more increasing. There is also the rapid increase in electric vehicle production, with a push to increase the adoption of EV's, 17.3 million cars were produced in 2024 [3] alone with a recent 20% average year-on increase. Lithium Ion batteries (LIB's) are the most common currently used batteries due to their desirable characteristics in energy density, aging properties, cost and more.

EV's and the energy sector account now account for 90% of the total lithium ion battery demand since 2016, the total lithium-ion battery demand is 10-times larger [4] since 2016. Different resources predict different forecasts of total battery growth [5, 6], regardless, it appears the rate of demand will not be decreasing in the near future.

LIB's, like all batteries and decrease in performance and capacity [7] until they are deemed unsuitable for their current use. This means eventually, all current batteries in use today will need to be disposed of, given that over 660,000 tonnes of earth metals were mined in 2023 alone, a strong case for slowing down the need for mining new materials is made, whilst keeping up with the demand (cite the iea thing). It's noted that battery chemistry is still a developing field, thus newer batteries may use less scarce materials, thus hard to truly predict the sustainability of mining these materials, for example, some reports (cite faraday) say cobalt supplies could be used entirely by 2040. Solutions do exist, recycling methods have been developed in order to extract the materials, termed battery metal recycling (BMR), however there are wildly different sources suggesting how much of current batteries actually are recycled (one showing 5%), (other showing 90%), and the technology to do so is still a developing field, there are many different methods (cite issues), since most of the rare earth elements are within the battery's cathode, methods such as hydrometallurgical process can extract these, but at the cost of severe reduction in lithium yield (cite enji) - although there are

promising methods with some proposing a lithium recovery needing less than 40% the energy compared to mining the virgin material (cite enji yoo) whilst still recovering nickle and cobalt. There is also the rising interest in reusing the batterys before recyling, these batterys are ferrerred to as second-life batteries (SLB's); in the EV use-case, the majority of the batteries are deemed finished once their usable capacity drops below 80% (cite), but often, due to the other parameters of the batteries needing to be of high standards for EV use, the 'dead' batteries can still provide a very usefull serivce in less demanding applications, a common one being energy storage systems (ESS) [8], with claims resuing can reduce CO<sub>2</sub> emmisions by 56% as apposed to using natural fuel gas in situue. However there are again challanges associated, for saftey there is the need for robust testing, asorting the batteries based on their current health states, non automised methods of extracting cells from their original pack. These additional steps mean the price of SLB's could become at a point where they are not much cheaper than new batteries, making the solution less attractive to many sectors [8].

In summary, there are methods that are devloping to reduce the need for mining new materials and decreasing recycling emrgy, but ultimately, providing methods to increase the usable life of the current batteries serves as a direct way reduce the impacts of batteries themselves and to meet their growing demand. If just 1 extra life cycle could be added to all EV's currently on the road ( 60 million (citr)), this could power all of the UK's energy needs for one day (cite govengy); as most batterys cycle life are well over 1000, any incament in cycle life can be greatly beneficial.

Much research has been done into both modeling LIB's and optimising their usage from both an energy and aging perspective.

Moddeling and predicitng how batteries degrdeade over time is pivotal for the growing use of lithium batteries as it allows informed descisions on how to best charge and use battereis to prolong life, as well allow optimisations on the charging throughout the batteries life.

## 1.1 Project Aims

This project in essance aims first to characterise any battereies behaviour by parameterisation without ex-situe tests. This data will then be used in combination with work previously done to form the charging protocol based off minimising different objective functions (the level of affects the previously proposed objective functions will be also verified by acting these tests). Data from this

will be used to form the basis of a machine learning model in the hopes this model can, over time, allow for a much simpler method of predicting a batteries future behaviour. If this model can show how different charging currents can affect degredation, a charging protocol which is derived from minimising such model will be tried in the labs. If this isn't achieved, atleast this project can validate existing predicted charging to minimise degredation will be tested, and the parameterisation of the batteries during degredation will be researched by using optimisation tools.

Figure x highlights the original idealised goal, to have a purely data driven model that can predict the output voltage over any cycle, thus being able to derive an idealised charging current to maximise the lifespan.

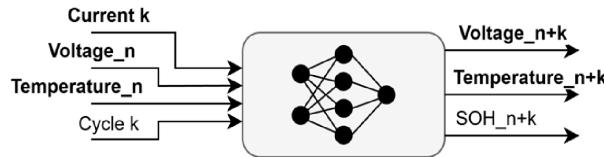


Figure 1: Initial end objective: Black Box Battery modeling degredation

### 1.1.1 Objectives

- Analyse ICLOCS2 and other methods in parameterising batteries under realtime use
- Modify previously developed charging methods for running in a lab to test actual results, inspect the affects of each method
- See how effective adapting the charging profile over the degredation is in increasing battery life
- Investigate ML methods to model the attained data to predict degredation
- Use the model to find a new charging method and validate

## 2 Literature Review

### 2.1 Lithium based battery degredation modes

**Notice:** Throughout the research and not coming from an electrochemical background, various literature denotes the meaning of *potential* and *overpotential* as slightly different given the context - there is likely equivalences, but of which the author of this report can't explain. For example cite(potential for confusion) shows a clear distinction between the common  $\phi$  symbol for potential as the *electrical potential*, however when talking about volts measured in the real world, the *potential difference* is usually the *electrochemical potential difference* (specifically of electrons), for two given points denoted by  $\Delta\tilde{\mu} = \Delta\mu + \Delta zF\phi$ . Overpotential in some instances, such as the Butler-Volmer model for current exchange, is a function of overpotential  $\eta$  and from cite gregg is a difference in the current *electrical potential* and equilibrium potential, yet papers like S2352152X2400584X show overpotential more generally as the difference between any equilibrium potential and current potential. Thus confirmation should be made in regards to what type of potential and overpotential. Assumptions are given that potentials are a form of energy state, with a difference between two points causing a force, and overpotential as additional energy for an event to occur.

### Basic Background of Lithium Ion Batteries

Lithium-ion based batteries are favorable largely due to the highly reducing nature of Lithium, taking the potential relative to hydrogens reduction, lithium's half-reaction is  $-3.01V$  (cite gregg) relative to hydrogens half-reaction, meaning lithium can release its outer shell electron relatively easily. Any cell's potential difference is the difference in potentials of the negative and positive solid state electrodes  $V_t = \phi_s^+(t) - \phi_s^-(t) - IR_{cc}$  where  $R_{cc}$  is the current collector or tabs ohmic resistance (cite liuying), so having negative half reduction of lithium, allows a variety of positive electrodes (where the oxidation occurs), to yield a high battery voltage. Coupled with Lithium's low molecular weight, a high energy density cell can be achieved. The force produced by the potential difference between the electrodes drives the electrons via the external circuit, providing useful work, allowing lithium batteries to act as an energy storage medium.

Lithium batteries all follow the same basic principle of operation, as shown in .... They consist of a positive and negative electrode, electrolyte, a separator and current collectors. Unlike many

other battery chemistries, where the metal ions undergo chemical reactions at the electrodes which change the composition of the electrodes, lithium ions intercalate and deintercalate within the electrodes structure - they are in essence absorbed to and from the electrode structures (cite greg p). The negative electrode is usually of a graphite based structure, allowing up to 1 lithium atom to be stored per 6 carbon atoms, whilst the positive electrode can vary greatly between different lithium batteries; the most common are often composed of transitional metal oxides such as LCO, LMO, NMC, NCA (cite Alex K Hoech et al). The electrochemical state of lithium in the graphite is similar to that of individual lithium atoms, thus the electrode potential of the negative electrode is very similar to that of pure lithium ( -3V) (cite liquin), although its lithium storage abilities are usually lower than the positive electrodes. The lithium ions within the positive electrodes are in a much lower energy state, thus their reaction potential ranges from -1 – 2V, therefore, overall there is a large potential difference created by the want of the positive electrode gaining electrons and the lithium ions, and the want of the lithium within the carbon of the negative electrode to give up the lithium ions and electrons (relative to each other). In general, the negative electrodes used currently are carbon based, their capacity to hold the lithium (per unit volume) is greater than the positive electrodes used today as shown in figurexx (cite Alex), but as discussed later in this section the negative electrode is often the key limiting factor in degradation. The positive electrode materials vary greatly in material, but since this electrode has the biggest electrode potential, it has a largest impact on the overall cell voltage, and thus energy density of the cell, in addition since per volume it holds less lithium, electrode material with higher lithium capacity will be of greater affect than improving the negative electrodes capacity. The two reactions with lithium with the battery electrodes chosen for this project are shown below (during discharge, the reactions proceed from left to right, for the charging process, it's right to left):



The electrolyte is a medium in which the lithium ions can be transported via diffusion to the electrodes, the electrolyte does not however allow electrons to flow, only via an external circuit can they flow, . The separator acts as a structural barrier to prevent the opposite electrodes from touching, which would allow both electrons and ions to flow, causing major fire risks from the uncontrolled reactions. During the discharging process, a path for electrons is provided externally across the current collectors, (these collectors are not part of the reactions and are just a means to electrically

connect the eleoctrolites to a usefull surface for soldering) the lithium stored within the negative electrode deintercalates, released as the posotive lithium ion, whilst the electron leaves the electrode, traveling acros the external circuit to the posotive electrode, whereby the lithium ions meet the electrons. During charging, the applied voltage at the terminals will be above the difference of the electrode potentials, this applied overpotential causes the lithium ions within the posotive electrode to deintercalate, traveling across the electrolyte to the negative electrode, where they intercalate within the graphine structure as the ions combine with electrons. The speed at which the ions flow is far slower than the electron transfer (cite greg), which contributes to the behaviour of lithium batteries.

Mention diffusion differences between charge and discharge (cite micheal j lain) Whiney well

### 2.1.1 Degredation methods

Simon et al. [9] simon e j o summerises the key 5 modes of degredation caused within lithium ion batteries

**Lithium plating** - During discharge, the lithium ions intercalate into the posotive electrode. Under certain charging conditions, the lithium ions within the electrolyte will join with the electrons outside the negative electrode, producing pure lithium metal - commonly reffered to as dentrites, depicted in figure ... There is still ongoing research into finding the key causes and which factors speed up this process, but it's most understood cause is when the negative electrode (carbon in the projects battery case) potential falls below that of lithiums own potnetial ([10, 11] shichun yang + Michael.J. Lain). From the Doyle-Fuller-Newman brefily described later (cite dfn), the electrode pot As previously mentioned, the lithinated carbon potnetintal is slighlty higher than that of pure lithium. From electrochemical models, the potential at the electrodes is the sum of their open circuit potentials and their overpotential, overpotentials are caused from the dynamics of the battery, i.e during charge and discharge, thus, the overpotentials can drive the battery below that of lithium, aswell as the SoC of the battery which increases the natural potentials (cite zhiqiang). Meaning the more favourable reaction is to form lithium as apoused to intercalate. The overpotential is largley due to the kenetic overpotential at the interface of the electrolyte, sei and electrode; it's shown that low temperature, high currents and high SoC can cause the negative potential to drive lower (cite zhiqiang). Modelling aims to characterise and capture potentials to help with controling

dendrite formation, methods from numerical electrochemical models like the p2D thing, using the butler-volmer kinetics to show key overpotentials, as well as state estimation approaches for realtime - however they all require many parameters about the specific batteries.

**SEI Layer growth** - A layer known as solid electrolyte interphase is formed as soon as the electrolyte solution comes into contact with the negative electrode causing salts like  $\text{Li}_2\text{CO}_3$  to produce acids, followed by further reactions; this barrier acts to prevent electrons further reducing and using up the more of the electrolyte, whilst allowing passage of the lithium ions to intercalate[12]. If this SEI breaks apart, new SEI will form, taking more lithium up causing a reduction of lithium available for charging. Having the battery at very high and very low SoC can cause the SEI layer to thicken also [13]. SEI formation takes up electrons within its reaction, and thus c

**Particle fracture** - The physical volume of the electrodes can change during the intercalation and deintercalation can cause

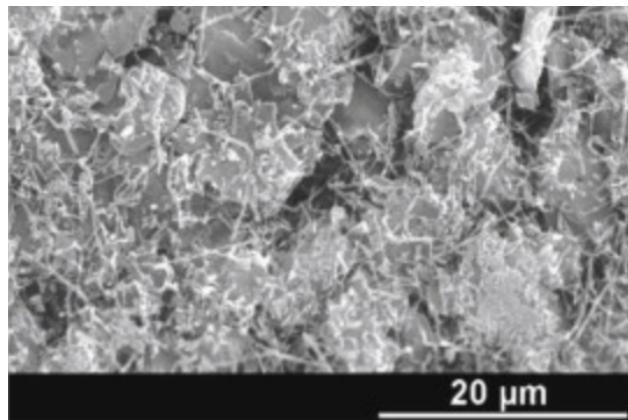


Figure 2: Lithium deposits shown in lighter grey on the graphite electrode [14]

Causes increased ageing and safety risks, it's the deposition of metallic lithium on the anode 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 when charging is forced, local overpotential can cause the lithium plating, can cause dendrites

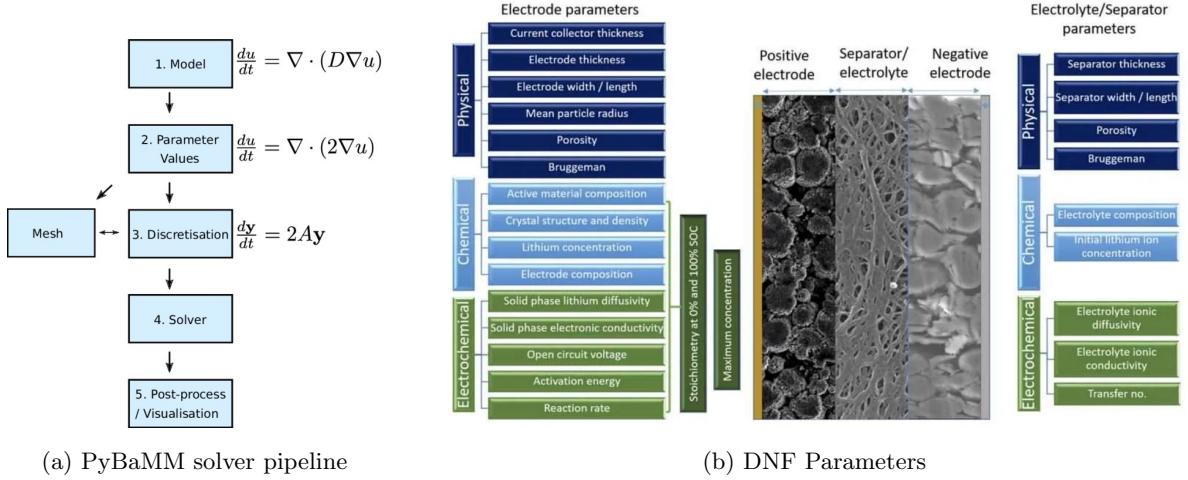


Figure 3: Parameters and solution steps for physics based modeling

## 2.2 Equivalent Circuit Model

There are many ways a lithium battery can be modeled, depending on the accuracy required, parameters available and computational power available. The two main categories are the equivalent circuit models and physics-based models (cite greg). The physics-based models integrate conservation laws as well as dynamical behaviour which leads to a set of PDE's with both scalar and gradient based boundary conditions. These require discretisation within the physical dimensions of the model to yield a set of ODE's which can be solved for, PyBaMM is a popular framework for such modeling and its process is shown in figure xx. Popular physics based models in order of computational complexity cite(juliasim) are the Doyle-Fuller-Newman model (cite doyle), Single-Particle Model with electrolyte (SPMe) and SPM. The key problems of PBM is some require over 30 parameters to fully describe the properties and errors of such can accumulate over time, and depending on accuracy needed, the discretisation can yield hundred of ODEs (cite battery design).

Equivalent circuit models use standard lumped electrical elements to match the behaviour to that of a real lithium battery dynamics, it is this type of model most common in BMS systems today. T.Kalogiannis *et al* [15] provides common methods for obtaining the parameter values used in ECM's. The most common version is shown in figure xx , which is static in its dynamics. The key component is the  $V_{oc}$  ideal voltage source, this value becomes a function, (when neglecting temperature, degradation, charging-discharging hysteresis) of the batteries state of charge SoC,

given by

$$SoC(t) = z(t)/Q = (z(t_0) + \int_{t_0}^t i(\tau) d\tau)/Q$$

where  $Q$  is the batteries nominal maximum capacity and  $z$  is the current charge capacity. The  $R_0$  and  $R_1C_1$  branch are used to model the difference in terminal voltage compared to that of the  $V_{ocv}$  for a given instantanious SoC.

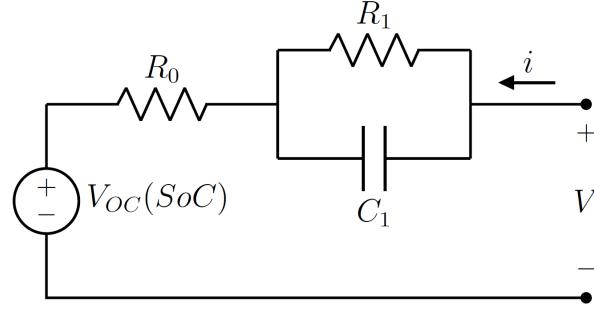


Figure 4: ECM model with 1st Order Polarizing dynamics

The common state space form of this system is given below

$$\begin{bmatrix} \dot{v}_1(t) \\ \dot{z}(t) \end{bmatrix} = \begin{bmatrix} -\frac{1}{R_1 C_1} & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} v_1(t) \\ z(t) \end{bmatrix} + \begin{bmatrix} \frac{1}{C_1} \\ \frac{1}{Q} \end{bmatrix} i(t) \quad (3)$$

$$V_{batt}(t) = V_{oc}(z) + i(t)R_0 + v_1(t) \quad (4)$$

S2352152X2400584X provides the equation for the total overpotential within the battery derrived from the Fuller-Newman electrochemical mode, here, the total overpotential  $\eta_{batt}$  is equal to the difference from the equilibrium battery potential  $U_{batt}$  and terminal voltage potential  $V_{batt}$ , i.e  $V_{batt} = U_{batt} - \eta_{batt}$ . This is analgous to the ECM model given above, whereby the overpotential (dynamical behaviour) is modeled by  $i(t)R_0 + v_1(t)$ , where the equilbrium potential is  $V_{oc}(z)$ . Despite the large complexity reduction, reports show that accuracy can be very good,

$$\eta_{\text{batt}} = \left[ \begin{array}{l} \underbrace{\left( \Phi_{2,p}|_{x=L_p} - \Phi_{2,n}|_{x=0} \right)}_{\text{Electrolyte overpotential } (\eta_2)} \\ + \underbrace{\left[ \left( U_p(c_{1,p}^s)|_{x=L_p} - U_p(\bar{c}_p)|_{x=L_p} \right) - \left( U_n(c_{1,n}^s)|_{x=0} - U_n(\bar{c}_n)|_{x=0} \right) \right]}_{\text{Li concentration overpotential } (\eta_1^c)} \\ + \underbrace{\left( \eta_p^{ct}|_{x=L_p} - \eta_n^{ct}|_{x=0} \right)}_{\text{Kinetic overpotential } (\eta^{ct})} - \underbrace{R_f I_{\text{app}}}_{\text{Electrode ohmic overpotential } (\eta_1^\Omega)} \end{array} \right] \quad (5)$$

Whilst the voltage dynamics of lithium batteries do depend on temperature, this project keeps the ambient temperature to 30deg nd moderatley low temperatures, thus realtime affects are minimal. However moddeling of the temperature is vital since temperature does directly affect degredadion and theroisred to help the ICLOCS parameterisation. cite the thermal paper. The irreversible is much easier to directly relate to the ecm, by basic ohms law. However irreverisitbility can not be directly infered from the ecm model. Cite dodgey paper, equated it to proportional to  $\partial U/\partial T$  where  $U$  is the OCV and  $T$  is the temperature, this value does change over the SoC of the battery and paper et all calculates the curve for a battery of similar to the test battery shown in figure x.x

$$mCp \frac{dT}{dt} = \underbrace{I^2 R_0 + IV_1}_{\text{irreversible}} - \underbrace{IT \frac{\partial U}{\partial T}}_{\text{reversable}} - \underbrace{hAT}_{\text{dissipation}} \quad (6)$$

cite Alexander Farman, shows that the OCV of lithium batteries can change throughout degreda-diton, for phosphate batteries they showed a 20mV difference in regions of the SoC after aging of 500 cycles at 1C of charge and discharge. Additionally, while there exits methods of extracting an accurate OCV curve, it can take hours to accuratley obtain to minimise overpotentials [15]. This is where numerical methods could be utilised to obtain the OCV curve and the other ECM parameters by fitting against a grey-box model of the dynamics, ICLOCS2 cite, will be used heavily throughout this project to see it's ability to parameterise the battery dynamics.

## 2.3 Charging methods

There was a paper copmparing them in general, taljk aboutr the advantage of the different ones ect.

Talk about CC, MultiStage CC, ConstantPower, George Tuckers minimisation functions

There exists many techniques to charge batteries with a graphical summary of the common methods shown in figure xx, with the most common method known as CC-CV. This is where the bulk charge is done such that the applied overpotential to the battery causes a constant current to flow, the voltage potential of the battery rises to a defined maximum point, the charging device then switches to a constant voltage charging mode, this fixed voltage is held until the charge current decays to a negligible or fixed amount - current still flows during this stage as there is still an overpotential between the batteries equilibrium state and the applied constant voltage. This is the simplest to implement without the need for an accurate SoC reading to risk overcharging (like would be with pure CC charging), CV charging can be too dangerous given the large current draw at low SoC. Some of the data used within this project is charged via CC-CV and is highlighted in figure xx.

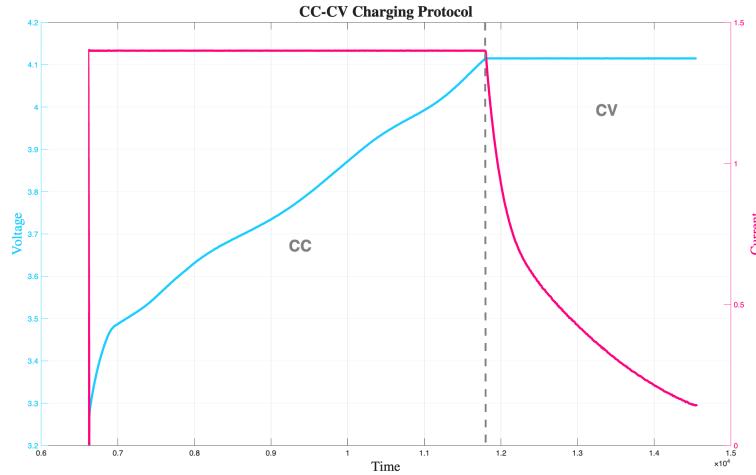


Figure 5: Charging segment extracted from the UoS dataset

multistage

AC

## 2.4 Modelling degredation

Talk about how stevensons linear model uses the change in voltage overtime (first 100 cycles).

**Downside -** This requires a slow cycle to get the right features for the model, also only predicts EOL figure, useful for strong indication of battery prediction. However can not fully capture the input affects of current, only fitting from the affects of it. Additionally does not show how specific

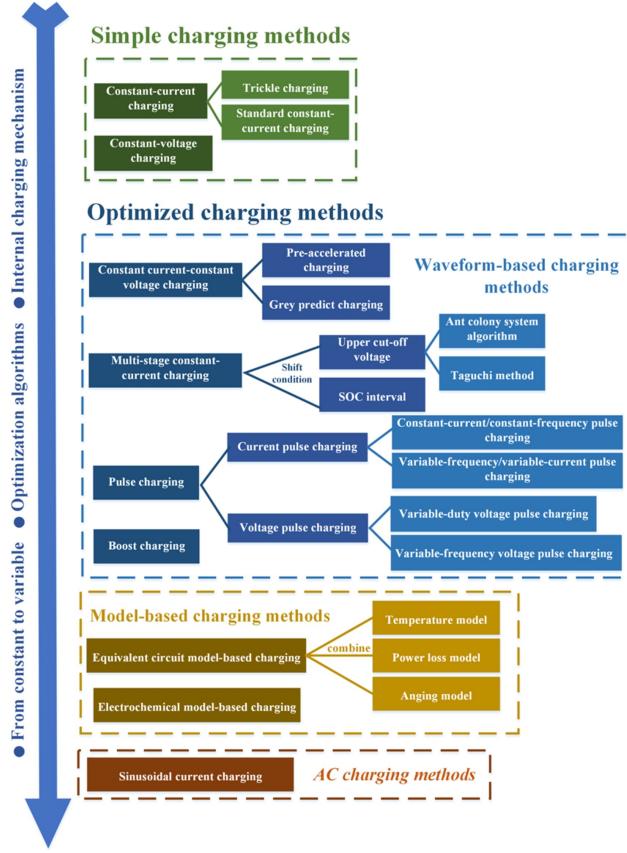


Figure 6: Common charge techniques, cite qian lin towards smarter

characyeristics change.

Attia takes the use of steverson to great use, using the model to predic how well differenct charge cycles last

There are three main categorical methods to predict the degredation of lithium ion battereies: Purley data driven methods, physics-based models and a hyrbdid (phuysics informed). Fujin Wang et al highlights the advantages of the hybrid approach, stating the main issue with pure data-driven and pure physics model, they also present a means of categorising the common hybrid approaches, given in figure x.

Papers focusing on the physics based moedeling usually focus on a subset of degredadion modes, such as SEI thickness growth cite Mixed Mode Growth Model for the Solid Electrolyte Interface. Most models start with the Doyle-Fuller-Newman model cite Dole Fuller to describe the transport of lithium within the battery (including potentials), then further sub-modules representing degredation mechanisms are intergrated to yeild the required models. For example simon e j okane adds

sei, li paritcle crackiong anmd lam as the the degredadion models. this can be represented similar to . These approaches can model intericate parts within the battery, but require a lot of parameters about each battery under test, additionally, the discritised solutions are only ever as accurate as the models used. E j okane shows a more complete set of degredadtion modeling whulst Jishun applies ML to effectivlye learn the missing modes with good results.

Purley data-driven appraches have the ability to provide the most accurate predictions, however on their own suffer the problem that there not currently a large enough set of data to train on - this is a problem as lithium batteries have mutliple degredadtion modes as discussed, as well as a highly dynamical system when viewed as

Jishnu Ayyana by representing the electrochamiecal dynamics as  $\frac{d\mathbf{x}}{dt} = f(\mathbf{x}, \mathbf{z}, \mathbf{u}, t; \alpha)$  and couplining to degradation dynamics  $\frac{d\mathbf{z}}{dt} = f(\mathbf{z}, \mathbf{x}, \mathbf{u}, t; \theta)$  where  $\mathbf{x} \in \mathbb{R}^{n_1}$  and  $\mathbf{z} \in \mathbb{R}^{n_1}$  (once discritised), representing the battery electrochemical and degredadtion state variables respecitvey

Steverson aims to

- Fmincon
- Greyest
- ICLOCS
- **2.4.1 Machine Learning**
  - General Understanding
  - LSTM
  -

### 3 Self Review

Choosing this final year project has, and will continue to, be a big personal undertaking. I knew nothing about batteries other than the very basics when starting, I also knew very little within systems & control other than simple LTI systems. Research has also been a struggle for me as

many papers incorporate control methods or electrochemical background of which i dont have, a high amount of papers regarding the use of AI in modeling degredadtion are also behind paywalls.

A large amount of time has been spent of narrowing down the focus of the project, as well as preparing the optimised control designs for the lab testing. As of 01/12/2025, the first two batteries are undergoing characterisation tests and the software side is nearly done. Focus will now be spent on researching more about the machine learning and ways to optimise charging from the modeling of the battery.

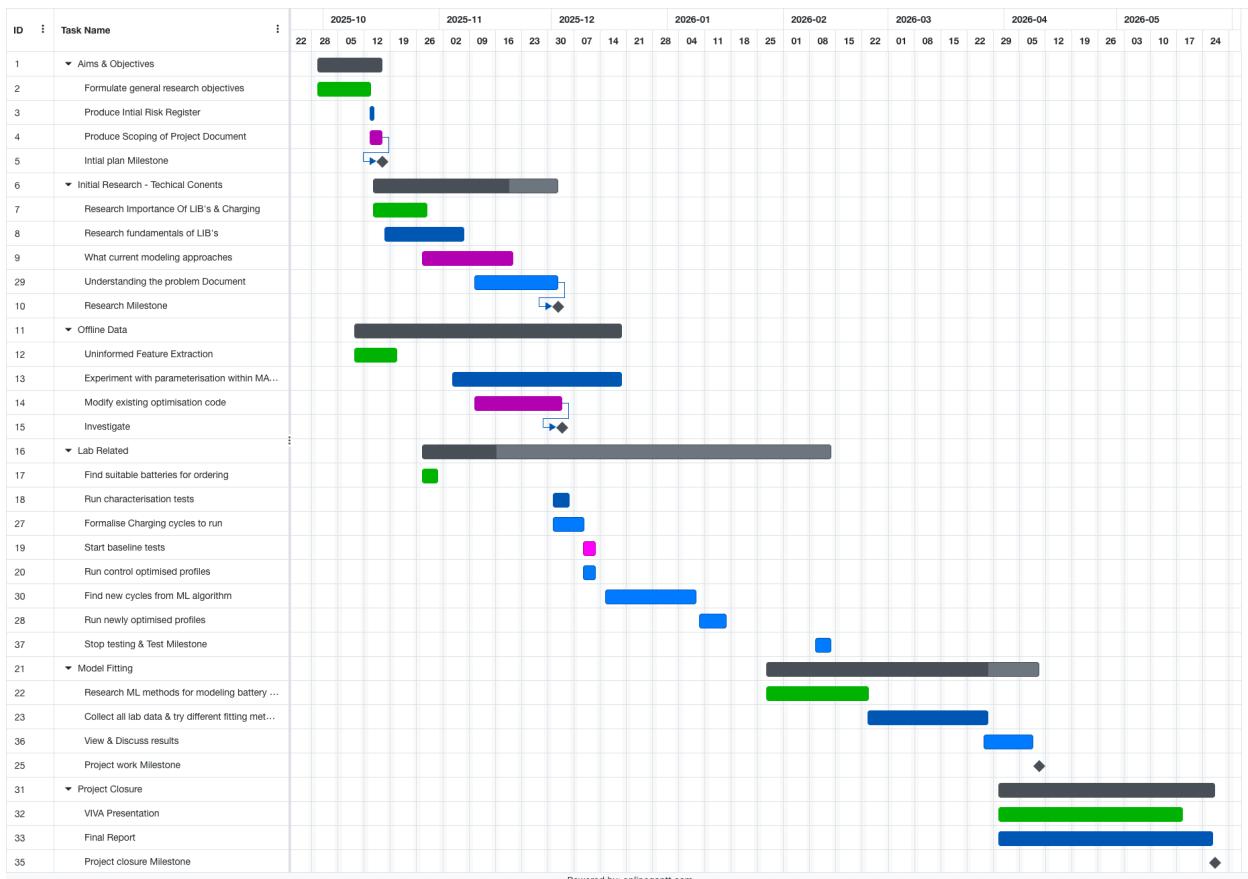


Figure 7: Gantt Chart of current project plan

## References

- [1] 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>
- [2] 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>
- [3] 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>
- [4] “Executive summary – Batteries and Secure Energy Transitions – Analysis.” [Online]. Available: <https://www.iea.org/reports/batteries-and-secure-energy-transitions/executive-summary>
- [5] 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>
- [6] M. Lucu, E. Martínez-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.
- [7] 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>

- [8] 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>
- [9] 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>
- [10] 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>
- [11] 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>
- [12] 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>
- [13] 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>
- [14] 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>

- [15] 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>
- [16] 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>
- [17] 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>
- [18] 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>
- [19] 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>
- [20] 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>
- [21] 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>
- [22] 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>
- [23] “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/>
- [24] K. A. Severson, P. M. Attia, N. Jin, N. Perkins, B. Jiang, Z. Yang, M. H. Chen, M. Aykol, P. K. Herring, D. Fragedakis, 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>
- [25] 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>
- [26] 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>
- [27] H. Ritchie, P. Rosado, and M. Roser, “Access to Energy,” *Our World in Data*, Sep. 2019. [Online]. Available: <https://ourworldindata.org/energy-access>
- [28] “Global Electricity Review 2024.” [Online]. Available: <https://ember-energy.org/latest-insights/global-electricity-review-2024>
- [29] H. Ritchie and P. Rosado, “Energy Mix,” *Our World in Data*, Jul. 2020. [Online]. Available: <https://ourworldindata.org/energy-mix>
- [30] 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>
- [31] “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>
- [32] 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>
- [33] 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>
- [34] 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>
- [35] 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>
- [36] 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>
- [37] 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>

- [38] “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>
- [39] 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>
- [40] 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>
- [41] S. Gifford, “Lithium, Cobalt and Nickel: The Gold Rush of the 21st Century,” no. 6.
- [42] 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>
- [43] 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>
- [44] H. Ritchie, “Tracking global data on electric vehicles,” *Our World in Data*, Feb. 2024. [Online]. Available: <https://ourworldindata.org/electric-car-sales>
- [45] “Energy Consumption in the UK 2024.”
- [46] “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>
- [47] 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>
- [48] 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>
- [49] 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.
- [50] 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>
- [51] ——, “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>
- [52] 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>
- [53] 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>
- [54] 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>

- [55] 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>
- [56] 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/>
- [57] 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>
- [58] 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>
- [59] 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>
- [60] 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>