

Understanding the problem



University of
Sheffield

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

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1 Introduction

The global consumption of energy is rising by 4.5×10^{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 finitie-life nature, poses a constant need to increase usage of renewable sources. However, a large set of renwable generation methods fall under the category of variable renewable energy (VRE) sources [1], thus requiring a robust form of energy storage to solve the itermitten availability - as battery techonolgy increases, the use of battery as a storage medium for the energy sector are ever more increasing. There is also the rapid increase in elecricit vehicle production, with a push to increase the adoption of EV's, 17.3 million cars were produced in 2024 [2] alone with a recent 20% average year-on increase. Lithium Ion batterys (LIB's) are the most common currently used batterys due to their desirbale characyeristics 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 [3] since 2016. Different resources predict different forecasts of total battery growth [4, 5], regardless, it appears the rate of demand wil not be decreasing in the future.

LIB's, decrease in performance and capacity [6] until they are deemed unsuitable for their current use. Eventually, all current batterys in use today will need to be disposed of, in 2021 436,000 tons of lithium was mined for batteries alone , a strong case for slowing down the need for mining new materials is made, whilst keeping up with the demand [7]. It's noted that battery chemistry is still a developing feild, thus newer batteries may use less scarce materials, thus hard to truly predict the sustaniability of mining these materials, for example, some reports (cite faraday) say cobalt supplies could be used entirley by 2040. Solutions do exits, recycling methods are been developed in order to extract the materials, termed battery metal recycling (BMR), however there are wildly different sources suggesting how much of current batterys actually are recyled (one showing 5%), (other showing 90%), and the techonolgy to do so is still a devloping feild, there are many different methods (cite issurs), since most of the rare earth elements are within the batterys cathode, methods such as hydrometallurgical process can extract these, but at the cost of severe reduction in lithum yeild [8] - although there are promising methods with some proposing a lithium recovery needing less than 40% the energy compared to mining the virgin material [9] whilst still recovering nickle

and cobalt. There is also the rising interest in reusing the batteries before recycling, these batteries are referred 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 useful service in less demanding applications, a common one being energy storage systems (ESS) [10], with claims reusing can reduce CO2 emissions by 56% as opposed to using natural fuel gas. However there are again challenges associated, for safety there is the need for robust testing, sorting the batteries based on their current health states, non automated 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 [10].

In summary, there are methods that are developing to reduce the need for mining new materials and decreasing recycling energy, 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 (cite)), this could power all of the UK's energy needs for one day (cite gov.uk); as most batteries cycle life are well over 1000, any increment in cycle life can be greatly beneficial.

Modeling and predicting how batteries degrade over time is pivotal for the growing use of lithium batteries as it allows informed decisions on how to best charge and use batteries to prolong life, as well allow optimisations on the charging throughout the batteries life.

1.1 Project Aims

This project aims first to characterise Lithium batteries behaviour by parameterisation, without ex-situ tests. This data will then be used in combination with work previously done to form the charging protocol based off minimising different objective functions. 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 degradation, a charging protocol which is derived from minimising such model will be found and be tried in the labs to compare. If this is not achieved, at least this project can validate existing predicted charging to minimise degradation will be tested, and

the parameterisation of the batteries during degradation 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 been able to derive an idealised charging current to maximise the lifespan.

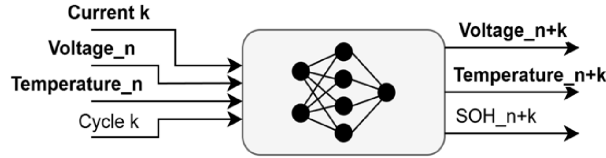


Figure 1: Initial end objective: Black Box Battery modeling degradation

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 effects of each method
- See how effective adapting the charging profile over the degradation is in increasing battery life
- Investigate ML methods to model the attained data to predict degradation
- Use the model to find a new charging method and validate

2 Literature Review

2.1 Lithium based battery backgrounds

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 ϕ 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 η and from G. Plett[11] is a difference in the current *electrical potential* and equilibrium potential, yet papers like [12] 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.

Lithium-ion batteries are favourable largely due to the highly reductive nature of lithium. Taking the potential relative to the standard hydrogen electrode (SHE), the half-reaction of metallic lithium is approximately $-3.01V$ [11]. The 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 [13], having a large negative reduction potential allows for a variety of positive electrodes, yielding a high battery voltage. Coupled with Lithium's low molecular weight, a high energy density cell can be achieved too.

All lithium-ion batteries follow the same basic principle of operation. They consist of a positive electrode, a negative electrode, an electrolyte, a separator, and current collectors. Unlike many battery chemistries where active materials undergo conversion reactions that change the electrode's chemical composition, lithium-ion electrodes typically store lithium through intercalation and de-intercalation — the lithium is inserted into or extracted from [11]. The negative electrode is usually graphite, able to store up to one lithium atom per six carbon atoms. The positive electrode can vary greatly, the most common are often composed of transitional metal oxides such as LCO, LMO, NMC, NCA [14]. The electrochemical state of lithium in graphite is similar to that of metallic lithium, so the negative electrode potential lies close to $-3.0 V$ vs. SHE. Positive-electrode lithium is in a lower electrochemical energy state, giving typical reaction potentials of roughly $0-1.3 V$ vs. SHE, overall there is a large potential difference created. The negative electrode is often the key limiting factor in degradation as discussed later. 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 that allows lithium ions to travel between the electrodes; however, it does not allow electrons to flow, which instead travel via the external circuit. The separator acts as a structural barrier to prevent the opposite electrodes from touching, allowing only ions to pass and thus preventing uncontrolled reactions that could cause major fire risks. During the discharging process, an external electrical path is provided between the collectors. The lithium stored within the negative electrode deintercalates, releasing lithium ions into the electrolyte, while the electrons leave the negative electrode, traveling across the external circuit to the positive electrode, where the lithium ions recombine with electrons and intercalate into the positive electrode structure. During charging, the applied voltage at the terminals is above the difference of the equilibrium electrode potentials. This applied overpotential drives lithium ions to deintercalate from the positive electrode, travel across the electrolyte, and intercalate into the negative electrode, where they combine with electrons. The speed at which the ions flow is much slower than the electron transfer, which contributes to the characteristic behavior of lithium batteries [11].

2.2 Lithium based battery degradation modes

J'O. Kane et al. [15] summarises the key 3 modes of degradation caused within lithium ion batteries described below. Calendar aging is neglected in this discussion.

Lithium plating - Under certain charging conditions, the lithium ions within the electrolyte will join with the electrons outside the negative electrode, producing pure lithium metal - which can grow forming dendrites, depicted in figure xx. The most understood causes which accelerate this is when the negative electrode potential falls below that of lithium's own electrode potential potential [16, 17], becoming the most thermodynamically viable reaction. From electrochemical models, the potential at the electrodes is the sum of their open circuit potentials and overpotential.

The overpotential is largely due to the kinetic overpotential at the interface of the electrodes, the Butler-Volmer equation shows as the current density j increases, overpotential η .

$$j = a_s i_0 \left[\exp\left(\frac{\alpha_a F}{RT} \eta\right) - \exp\left(-\frac{\alpha_c F}{RT} \eta\right) \right]$$

Low temperatures and high SoC also increases Lithium plating, since it becomes harder for the lithium to intercalate within the carbon, the current effects are shown in figure xx in sections below.

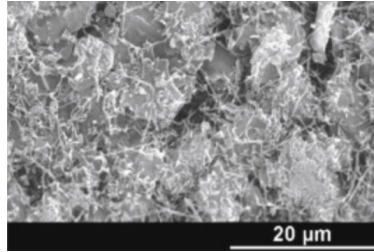


Figure 2: Lithium deposits shown in lighter grey on the graphite electrode [18]

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 Li_2CO_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 [19]. 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 [20]. SEI formation takes up electrons within its reaction, thus reducing battery capacity.

Particle fracture - The physical volume of the electrodes can change during the intercalation and deintercalation, this is a degradation feature that cannot be avoided in order to charge and discharge a battery, some electrodes exhibit more contraction than others, silicon is significantly greater than graphite [11]. Concentration gradients, caused by high currents, within the electrode can also cause internal stress. This can overtime cause the electrodes to break down, either resulting in more SEI grown, reducing more lithium; inability for areas of lithium intercalation, reducing charge capacity; and separation from the binder causing either increased ohmic resistance or loss in capacity

In summary, high charging currents, extreme temperatures and extreme states of charge can accelerate degradation, thus to reduce this, charging and discharging at infinitesimally small rates and at optimal temperatures is best, however this neglects considerations such as charge times, thus a

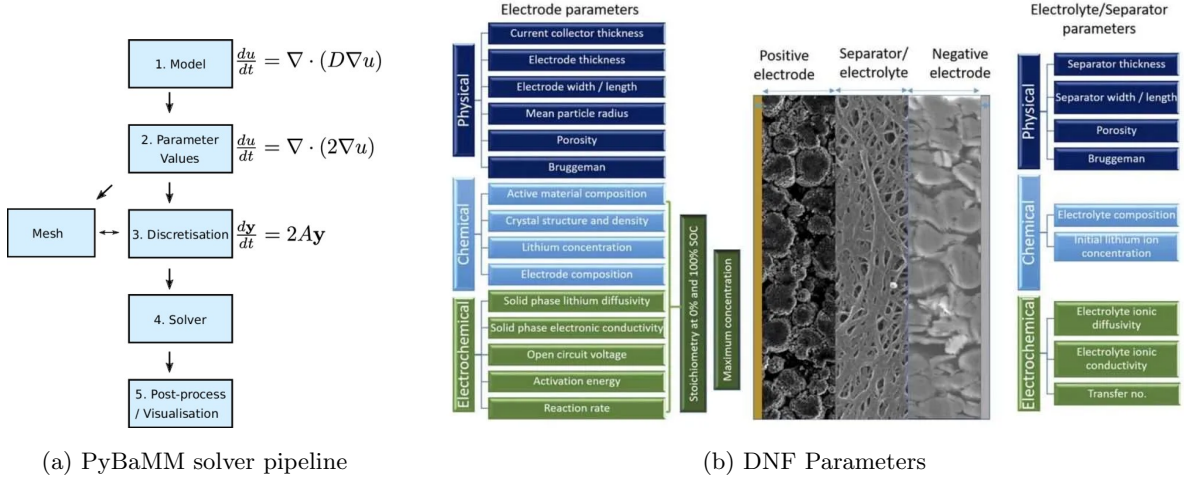


Figure 3: Parameters and solution steps for physics based modeling

balance between these constraints should always be taken into account and the charging strategies used in this project attempts to do so. The impact on degradation can change between charging and discharging. Mention diffusion differences between charge and discharge shown by J. Lain *et al* [17].

2.3 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 [11]. 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 [21] are the Doyle-Fuller-Newman model [22], 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* [23] 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

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

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_{oc} for a given instantaneous SoC, and η here is the coulombic efficiency, usually 0.99 for lithium batteries, since some current will be used in irreversible chemical reactions within the cell[11].

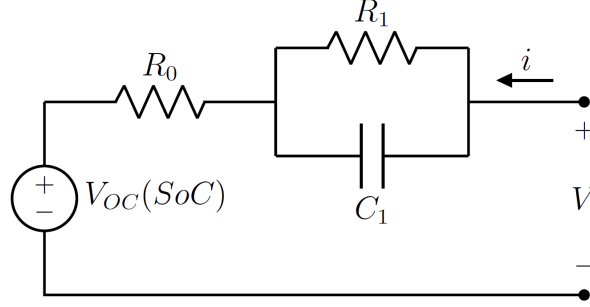


Figure 4: ECM model with 1st Order Polarizing dynamics

The common state space form of this system is given below

$$\begin{bmatrix} \dot{v}_1(t) \\ \dot{z}(t) \end{bmatrix} = \begin{bmatrix} -\frac{1}{R_1C_1} & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} v_1(t) \\ z(t) \end{bmatrix} + \begin{bmatrix} \frac{1}{C_1} \\ \frac{1}{Q} \end{bmatrix} i(t) \quad (3)$$

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

W. Appia *et al* [12] provides the equation for the total overpotential within the battery derived from the Fuller-Newman electrochemical model, here, the total overpotential η_{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 analogous to the ECM model given above, whereby the overpotential (dynamical behaviour) is modeled by $i(t)R_0 + v_1(t)$, where the equilibrium potential is $V_{oc}(z)$.

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

Whilst the voltage dynamics of lithium batteries do depend on temperature, this project keeps the ambient temperature to 30, thus realtime affects on the electrical dynamics are minimal. However modeling of the temperature is vital since temperature does directly affect degradation. L. Mattia *et al.* [10] explains the various thermal modelling approaches and shows which contributions are key in heat production, with the main equation given below. Reversible heat generation can not be directly inferred by the basic ECM model shown in figure 4. J. Xu *et al.*, equated it being 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 al calculates the curve for a battery of similar to the one used in this project, shown in figure 5

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

A. Farman *et al* [24], shows that the OCV of lithium batteries can change throughout degradation, Lithium phosphate batteries showed a 20mV difference in regions of the SoC after aging of 500 cycles at 1C of charge and discharge. Additionally, while there exists methods of extracting an accurate OCV curve, it can take hours to accurately obtain to minimise overpotentials [23]. 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 [25], will be used heavily throughout this project to see its ability to parameterise the battery dynamics. A.A. Mohamed *et al.* [26] cite shows the many methods to obtain ECM parameters with methods ranging from analytical approaches based on various current inputs, to meta-heuristic optimization algorithms.

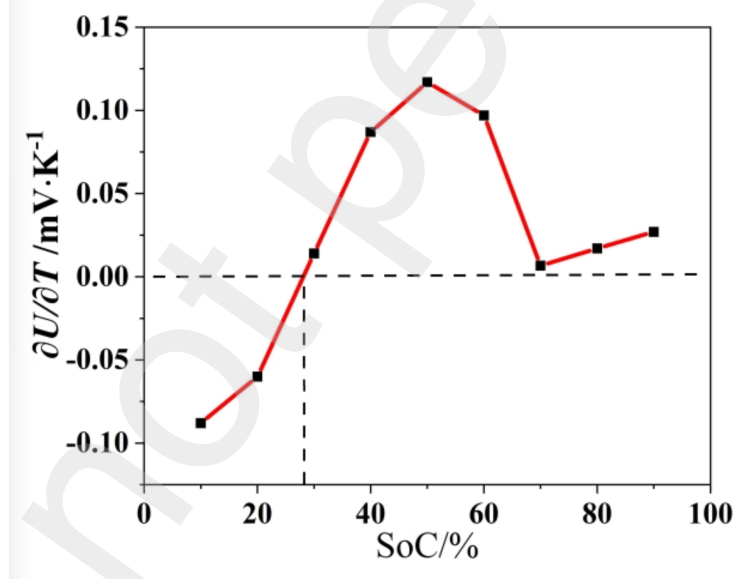


Figure 5: Charging segment extracted from the UoS dataset

2.4 Charging methods

There exists many techniques to charge batteries with a graphical summary of the common methods shown in figure 8. Q. Lin *et al.* [27] highlights the different methods described below. The most common method is known as CC-CV charge. 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 battery's 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 is another method such that the voltage applied is the battery's maximum at full SoC, but since lithium batteries have low internal resistances, this can lead to a very high current draw at low SoC (where the equilibrium voltage is low), hence can cause accelerated degradation, cite quan mentions 40% capacity decrease after only 160 cycles. Boost charging provides a high current increase at low SoC, but only for brief periods and can significantly reduce degradation rate compared to CV.

AC charging is another method which aims to minimise the frequency dependant impedance of the

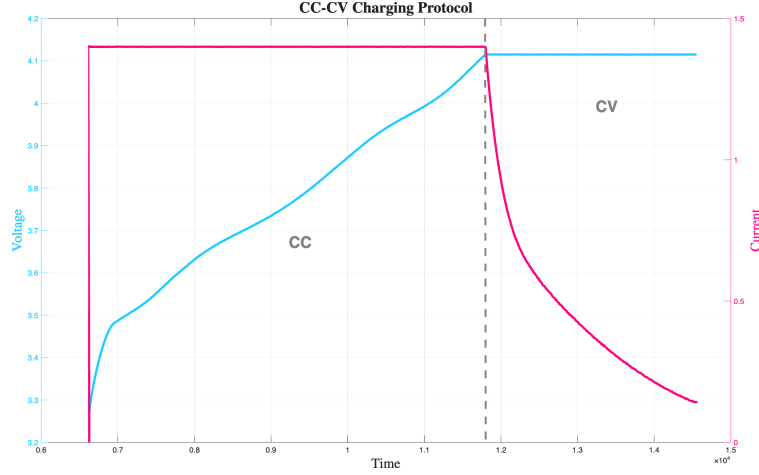


Figure 6: Charging segment extracted from the UoS dataset

battery, effectively allowing to charge the battery with a lower effective overpotentials, however as Q. Lin *et al.* mentions, there are disputes on the effectiveness of this method; coupled with the fact EIS (electrochemical impedance spectroscopy) is required to find the frequency points of interest to target, this method won't be further researched within the project.

Multistage CC is a popular method in research as it allows for the customisation of the charging throughout the cycle, this means various models can be used to optimise for a specific goal. G. Tucker *et al.* [28] for example, simulates various functions to minimise based on the ECM model provided in the section above, showing that the physics optimisation correlates closely to optimised degradation obtained through purely data-driven methods. Electrochemical based models allow for a finer level of optimisation, such as ensuring the negative electrode does not reach a potential to cause lithium plating, [13] models an observer to estimate the potentials, which could be used within optimisation as one of the constraints, figure 7 shows their predicted potential voltages.

The multistage CC charging method provides a good framework to trial different charging methods, its balance of ease of implementation and adjustability means it is this method which will be used in the project to optimise for degradation.

2.5 Modelling degradation

There are three main categorical methods to predict the degradation of lithium ion batteries: Purely data driven methods, physics-based models and a hybrid (physics informed). F. Wang *et*

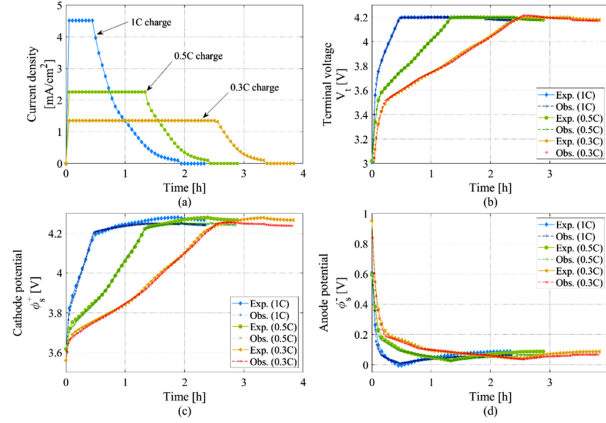


Figure 7: Estimated potentials in response to charge current

al. [29] highlights the advantages of the hybrid approach, stating issues and advantages with pure data-driven and pure physics model, they also present a means of categorising the common hybrid approaches.

Papers focusing on the physics based modeling usually focus on a subset of degradation 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 Doyle Fuller to describe the transport of lithium within the battery (including potentials), then further sub-modules representing degradation mechanisms are integrated to yield the required models. For example J. Okane *et al.* [15] adds SEI, Electrode cracking and loss of active material (LAM) as the degradation models. These approaches can model intricate parts within the battery, but require a lot of parameters about each battery under test, additionally, the discretised solutions are only ever as accurate as the models used.

Kuzhiyil *et al.* [30] by representing the electrochemical dynamics as $\frac{d\mathbf{x}}{dt} = f(\mathbf{x}, \mathbf{z}, \mathbf{u}, t; \alpha)$ and coupling 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 $\mathbf{z} \in \mathbb{R}^{m_1}$ (once discretised), representing the battery electrochemical and degradation state variables respectively by separation of the speed of dynamics,

Severson *et al* [31], provides one of the largest available dataset for battery charging. This paper takes uses a purely data driven approach in modeling, but uses engineered features such as the change in discharge voltage curves between cycle 0 and cycle 100. Using a linear regression model, they predict the cycle to failure (defined when the capacity drops to 80% of original), it shows upto

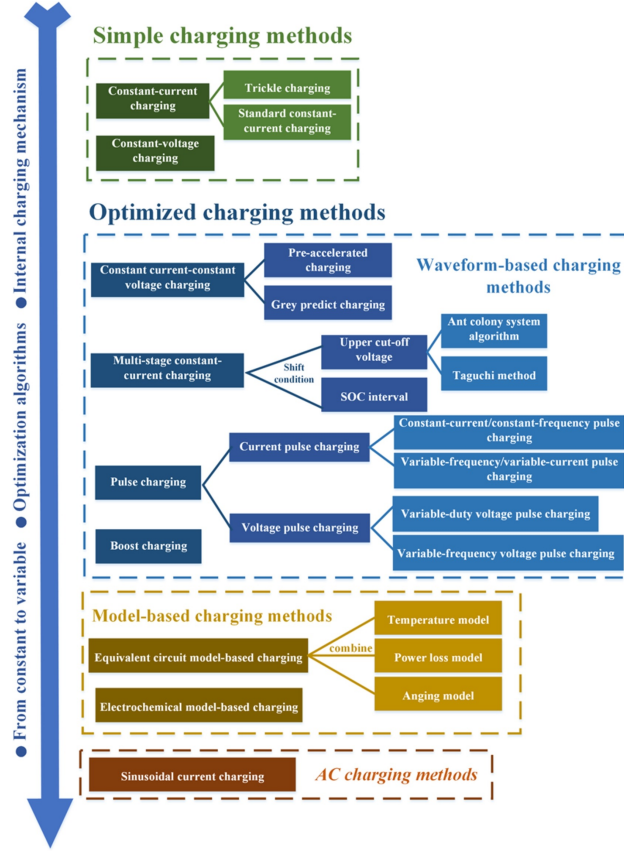


Figure 8: Common charge techniques summarised

a 9.2% accuracy. Attia *et al.* [18] takes the work of Severson *et al.* to great use, using the model to predic how well differenct charge cycles last by cycling the batteries under random multistage CC cycles, predicting the degradedadition and using a bayesian optimisation strategy[32] to find the next appropriate charging protocol - in a closed loop feedback shown in figure 9

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 degradedadition are also behind paywalls - now more than ever on my 5th univervity year do I feel failing may well happen. I understand

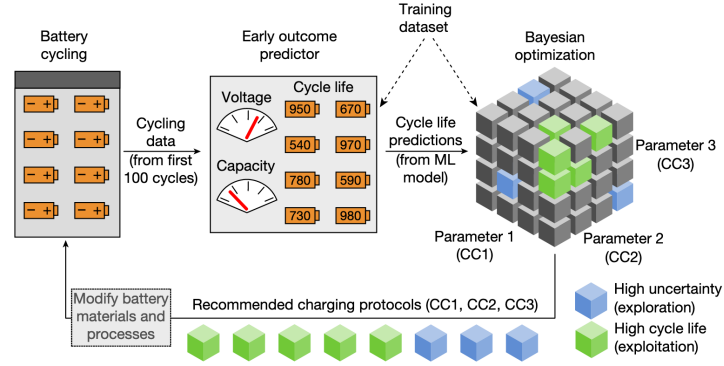


Figure 9: Closed loop workflow for finding optimal CC charging

this document does not have indepth explanations of the use of AI within the modeling and may be vague in the project steps, the project is very much in the sense adapting to what can be done. Work in general AI was done early in the project, I was able to learn the basics in pure neural-nets and produced a basic image classifier within pytorch but took a pause to work on other aspects of the project and university modules.

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.

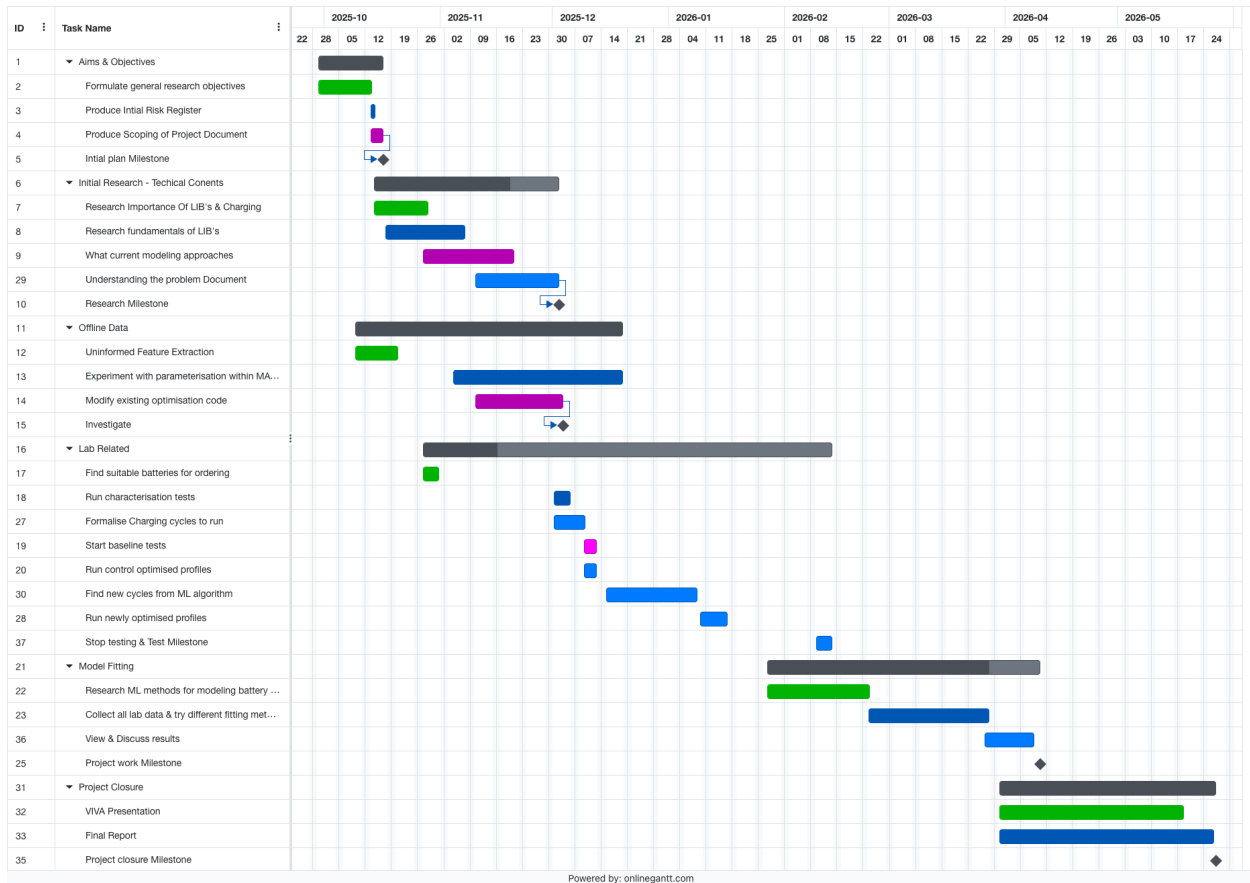


Figure 10: Gantt Chart of current project plan

Risk Assessment Table - Refer to risk Grid on tab 2, R=L*S								
Risk and Opportunities	Pre Mitigation			Mitigation Methods	Residual			Risk Owner (should be the best person to manage the risk!)
	L	S	R		L	S	R	
Data availability issues: Being unable to find adequate data to add to learning set & analysis	3	4	12	There is relatively limited data available for the required data set. The university have tested & collected significant data which should be enough for atleast a form of modeling. Being flexible and communicating with suprvisor should mean there will be an outcome in modeling regardless	2	2	4	Student
Lab Data breach	2	1	2	Data recorded is not sensitive nor contain any information about people. However ensuring the basics of data safety are utilised should help reduce the chance any data breach does occur. By ensuring computers holding the information are pasword protected and not left open when unattended.	1	1	1	Student
Data loss	2	4	8	Data from the univerty is held locally and few people have the data locally, thus there should atleast an option to recover data - although the chance of needing to do this should be minimised to reduce any delays. Data collected online should be downloaded (respecting any IP rights) incase of changes out of our controll. Data from the lab experiments should be held in more than one place. For all the data, having atleast one location locally, and another in the google drive cloud should provide enough redundancy	1	3	3	Student
Lab testing issues: For the testing and recording of data needed in order to test the charging protocols and gather data from, there may be no room in the cyclers	3	5	15	Plan the time allocated for the lab as early as possible. Ensure basic training & understanding of the battery cyler has already been obtained to ensure time is best spent in the lab. If data can not be obtained, look into the electrochemical models to provide data, such as PyBaMM	2	2	4	Student / Lab leader
Lab safety: Dealing with charging & discharging of batteries to their near complete lifecycle pose a health and safety risk	2	5	10	Ensure all required healt and safety preperation is done before entering the labs and ensure they are practised during the lab testing	1	3	3	Lab leader
Tests not started in time for degredadition to imerge	4	5	20	Ensure the charging protocols are provided as soon as possible, plan the general lab plan in advance such that the lab tecnitians are well prepared	2	5	10	Student
Data such as temperature reading may be corrupted during cycling	2	4	8	Run more than one battery for key cycles for redundancy	2	2	4	Student
Failure to adapt existing code for optimisation charging to work with existing data and ready for the lab	3	4		Spend as much time as possible to analysie the code, atleast modify in stages so atleast a working form can be provided whith the tested batteries	2	2	4	Student
Overcomplex / inability to learn the ML skills for neural networks	3	4	12	Reasearch as much as possible to gather information. Break down steps bit by bit and understand when enough is enough in order to atleast perform the tasks. MATLAB offers many AI tools in digestible usable forms	2	2	4	Student

Figure 11: Current risk register

Note: The following references may have duplicates and unused references, this should hopefully be fixed for the final report

References

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