Investigation into partial cycling of lithium-ion cells

Report

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Introduction

Lithium ion battery lifetime is typically rated by their ability to fully charge and discharge for a certain number of cycles. However, there are many variables which change the cycle life of a battery, such as temperature, depth of discharge and discharge rate, amongst others.

Some applications can have a typical cycle profile that greatly differs from a simple charge and discharge. For example, for a grid connected battery performing EFR, a battery may be cycled between 40% and 60% state of charge (SOC) and have many partial cycles between that.

In this type of application, it is important to have an ability to estimate the lifetime of cells. Currently however, there is no standard way to specify a partial cycle life and it is not given by manufacturers of cells.

This project will be considering the effects of partially cycling a Lithium-ion battery in order to understand how long these types of cells may last in different applications. This is important in order to better verify the economics of a Lithium-ion battery energy storage system, knowing how long a battery might be able to remain in service for.

Literature Review

In order to model and simulate batteries in different applications, the applications must first be understood which this section aims to do. When using a battery on the grid, there are several methods to generate income which have been categorised as either grid services [1] or energy trade strategies [2] which will be explored.

Grid Services

EFR

Enhanced Frequency Response (EFR) is an Ancillery grid service with the aim to stabilise the UK National Grid frequency through rapid response to deviations. The requirement for EFR is to achieve a power output or input in less than 1 second. This should last for at least 10 seconds until primary frequency response services have become operational.

This type of service is becoming more of a necessity as the number of large synchronus generation machines [3] which provide grid stability is decreasing. This makes the frequency more volatile and therefore a faster response to frequency changes is required to prevent blackouts.

There are two services in EFR, both narrow and wide band. In narrow band, the deadband is small so the EFR service operates more regularly whereas in wide band there is a larger deadband so the total EFR service operating time is lower. The graph below in Figure 1 shows how the service envolope for EFR operates, where the deadband in narrow EFR is 0.03Hz and for wide is 0.1Hz.

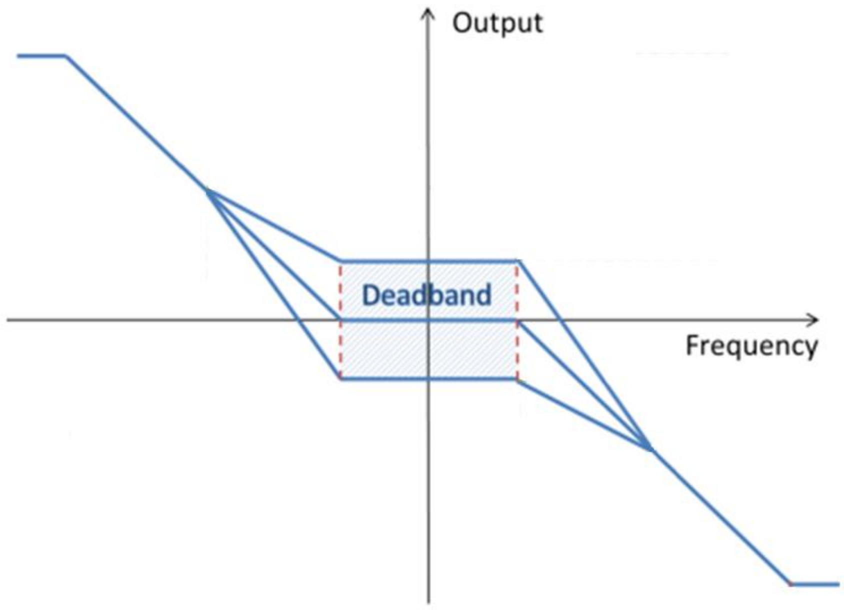

Figure 1: A Graph showing EFR Output requirement depending upon frequency [4]

FFR

Firm Frequency Response (FFR) is another UK grid service which exists to maintain the system frequency between 49.5Hz and 50.5Hz, although it generally is maintained between 49.8Hz and 50.2Hz. In FFR, there are three types of response: Rapid, Primary and Secondary [5] where a system must respond within 5, 10 or 30 seconds respectively. A Rapid or Primary response should be sustained for at least 20 seconds and secondary should be sustained for at least 30 minutes.

These can also be further categorised as dynamic or static. In Dynamic FFR, a varied response is continuously delivered for varying frequency (along with a dead band), whereas in static FFR (also known as non-dynamic) there is a step change in output once a certain threshold is reached. This is shown below in Figure 2.

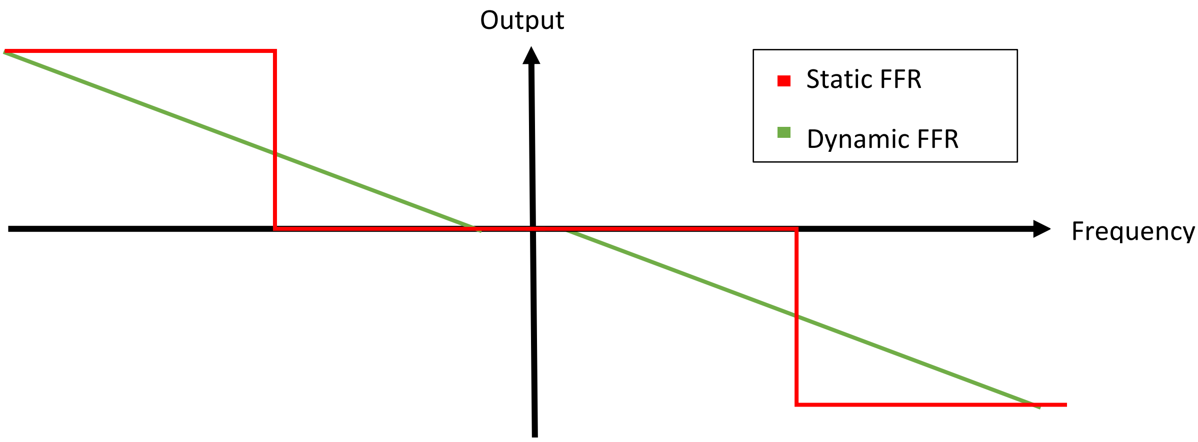

Figure 2: A Graph showing FFR Output requirement depending upon frequency

FFR is a service that is currently generally provided by generators, varying their output in order to regulate frequency. Grid connected batteries provide an alternative method for performing FFR and it will be considered how performing these ancillary grid services might affect the life and performance of a Lithium-ion battery.

Energy trade strategies

Triad Avoidance

Triads are the three half hour periods with highest demand during one season on the UK electricity grid. [6] These are set by the National Grid and are designed to reduce peak load by charging a higher amount for energy during this time, ranging from £16 to £29 per kW. Avoiding energy use during these periods greatly reduces cost for users and increases security of supply through a larger generation ‘buffer’.

Triad information is only published after the triad season, and therefore customers must predict these periods. Predicted triad periods occur around 20-30 times per year and so demand is reduced during these periods. [7] Naturally reducing demand during these periods means a loss of productivity and whilst electricity expenditure will reduce, so will income. Batteries could be used during the triad periods to minimise power drawn from the grid to maintain productivity whilst reducing grid demand. [8]

A battery operating in this manner would likely see a full charge and discharge cycle around 20-30 times per year in line with the number of triad predictions per year.

Arbitrage

Arbitrage involves purchasing off-peak electricity at a low price and selling it when the electricity is expensive. There can be multiple price peaks and troughs during a single day, as shown in the EPEX

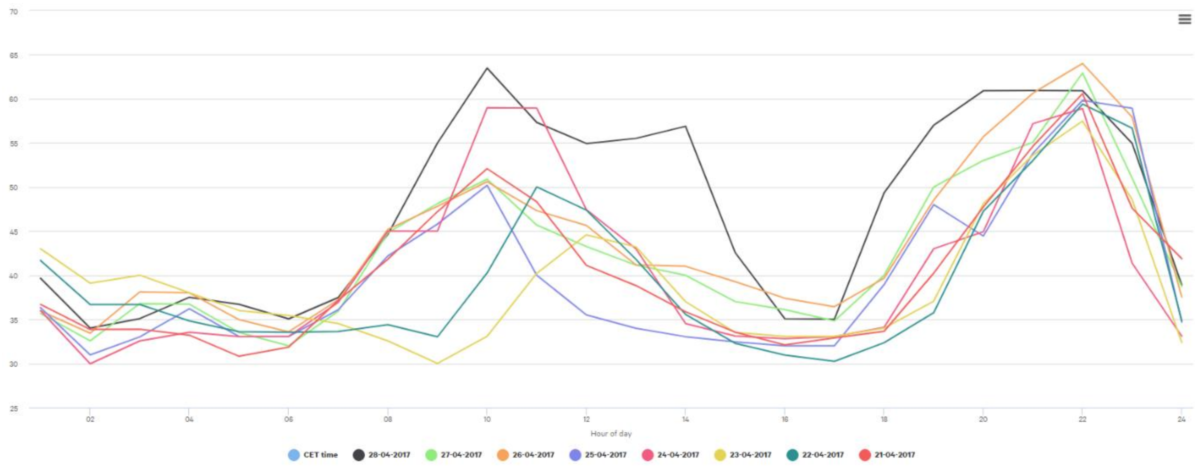

Figure 3: A graph showing the Daily EPEX SPOT Power UK Auction price for a week during April. [21]

SPOT Power UK Auction chart below.

It can be seen that there are generally 2 peak and 2 off peak periods per day, with varying levels of change between peak and off-peak prices. With a round trip efficiency of a battery energy storage system in the higher region of 80%, the vast majority of these price differences will be sufficient to make a profit. It can therefore be assumed that there will be 2 full charge-discharge cycles per day or 730 per year. Considering the effects this might have on the life of a battery is important in order to determine the profitability of such a grid connected battery energy storage system performing arbitrage on an electricity grid.

Effects on a battery

With an understanding of how grid services operate, the effects that might be seen by a battery can be further determined. Using a battery to provide a service such as EFR would produce an output as shown in Figures 4 and 5 below. It can be seen that over a period of 24 hours a battery sees numerous charge and discharge cycles. These are not full but instead partial cycles, where the battery will rarely become fully charged or discharged. It is important to understand how this will affect the life of a battery when used in a grid connected storage system.

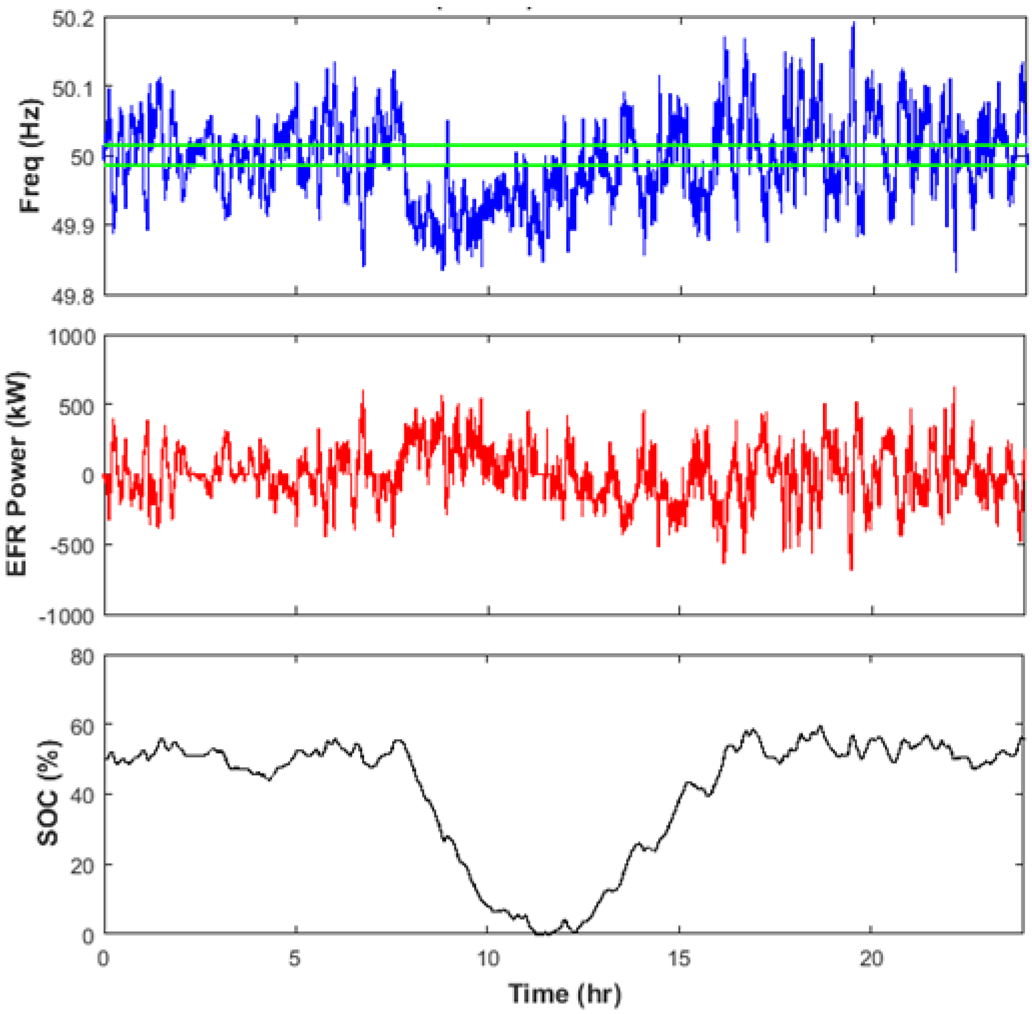

Figure 4: Data showing simulated response of a 1MWh battery performing EFR over a 24 hour period

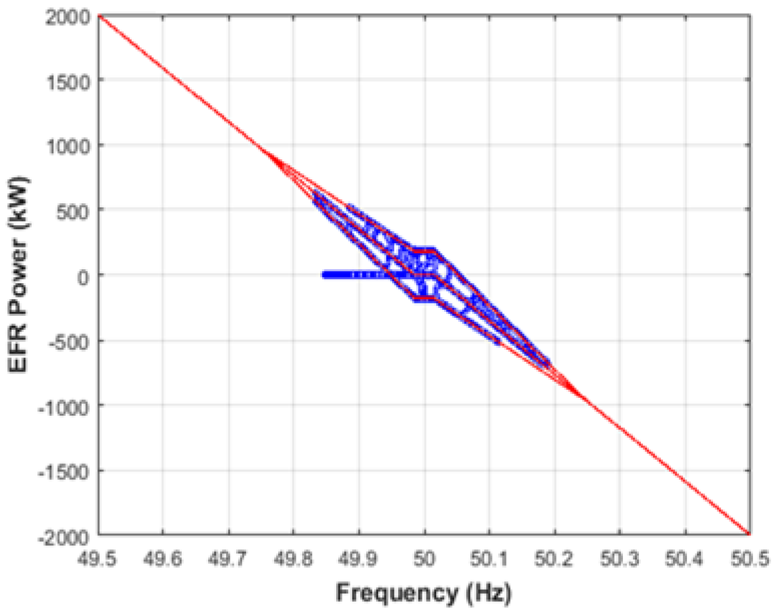

Figure 5: Simulated data showing the performance of a 1MWh Battery performing EFR over a 24 Hour period, deamonstrating how well it meets the EFR contract [9]

Future applications for battery energy storage systems may be found in the form of vehicle to grid, [10] and performing these types of services with an EV could have an impact on the lifetime of the battery. It is therefore important to understand how seriously a battery will be affected by these partial cycles.

It is understood that performing less aggressive cycling, for example between 80% and 20% as opposed to full cycling will improve the cycle life of a battery. [11] Models do exist, and it is shown that degradation of a battery is affected largely by temperature and depth of discharge. Keeping a battery around 50% SOC would be best to maximise the life of the battery. Fortunately, when performing grid frequency services such as in the above example, this will generally remain the case, suggesting that lithium ion batteries may have a very long life in such an application.

State of health

State of health (SOH) is the condition of a battery relative to the ideal condition. Naturally, it is important to know the state of health of a battery in order to know when it may need replacing and accurate modelling and simulation is key to this research in batteries. There are many methods to find and estimate this, which this section will explore.

Coulomb Counting

One method for estimating state of health is through coulomb counting. This involves measuring the total Ah discharged from a battery, and comparing it with a known value that is the maximum releasable capacity from the battery. [12] The most basic form requires a basic full charge and discharge cycle, measuring the current and time and can be compared with the rated battery capacity to give the state of health.

Extending this, comparing the Ah released from the battery along with the voltage and state of charge estimation, a value for state of health of a battery can be found at any part of a charge cycle. Coulomb counting has issues with drifting (where accuracy errors increase over time), and if the battery is not fully cycled, the SOH measurement will become less precise. On a full battery cycle, the SOH measurement is re-calibrated, giving a more useful measure.

Impedance measurement

Using Electrochemical Impedance Spectroscopy (EIS), the state of health of a battery can be estimated. It is widely known that battery impedance increases with ageing and this can therefore be used diagnostically to determine the health of a battery. With EIS, the impedance is measured at a wide range of frequencies, each corresponding to different battery dynamics. For example, at lower frequencies the impedance is more ohmic and capacitive effects are important, whereas at high frequencies inductive effects are more prominent. This information can be used to give an increased understanding of which particular elements of the battery is causing the degradation and it can be better understood how to operate the battery in a fashion that eliminates this.

Estimating the State of Health from the EIS results is performed using equivalent circuit models such as the one in Figure 6 below. Finding values for the components in the equivalent circuit allows an estimation for the capacity to be found, which can then be compared with the rated capacity to give the SOH. [13]

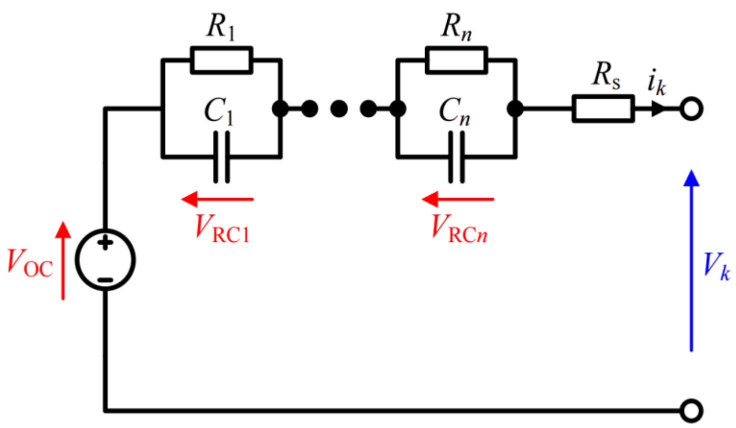

Figure 6: An n-RC circuit equivalent model for a battery

This estimation for SOH is reasonably simple to compute, using fairly simple models and is therefore fast to determine. However, it also has a fairly low accuracy and alone is not necessarily suitable in all applications for a measure of State of Health.

Modelling

Both coulomb counting and EIS use measurements and simple models to calculate an estimation for state of health. They are excellent for online battery monitoring as they are relatively quick and are sufficiently accurate. However, they are not the most accurate by far and require checks and calibration regularly.

More complex models and estimation methods can be used which input more data better estimate the state of charge. These use much more advanced algorithms that can estimate the state of a battery, generally at any point in its cycle.

Kalman Filters

A Kalman Filter is an 'adaptive' method for estimation, which inputs a series of measurements over time and is commonly used in battery applications. [14] The basic version uses a linear state space model for the battery and begins by using the first measurement to give a basic estimation for the SOH. Then with each further measurement the estimation is updated, reducing the uncertainty in the estimation. This recursive technique is proven to be highly accurate and therefore is a good method for estimating SOH. [15] The more parameters that are used the more accurate the estimation. With one example a Kalman filter has been used that inputs cell voltage, current and temperature, producing a suitably accurate measure for SOH.

In addition to the basic Kalman filter, there are several variations which produce a more accurate model and estimation. Extended Kalman Filters include the ability to handle a non-linear model and an unscented Kalman filter is an algorithm in which the observation made is performed as a series over time to increase precision. A Dual Kalman filter can also be used which as the name suggests uses two Kalman filters in its estimation. [16] For a battery application, one estimates the parameters, updating the model over time and the other estimates the battery states.

As is clear, there are multiple varieties of modelling and estimation algorithms to use for SOH estimation. The above examples of Kalman filters have all been used as a method for estimating SOH, and it is important to understand these in order to determine which one to use. There are many advantages and disadvantages to each one, leading to different types being best suited to different applications, depending largely on the computational and accuracy requirements

One issue with this however is that different battery types will require a different model, which can be difficult and time consuming to produce.

Cycle Data

As has been extensively mentioned, having the ability to understand how batteries will respond in different applications is key. The next step is in deciding what specific types of tests are required, and where gaps are in knowledge that can be filled.

Data that is widely available with Lithium-ion batteries includes general battery cycling at different 'C' rates. This also relates to temperature, where higher C rates are associated with higher temperatures which increases the rate of degradation.

Data produced by NASA [17] shows that when fully cycling a battery, it degrades, however given rest it will somewhat recover. This is the cause of the spikes in the data. Despite the peaks, the discharge capacity degradation is fairly linear, with a reduction in capacity of almost 50% around 160 cycles. These particular data sets come with little information, but it is known that they are "Li-ion" cells. Given the lack of information, they cannot be compared to other cells, however it is important to note that the cells reached a reasonably high temperature of 40 degrees during discharge. In a grid application therefore, cooling the batteries will result in an increased cycle life. However, the amount of cooling will have to be quantified as there will be an increased cost in running HVAC (Heating, Ventilation and Air Conditioning) equipment to reduce cell temperature.

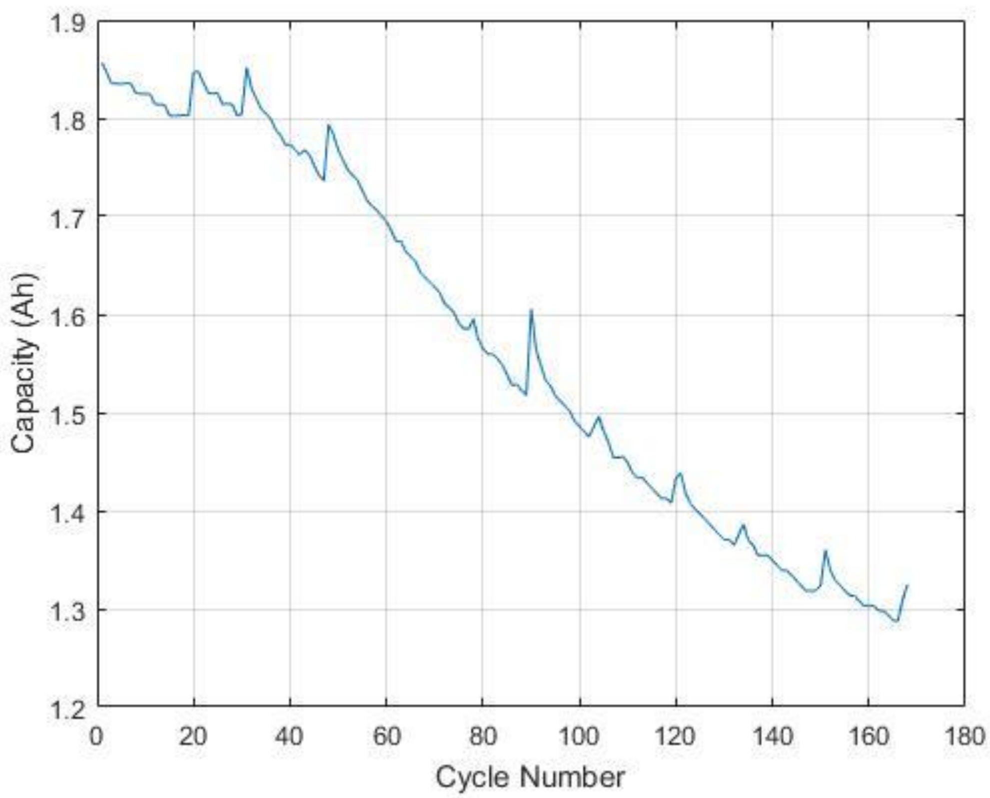

Figure 7: A graph showing the capacity of a Lithium-ion battery when subject to cycling to 100% DoD

There are also some studies focusing around depth of discharge, and restricting charge to below 100% SOC.

Studies [11] [18] show that batteries will age faster with a higher depth of discharge as shown in Figure 8Figure 1 below. As previously shown, during EFR services, the depth of discharge will rarely reach 100%, and therefore should mean there is low degradation.

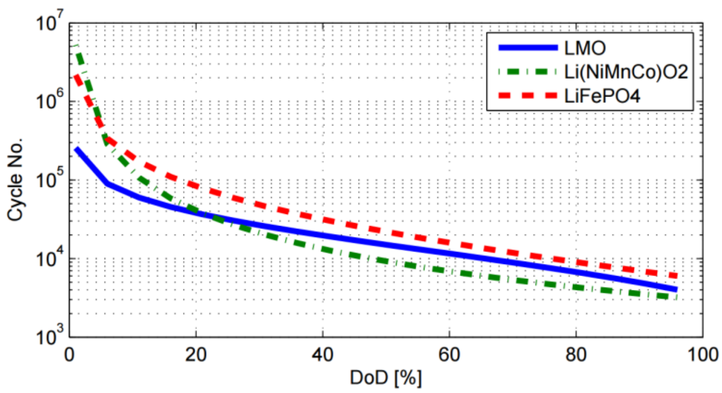

Figure 8: A graph showing how cycle life changes depending upon DoD

Current data that exists that could provide an insight into how a battery might respond under grid frequency response services include further data from NASA that cycles a battery with a "Random Walk" profile. [19] This is where the battery is subjected to a load that is chosen at random from a series of steps between 4.5 and -4.5A. This equates to a charge rate of approximately 2C to -2C. The load is changed every 5 minutes and then is fully cycled every 1500 steps (~5 days) in order to find the capacity. As is clear in Figure 9 below, the cell degrades by 50% over 6 months. This is somewhat comparable to performing grid services alongside other trade strategies such as triad avoidance or arbitrage. However, this data is limited, and shows the extent to which further testing is required.

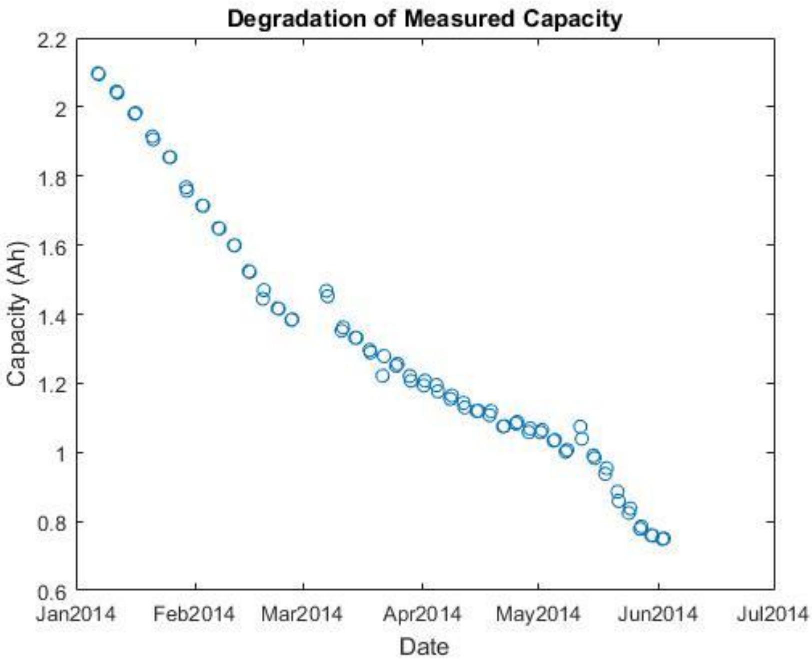

Figure 9: A graph showing how capacity decreases when Lithium ion batteries are cycled with a "Random Walk" profile

Required Experimentation

The models produced can provide a good insight into how the batteries might perform. However, these models must be correctly characterised using experimentation, then verified through performing different tests. Therefore, experimentation must be performed. Due to the limitations of lab space and equipment, there is a limit of around 40 channels which can be used to perform cell testing between the research group. Test procedures must therefore be well justified, which this section will begin to explore.

As shown previously, the data that exists shows little about micro cycling. Whilst the random walk test is helpful, it is at a reasonably high C rate and data from EFR simulation [9] suggests that the discharge rate will rarely exceed 0.25C. Furthermore, the cycles often occur far quicker than every 5 minutes. For this reason, some further testing around EFR is required with chemistries that are likely to perform this service, which will include NMC and Lead cells. The current provision for EFR only includes the narrow band service for batteries, and therefore the narrow band service will be tested. This will be tested using historical grid data across a year which should give a fairly accurate representation of any other year in terms of EFR requirements.

Further tests to be performed will include a hybrid of different cycles. It has been mentioned that performing EFR using vehicle to grid is a possibility. Testing EFR alongside a typical drive cycle for cars will prove some usefulness in understanding this. [20] The drive cycle used will be ARTEMIS (Assessment and Reliability of Transport Emission Models and Inventory Systems) which provides typical drive cycles in road vehicles. This can be used to produce a battery cycle and then included with some time performing EFR to determine how this might affect the life of an EV battery.

Conclusions

In conclusion, a significant amount of further work is required in order to determine the full effects of partially cycling Lithium-ion. This is largely due to the number of different applications and different levels to which the cells are partially cycled, as although a basic knowledge has been attained, testing is required to ensure it is robust. The good understanding of the applications achieved through this report will assist with the future work in modelling batteries undergoing partial cycling.

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