Advanced Management Systems for Large Lithium-Ion Battery Packs

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Abstract

Electric vehicles are a potential method of low-emission transportation and have seen significant early adoption in recent years. Core aspects that would facilitate and accelerate their transition into mainstream products include a reduction of vehicle cost and an increase in driving range.

Modern electric vehicle drivetrains are powered by a lithium-ion battery pack consisting of between tens and hundreds of individual cells. Each individual cell is chemically limited to a maximum voltage, so in order to provide power efficiently many individual cells are connected in series. Series-connected cells share current but due to differences in both initial manufacturing and operating conditions, can become unevenly charged. As a result, battery management is required to ensure reliable and durable operation. Furthermore, in addition to the drivetrain powered by the high-voltage battery, a low-voltage supply is required for lights and other uses. A reliable supply that functions even when the main battery is isolated typically necessitates using a voltage converter as well as an additional lead-acid battery.

This thesis outlines modelling and cell experimentation research conducted to improve the understanding of battery cell and pack behaviour. It further describes the development, construction and testing of a battery management structure that optimises the utilisation of individual cells in the high-voltage battery and overcomes the need for the additional low-voltage battery. The developed system holds potential for both decreasing the capital cost and increasing the range of electric vehicles.
Declaration

This is to certify that

1. the thesis comprises only my original work towards the PhD,

2. due acknowledgement has been made in the text to all other material used,

3. the thesis is less than 100,000 words in length, exclusive of tables, maps, bibliographies and appendices.

Valentin Muenzel, August 2016
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Chapter 1

Introduction

ELECTRIC vehicles coupled with low-emission energy generation and transmission hold strong potential for a less emission-intense future. The prevalence of electric vehicles on worldwide roads has grown substantially in recent years and as of the publication date of this thesis stands in excess of one million. However, the transition of electric vehicles into a mainstream means of transportation would be considerably facilitated by improvements on two core fronts: a reduction in capital cost, and an increase in driving range.

In pure electric vehicles the battery pack is both the single most expensive component and the core component responsible for providing energy storage capacity that enables driving range. It therefore represents a logical point of focus in terms of the aforementioned core improvements.

This thesis details research work conducted with the objective of improving the efficiency and cost-effectiveness of battery management systems for lithium-ion batteries used in electric vehicles. The work is divided into three distinct sections: on battery modelling, experimental testing and battery management system design. Each of these is covered in one chapter of this thesis.
1.1 Research Aims

To develop models for battery cell self-discharge and ageing

Cell capacity degradation and self-discharge are the core causes of cell-to-cell differences within series-connected strings. Being able to predict these processes is crucial for developing energy- and cost-efficient battery management systems. However, current prediction methodologies have significant limitations. The first aim of this thesis is to develop battery ageing and self-discharge models that can be used as a basis for developing battery management systems. The work towards this aim is presented in Chapter 3.

To experimentally investigate cell-to-cell differences in Li-ion batteries

The second aim is to investigate experimentally how much individual, supposedly similar Li-ion battery cells differ from one-another. Factors to be investigated include differences between identical cells and between different types of cells, both when new and after some operating time. Chapter 4 details the cell testing research done in this thesis.

To design and evaluate a non-dissipative balancing system that utilises external loads

The third aim is to use the developed insights and processes to design, build, and evaluate a new balancing system methodology. The proposed system has the ability to supply EV-typical secondary loads including the lights at a low voltage without the need for an additional battery or voltage converter, whilst at the same time utilising the load to ensure suitable balance between the battery cells within. The relevant work is described in Chapter 5.
1.2 Contributions

The main academic contributions of the work presented in this thesis are:

1. Development and demonstration of an equivalent circuit-based multi-cell Li-ion battery model that captures self-discharge as a function of both state-of-charge and temperature (Section 3.2, published as paper in [1]).

2. Development and demonstration of a Li-ion battery cycle life prediction model considering temperature, charging and discharging currents, state-of-charge and depth-of-discharge (Section 3.3, published as paper in [2]).

3. An experimental comparison study of commercially-available 18650 cells including testing of physical parameters, initial capacity, cycle ageing and internal resistance through electrochemical impedance spectroscopy (Section 4.2-4.8, published as a paper and corresponding addendum in [3] and [4], respectively).

4. Development of a new balancing system layout for electric vehicles that removes the need for a backup battery, including design, feasibility study, prototype manufacturing and successful demonstration (Section 5.2-5.6, published as paper and filed as patents in [5] and [6, 7], respectively).

Secondary contributions of the associated work are:

1. Development of battery models and payback analysis calculations for use of Li-ion as customer-side storage alongside PV (published as paper in [8]).

2. Development of battery models for use in simulations of the distribution power grid impact under various assumptions of electric vehicle charging (published as papers in [9-11]).

3. The translation of associated research outcomes into mainstream media publications that have collectively reached an audience of over one million readers ([12-15]).
1.3 Publications

In the course of the candidature associated with this thesis, the following work was published:

Journal Articles

1. V. Muenzel, A.F. Hollenkamp, J. de Hoog, M. Brazil, D. Thomas, A. Bhatt, I. Mareels; A comparative testing study of commercial 18650-format lithium-Ion battery cells; *Journal of The Electrochemical Society*, 162.8, A1592-A1600, 2015.

2. V. Muenzel, A.F. Hollenkamp, J. de Hoog, M. Brazil, D. Thomas, A. Bhatt, I. Mareels; Comment on: A comparative testing study of commercial 18650-format lithium-ion battery cells; *Journal of The Electrochemical Society*, 162.12, Y11-Y12, 2015.


Conference Articles


3. V. Muenzel, J. de Hoog, M. Brazil, D. Thomas, I. Mareels; Battery management using secondary loads: a novel integrated approach; Proc. IFAC World Congress; 2014.

4. V. Muenzel, J. de Hoog, M. Brazil, D. Thomas, I. Mareels; Modeling reversible self-discharge in series-connected Li-ion battery cells; Proc. IEEE Tencon Spring; 2013.

5. J. de Hoog, D. Thomas, V. Muenzel, Tansu Alpcan, M. Brazil, I. Mareels; Electric vehicle charging and grid constraints: comparing distributed and centralised approaches; Proc. IEEE PES GM; 2013.

Patents

1. V. Muenzel, I. Mareels; PCT application: Battery balancing system and method; Australian Patent Office, Aug 2014.

2. V. Muenzel, I. Mareels; Provisional patent application: Battery balancing system and method; Australian Patent Office, Aug 2013.

Other

1. V. Muenzel; Four easy tips to make your batteries last longer; The Conversation - Online; Jun 2015. https://theconversation.com/four-easy-tips-to-make-your-batteries-last-longer-41172

2. V. Muenzel; Battery costs drop even faster as electric car sales continue to rise; The Conversation - Online; Apr 2015. https://theconversation.com/battery-costs-drop-even-faster-as-electric-car-sales-continue-to-rise-39780

3. V. Muenzel, J. de Hoog, I. Mareels, A. Vishwanath, S. Kalyanaraman; Affordable batteries for green energy are closer than we think; The Conversation - Online; Jul 2014. https://theconversation.com/affordable-batteries-for-green-energy-are-closer-than-we-think-28772
Chapter 2
Background

Introduction to Chapter 2

ELECTRIC vehicles increasingly represent a viable mainstream alternative to fossil fuel based transportation. From a policy perspective, the change is driven by an increased awareness of the contributions of fossil fuel burning to both local smog and global warming. To consumers, the vehicles also offer excellent driving performance, high comfort, and very low operating costs. However, using a fundamentally different drivetrain approach represents a formidable technical challenge towards which this thesis aims to contribute.

This section provides the context for the battery development work published in the thesis. It describes the technical state-of-the-art of electric vehicles, of energy storage, and particularly of Li-ion battery systems.

2.1 Electric Vehicles

2.1.1 History of Electric Vehicles

In contrast to the popular view of electric vehicles (EVs) being very new and innovative, the fundamental technological approach was actually invented several years before petrol- or diesel-driven internal combustion engine vehicles (ICEVs). Among the first manned EVs was a 0.1-horsepower, lead-acid battery powered tricycle built by Gustave Trouvé in 1881 [16]. In the two decades that followed, EVs became increasingly com-
petitive against the steam-engine powered vehicles that had previously dominated the transportation market. By 1900, EVs represented 38% of market share, only slightly lagging behind the 40% share of steam-engine vehicles, and almost double the 22% share commanded by early internal combustion engine vehicle[17]. However, the early rise of EVs in the transportation market was short-lived. By 1905 petrol ICEVs began dominating the market due to their lower cost, higher range and increased power compared to EVs.

Ever since this time, ICEVs have dominated the transportation market. For close to a century EVs were only used in niche applications such as golf karts and forklifts. Only the recent oil crises and an increased interest in pollution-reductions reignited the interest in EVs in the late 1970s and early 1980s. This led to the development and production of a small number of vehicles in the following decade. The most prominent of which was General Motors’ EV1, which was available for leasing between 1996 and 1999. However, due to a range of technical, economic and political issues, the EV1 was deemed a commercial failure, and the project and its vehicles were scrapped [18].

While the western automotive industries had focussed on the development of pure electric vehicles, Japanese manufacturers took a different approach. In 1997 the first Toyota Prius became available, which sported an electric drivetrain that worked in unison with a combustion engine. Unlike early pure electric cars, the Prius petrol-electric hybrid saw significant success and became an icon of sustainability, particularly in the US. While in the following years almost all other major automotive manufacturers responded by developing and releasing their own HEVs, initially little effort was redirected towards full EVs.

To some surprise, the relaunch of pure EVs did not come established automotive company but instead from a Silicon Valley start-up by the name of Tesla Motors. In 2008, Tesla Motor’s first vehicle, the Tesla Roadster sent shockwaves though the automotive industry. The Tesla Roadster showed that it was not only possible to produce a vehicle with an all-electric range of over 350km but that EVs could be trendy, fast and fun. Major automotive manufacturers including Mitsubishi, Nissan, and BMW announced full electric vehicles not long after.
2.1 Electric Vehicles

At the beginning of work on this thesis in early 2012, the number of both full and plug-in electric vehicle models available in Australia stood at two: the Mitsubishi iMiEv, and the Nissan Leaf. At the time of completion of this thesis, this number has grown more than five-fold and includes the Tesla Model S, the BMW i3, the Mitsubishi Outlander plug-in hybrid (PHEV). More detailed information on the uptake of EVs is provided in Section 2.1.5.

System Overview

Figure 2.1 illustrates the layout of the electrical system of a typical modern EV. The components shown herein are described in the following sections.

Figure 2.1: Typical EV electrical system layout
2.1.2 System Layout and Components

Electric Motor/Generator

In conventional cars, the internal combustion engine is the component immediately responsible for propulsion. In EVs, this task is done by one or more electric motors. The energy supplied by the energy storage system is turned into mechanical energy, which in turn drives the wheels. However, while the output is similar, the first major difference to a combustion engine is that an electric motor takes electric energy as an input whereas a combustion engine uses the chemical energy in fuel.

The second major difference is that unlike an ICE, electric motors are able to operate in reverse. This means taking mechanical energy from the wheels as an input and returning electrical energy, i.e. slowing the car while recharging the battery. This process, called regenerative braking, presents a huge opportunity to retain mechanical energy that would otherwise be lost as heat output from the mechanical brakes of the vehicle.

There are a number of different types of electric motors that can be used \[16,19\]:

- **Brushed DC (BDC) motors** are the simplest form of electric motors. Permanent magnets in the stator create a permanent magnetic field. By letting current flow through the rotor windings that run perpendicular to this field, the Lorenz force leads to rotation. For continuous rotation, each half-rotation requires a change of the direction of current flow. This commutation is achieved using mechanical brushes. BDC motors require no sophisticated control, which is why these motors were used in early EVs of the 19th and 20th century. While this means the technology is very mature, mechanical commutation requires notable maintenance and limits the maximum speeds possible. Also, the efficiency is limited by the electrical contact of the brushes and is therefore lower than for BLPM motors described below.

- **Brushless permanent magnet (BLPM) motors** can be seen as an inversion of the brushed DC motor’s stator and rotor arrangements. Instead of having windings, the rotor now incorporates permanent magnets and creates the magnetic field. The windings are now located in the stator. This means that commutation can now be done elec-
Electric Vehicles

Electrically using power electronic switching, eliminating the need for a mechanical connection. The price for brushless designs are that the motor control is significantly more complex. Not only does the motor require sufficiently fast switching arrangements but it also needs a position sensor and a processor to decide when the switching should occur. Permanent magnet motors have the additional downside that magnets of the size and weight required add to the expense of the motor. Even so, this design was chosen both for the current Nissan Leaf as well as for the 2013 Chevrolet Spark [20].

• **Brushless induction (BLI) motors** are also brushless motors and have a similar stator to brushless DC motors but differ in that the rotor does not contain permanent magnets. Instead the rotor carries a simple arrangement of conductors that become inductively powered due to the changing magnetic field in the stator. To allow transmit inductive power, the stator field has to rotate slightly faster than the rotor. The ratio of the difference in velocities to the stator velocity is called the slip. Induction motors are currently the most widely used type of electric motors, having been implemented in many vehicles including the Tesla Roadster.

• **Brushless switched reluctance (BLSR) motors** are similar to induction motors in that the stator has winding and no permanent magnets are used in the rotor. However, the rotor features teeth that differ in number from the poles of the stator. To turn the rotor, certain sets of stator coils are powered to which the rotor responds by aligning sets of its teeth with these coils in order to minimise reluctance. While BLSR motors are not currently implemented by a major automotive manufacturer, research has shown them to be very suitable for EV applications and small-scale use in mild hybrids has been implemented, e.g. by UK company SR Drives [21][22][23].

Power Electronics

The power electronics, frequently collectively called the motor controller, represent the brain of EV drivetrains. Taking into account inputs from the driver (e.g. throttle position),
the motor (e.g. hall-effect sensor), the battery (e.g. voltage and current) and frequently a number of other sensors (e.g. electronic stability control), they convert the high voltage DC output from the energy storage system into a signal required to actuate the motor. Typically this output takes the form of a very high frequency pulse-width modulation (PWM) signal.

Energy Storage

While the electric motor provides the actuation required to propel the vehicle, it relies on a substantial input of electrical energy. There are a number of energy storage technologies that have shown some promise, which are discussed in detail in Section 2.2. The currently far-dominant storage technology of Li-ion batteries which forms the core application of the work in this thesis is discussed in greater detail yet in Section 2.3. However, regardless of the storage technologies selected, high output voltage (typically 300-400V) is an imperative for keeping both the cable diameter and the associated ohmic losses during energy transition to the motor within acceptable limits.

Step-down Converter

With the exception of the drivetrain, most vehicle components, including headlights, the radio and entertainment system, and various sensors and actuators, run at a low voltage of around 12V. In a diesel or petrol car, this low-voltage DC power is provided from the 12V battery charged by an engine-connected alternator. In a typical electric vehicle, this output is derived from the high voltage storage output via a step-down converter, which also charges a 12V battery as discussed subsequently. In the past, conversion was done using resistors to linearly reduce the voltage, which leads to very high energy losses. Modern power converters use a switched-mode approach in which energy is temporarily buffered, which enables conversion efficiencies of 90% and higher.
2.1 Electric Vehicles

Figure 2.2: Underside of Holden Commodore EV converted by Australian collaborative venture EV Engineering. 1) Rear-wheel drive electric motor, 2) single-speed gearbox, 3) DC-DC converter, 4) motor controller and 5) Li-ion battery pack (not shown).

Back-up Battery

In battery-powered electric vehicles, to protect the main storage system against excessive depletion, the system automatically isolates itself when the vehicle is turned off and not required to power the drivetrain. However, various 12V devices continue to require a certain amount of energy. To provide this energy without fear of depleting the main battery, modern electric vehicle include a back-up battery in their vehicles, usually in the form of a traditional lead-acid car battery. This adds substantial weight.

2.1.3 Electric Vehicle Topologies

As indicated in Section 2.1.1 there are a range of different electric and hybrid electric vehicle configurations.

The general term Electric Vehicle (or EV) refers to any vehicle that uses one or more
electric motors to propel itself regardless of the energy storage medium used. However, given the dominance of batteries as an energy storage medium, the term EV is often used to describe a vehicle that uses batteries for energy storage.

Today, a wide range of different electric and hybrid drivetrain configurations has been developed. The following paragraphs will describe various types of battery-powered EVs in decreasing order of electric drivetrain performance and complexity, i.e. starting with vehicles only powered by an electric drivetrain and progressing to vehicles with increasing combustion engine input and decreasing electric performance.

Battery / Full Electric Vehicles (BEVs)

The first and most obvious class are battery electric vehicles (BEVs), sometimes also called full or pure EVs. These vehicles are special in that they store all their energy in batteries and use only electric motors for providing propulsion. This is the only type of battery-powered EV that does not require a combustion engine or a fuel tank. From a full charge most BEVs have a range of between 80-150km range depending on the conditions, although some luxury vehicles do offer more, such as the Tesla Roadster with over 300km. However, in order to recharge the batteries it is necessary to have a charging arrangement. This can be done e.g. via a charging chord or wireless inductive charging.

Hybrid and Plug-In Hybrid EVs

HEVs and PHEVs are vehicles that have both a fuel tank and an internal combustion engine (ICE) as well as a battery and an electric motor. While a range of configurations of the electric and liquid fuel drivetrains exist and will be discussed subsequently, it is important to mention that the electric drivetrain in HEVs and PHEVs is able to propel the vehicle without the support of the ICE. This differentiates these full hybrid vehicles as HEVs and PHEVs are sometimes described, from mild and micro hybrids which will be described in the following section.

The difference between HEVs and PHEVs can be derived from the name: PHEVs include functionality that allows them to recharge their battery when stationary by 'plug-
ging in’ while HEVs can only recharge their battery during use (either directly from the ICE or from regenerative braking). As adding plug-in functionality increases both the complexity and cost for the system it is often only implemented on vehicles with a notable battery capacity. In practice, this difference results in vehicle manufacturers usually only including plug-in functionality in vehicles with all-electric ranges of over 20km.

As mentioned previously, there are a number of configurations for PHEVs and HEVs that determine how the electric and liquid fuel drivetrains are used, what additional components are required and how efficient the system is. There are three primary configurations.

**Parallel configuration:** In parallel hybrids both an ICE and an electric motor are mechanically linked to the wheels. This requires a very sophisticated mechanical coupler but allows the system to choose one of the drivetrains to provide power or use both at the same time for maximum acceleration.

**Series configuration:** In series hybrids only the electric motor is linked directly to the wheels. The ICE is connected to the battery via an electric generator and is run only to add energy to the battery when extended driving means that the battery runs low. It is for this reason that series hybrids are sometimes also referred to as range-extended electric vehicles (REEVs). Advantages of these systems are that no complex mechanical coupler is required. Instead however, series hybrids require an additional electric generator that can recharge the battery while the electric motor powers the wheels.

**Series-parallel configuration** In addition to series and parallel hybrids, a number of configurations exist such as series-parallel hybrids in which the control system is able to change the configuration from series to parallel and vice versa in order to maximise the efficiency. An example of this configuration is the Toyota Prius which uses an engine that can be connected and disconnected from the wheels as well as two electric motors, both of which can also be used as electric generators depending on the driving mode [16].
Mild and Micro Hybrids

The last two classes of EVs are mild and micro hybrids. Mild hybrids are HEVs with a much smaller battery and electric motors that assist the engine during acceleration or can regenerate some electricity when braking. While the system itself is too small to be able to power the car alone at any point in time, it does provide sufficient power for all other vehicle loads such as air-conditioning. This allows the engine to turn off whenever the car stands still or even when coasting without requiring propulsion, giving the engine so-called start-stop functionality. Finally, a micro hybrid is essentially an ICEV that has a special starter-motor which can repeatedly restart the engine, thereby also enabling start-stop technology. Typical electric motor ratings for this application are around 10kW [24]. It should be noted that while these two last configurations are still described as hybrids, their electric components are significantly smaller and less complex than those of PHEVs or HEVs.

2.1.4 Environmental Performance

The most commonly-used argument for implementing electric vehicles is the potential reduction of greenhouse gas (GHG) emissions that have been shown to contribute to global warming. While different GHGs have different impacts on the environment, the global warming potential (GWP) can be used to look at the overall impact. The GWP is a ratio that describes the impact of a specific GHG to the impact of the same amount of carbon-dioxide (CO2) over a long time-span of usually 100 years following its emission into the atmosphere.

In addition to the different GHGs, it is also important to consider the range of processes that lead to their emission. While BEVs do not have any tailpipe emissions like ICEVs, the electricity used to recharge batteries usually comes from a mix of different electricity generation plants. The mix varies strongly from country to country and despite strong investments into renewables, most still rely on fossil fuels such as coal and gas for a large percentage of electricity generation, which is linked to GHG emissions. Furthermore, while the operation of vehicles is the main source of GHG emissions, it is
also important to take into account the emissions that are caused by the manufacture, the recycling or the disposal of vehicles. The following part will present a range of life-cycle assessments (LCAs) on ICEVs and EVs with Li-ion batteries based on different vehicle and grid assumptions.

Notter et al. conducted a GHG emissions LCA based on a vehicle with Volkswagen Golf-like dimensions with medium accessory load (air conditioning) [25]. They found that a BEV powered by the 2007 European average electricity production mix produced 36% less GHG emissions (in CO2 equivalent) than a similarly-sized efficient ICEV. This shows that the battery manufacture, which alone was found to account for 14% of total life-cycle BEV emissions, was easily offset by the reduction of operating emissions [25].

Ma et al. from Shell Global Solutions UK and Germany conducted a similar study for UK and US vehicles [26]. They compared the life cycle GHG emissions for 2015 ICEVs, HEVs and BEVs for two cases: a mid-size vehicle in the UK and a sports utility vehicle (SUV) in California, US. Based on an estimated average grid emissions in 2015, the mid-size UK HEV was found to save 5-23% and the BEV 16-46% of GHG emissions depending on the vehicle loading and additional energy drain (such as air conditioning). For the Californian SUV, the result was even more differentiated, finding GHG savings of 11-19% for the HEV and 37-54% for the BEV. While these results roughly fall inline with previously mentioned ones, the authors take a step further and suggest that instead of using average grid emissions one should use marginal grid emissions, which are the emissions from peak power plants and which are estimated to be 35% higher. Their reasoning was that EVs constitute a peak load and will need additional peak generation. In this case the large US BEV saves only 7-37% emissions. And the mid-size UK BEV performs between 25% better than the ICEV for a lightly loaded vehicle to 25% worse than the ICEV for heavily loaded vehicles. These results clearly show the importance of supporting a rise in EVs with an increase in low-carbon power plants and developing clear peak-shaving strategies to avoid increased use of peak power for EV charging.

In the Australian context, Sharma et al. evaluated the environmental and economic impacts of different stages of hybridisation [27]. It was found that for the 2011 Australian electricity mix, series and parallel hybrids offer the best environmental performance for
large vehicles (class E), ahead of both BEVs and ICEVs, due to higher embodied and in-service emissions, respectively. For a small vehicle (class B), the life cycle emissions for the electric vehicle were found to be higher than that of a comparable ICEV.

These findings contrast with the outcomes in previous international studies in that the fully electric vehicles are not found to be particularly environmentally beneficial. The key to understanding this lies in the electricity mix, which is dominated by coal. At the time of the paper, black and brown coal cumulatively accounted for around 75% of the generation, though by 2012-2013 this had reduced to 64%, potentially due to the incentives provided by an introduced carbon pricing policy [28]. However, coupled with charging using less emission-intense electricity mix, such as is present in Tasmania, Sharma et al. find the life cycle emission of a large BEVs to be half that of a comparable ICEVs [27]. Assuming charging via solar panels, which in Australia have seen tremendous uptake and are now on every seventh roof, this impact is lower yet [29].

2.1.5 Market Uptake

Throughout the work on this thesis, global electric vehicle sales have seen tremendous increases. In the US, which is the country with the largest number of vehicles sold, the sales have grown from less than 20k vehicles throughout 2011 to more than 100k vehicles sold throughout 2014, a five-fold growth in sales in just three years (Fig. 2.3). Over 280k vehicles have been sold in the US since late 2010 [30]. The second and third largest markets are China and Japan, respectively [31]. The market with the highest per capita density of electric vehicles is Norway, where electric vehicle registrations grew ten-fold over the same time period, constituting 13.8% of all 2014 car sales [32]. At the time of writing this thesis, the cumulative number of plug-in electric vehicles sold worldwide since 2003 has already exceeded 740k [33]. This compares with a yearly global vehicle production volume of 90M [34]. In conclusion, while globally electric vehicle numbers today represent <1% of vehicles sales, leading markets are seeing 5-10% and numbers continue to increase rapidly.
In absolute values, the number of electric vehicles on roads worldwide has increased from around 100,000 in 2012 to over 700,000 by the start of 2015. The number of plug-in electric vehicles on roads worldwide has surpassed 700k (ZSW-2015). Assuming an average battery storage capacity of 20kWh, electric vehicles entering the market since 2010 have a cumulative capacity of 15GWh. Assuming a 1h discharge rate, this already corresponds to around 10% of the power capacity of pumped hydro storage worldwide, which accumulated over many decades (Economist-2012). In Australia, the uptake of vehicles has thus far been slower than in many other countries. Nonetheless, the total capacity of batteries in hybrid and electric vehicles combined has already exceeded 100MWh. The significant rise in large-capacity plug-in electric vehicles including the Mitsubishi Outlander PHEV and the Tesla Model S, this number is growing rapidly.

Figure 2.3: Plug-in electric vehicle uptake since 2009 [33].


Electric Vehicle Uptake

The past years have brought with it a significant increase in registrations of electric vehicles worldwide. The US, Europe and Japan have seen electric vehicle share of total registrations grow from a fraction of a percent in 2012, to around 1% or more throughout 2014. In the state of California as well as the Netherlands, electric vehicle registrations are crossing 5%. And in Norway, the Tesla Model S represented the most sold vehicle for three months in 2014, contributing to a total electric vehicle share of almost 14% of new registrations. Electric vehicle sales worldwide have increased notably over the past three years (Yang-2015).

Figure 2.4: Plug-in electric vehicle share of total passenger car market by country [32].

1. First Life Uptake and Performance

A crucial aspect of the opportunities of second life batteries relates to the first application in electric cars. In particular, important aspects are: how many batteries are used in electric vehicles, how long will batteries remain in use before becoming available for the second life application, and how much degradation do they see in the first application.

Figure 2.4: Plug-in electric vehicle share of total passenger car market by country [32].

2.2 Overview of Energy Storage Technologies

There are a wide range of energy storage methodologies for electric vehicles. The storage methodologies need to be split into two types: baseload energy storage and peak energy storage. Baseload energy storage provides the bulk of electricity used, therefore the main
goal is high volumetric and weight-specific energy density as well as a low cost per unit storage. In all currently commercially available pure EVs the bulk energy storage is provided by the battery system. Alternative methods include fuel cells and compressed air storage. In contrast, peak energy storage is an optional additional energy storage system for short-term regeneration. Peak energy storage application requires the technology to absorb and provide very high rates of energy and show little performance degradation over very large numbers of charge and discharge cycles. Peak energy storage technologies include supercapacitors and high-velocity flywheels. Since 2009 these have been used in the kinetic energy recovery systems (KERS) in Formula One and Mazda has announced that it will start using a supercapacitor-based technology for regeneration in 2012 ICEVs [35]. It should also be noted that in mild-hybrid vehicles batteries are used as peak storage supporting the bulk energy provided by the fuel. However, given the context of this project, the literature review will look at the technologies from a perspective of their use in pure electric vehicles.

A Ragone plot comparing the specific energy and power values of energy storage devices is shown in Figure 2.5.

### 2.2.1 Batteries

Lead-acid batteries are long-known type of rechargeable battery that finds significant application in starter batteries of ICEVs. The battery is made up a negative elementary lead (Pb) plate and a positive lead oxide (PbO₂) plate separated by a 35% sulfuric acid solution in water (H₂SO₄(aq)). During the discharging process the sulfuric acid concentration in the electrolyte drops significantly while both plates form lead sulfate (PbSO₄) on their surfaces. Lead-acid batteries come either as flooded cells in which the electrolyte is lost due to evaporation and needs to be refilled or as valve-regulated lead acid (VRLA) batteries which strongly limit the amount of electrolyte lost and are therefore often called maintenance-free.

Lead-acid batteries offer a specific energy of up to 40Wh/kg and can supply a specific power of around 200 W/kg. Due to the low price of this technology as well as it’s maturity, lead-acid batteries were used in EVs ranging from the tricycle built by Gustave
Trouvé in 1881 to GM’s first generation EV1 available from 1996. However, in recent years lead-acid batteries have largely been superseded for use in EVs by batteries that can store more energy per unit weight.

Nickel-metal hydride (NiMH) batteries were invented in 1967 at the Swiss Batelle Research Centre and, after significant research and development input from Daimler Benz and Volkswagen, became available for consumer goods in the late 1980s. The positive and negative plates are made of nickel oxyhydroxide (NiOOH) and a metallic alloy, respectively, which are separated by an alkaline electrolyte such as potassium hydroxide (KOH). During discharging the negative metal hydride electrode releases hydrogen into the electrolyte while the positive electrode forms nickel hydroxide (Ni(OH)$_2$).

While more expensive than lead-acid batteries, NiMH batteries offer an energy density of up to 120 Wh/kg as well as a specific power of up to 1000 W/kg. Particularly due to the higher energy density, NiMH batteries superseded Lead-acid batteries in the second model of the GM EV1 and have been used in many hybrids including all Toyota
Prius and Honda Insight generations sold prior to 2012.

Lithium-ion (Li-ion) batteries were invented in the late 1970 and became commercially available in the early 1990s. While a whole range of positive and negative electrodes as well as electrolytes exist the chemical reaction is based on the lithium-based electrode materials interchangeably absorbing or supplying lithium ions into the electrolyte.

Li-ion batteries achieve specific energy and power values of around 200 Wh/kg and 300 W/kg, respectively. These capabilities enabled the construction of electric vehicles offering driving range of 150km and beyond. The Tesla Roadster and Model S, the Nissan Leaf, the Toyota Prius Plug-In and the Chevrolet Volt all use Li-ion chemistries.

Due to their dominance in BEVs and PHEVs at present and in the foreseeable future, Li-ion batteries were chosen as the main focus of this thesis. A more in-depth literature survey surrounding Li-ion batteries is presented in Section 2.3.

### 2.2.2 Supercapacitors

Also called electric double-layer capacitors (EDLCs) or ultracapacitors, supercapacitors are electrochemical devices that store energy electrostatically, i.e. due to an imbalance of charge at material surfaces or boundaries. To maximise the surface and thereby the storage capacity, the two plates of supercapacitors are coated with porous activated carbon to form the electrodes. To achieve electric isolation and limit leakage current with minimum space implications, the plates are separated by a very thin dielectric film.

The specific energy of modern supercapacitors of 5-10 Wh/kg is more than an order of magnitude lower than that of high density Li-ion batteries and roughly on par with lead-acid batteries. Additionally supercapacitor voltages are proportional to the square of the SOC, which means voltages are much less steady than in most batteries. In terms of life-cycle however, supercapacitors strongly outperform batteries by achieving more than 30,000 cycles with capacity drops of less than 20% at room temperature [37] [38]. Given the additional high specific power capabilities of 5kW/kg and beyond, supercapacitors offer outstanding characteristics for very short-term, high-power storage [39].

Hybrid systems using supercapacitors and batteries can be made in two ways: either using both components and switching between the systems or alternatively designing
hybrid supercapacitors that act both as batteries and as supercapacitors in the same device. Hybrid systems using separate supercapacitor and battery storage have shown in research to achieve cost-effective life extensions to batteries [40]. Hybrid supercapacitors based on battery technology have also been extensively tested. VRLA battery-based supercapacitors have been found to work outstandingly with a vehicle powered by this system driving more than 100,000 miles during testing by Australian research organisation CSIRO [41]. Li-ion battery based supercapacitors have also been tested with different device chemistries achieving certain trade-offs of the specific energy and power as well as cycle life ranging between the Li-ion battery and supercapacitor-based technologies as shown in Figure 2.6.

![Figure 2.6: Performance comparison between Li-ion batteries, supercapacitors (C/C) and various Li-ion battery-capacitor hybrids (LTO/LCO: $Li_4Ti_5O_{12}LiCoO_2$, LTO/LMO: $Li_4Ti_5O_{12}LiMn_2O_4$, LTO/C: $Li_4Ti_5O_{12}$activated carbon) [37]](image)

2.2.3 Flywheels

Flywheels can store energy in their rotational velocity, absorbing energy while speeding up and supplying energy while slowing down. As the energy stored is proportional to the square of the rotational speed as well as the inertia of the flywheel, which when cylindrical is proportional to the mass, to the height and to the square of the radius. Historically, the speed of flywheels was limited by material strength and significant flywheel storage
was achievable only by using a large radius and mass. This approach was quite suitable for stationary applications such as back-up power supplies for buildings. Conversely, for transportation its suitability was very limited, given a required flywheel weight of several tons to achieve tens of kilometres of travel as well as interesting steering effect due to the gyroscopic effect.

However, the increasing availability and decreasing cost of carbon fibre composites in recent years has led to a very different approach to flywheels: small, composite devices running at tens or hundreds of thousands of rotations per minute. This new class of flywheels can not only store significant amounts of energy but can do so in a very small and lightweight design, leading to a relatively high energy per unit weight and volume. The devices often use magnetic bearings to minimise friction losses and a continuous variable transmission (CVT) to connect the device to the driveshaft [42]. By mounting this compact flywheel on gimbals or having two counter-rotating flywheels, the gyroscopic effect can largely be avoided. While carbon-fibre flywheels have a theoretical limit of around 350Wh/kg without packaging, currently available devices achieve around 30 Wh/kg without packaging and 5 Wh/kg including packaging [39].

2.2.4 Fuel Cells

Fuel cells differ from batteries and supercapacitors in that they are not themselves the energy storage medium but instead are used for energy conversion. Similar to an ICE converting chemical energy in petrol or diesel into mechanical energy, the fuel cell converts the chemical energy in hydrogen or methanol into electrical energy.

The main advantage of fuel cells over batteries and supercapacitors is that separation of the energy storage and energy conversion steps means that the system can be sized separately for output power and range. This means that the range of a vehicle can be extended simply by increasing the size of the tank for the energy storage medium [16].

The most common energy storage medium for fuel cells is hydrogen. Hydrogen, which is a gas at room temperature, reacts with oxygen from the air to generate electricity and as a sole waste product form water. However, hydrogen storage presents a significant challenge due to its explosive reactivity if exposed to oxygen in an uncon-
trolled environment as well as needing to be in a pressurised and cooled liquid state to achieve suitable volumetric energy densities. As a result other media such as methanol, ethanol and borohydride are also receiving significant research attention [16].

While fuel cells are widely seen as a technology with significant potential for future transportation and are the focus of significant on-going development work, their cost and reliability challenges have to date delayed a significant market entry of vehicles based on this technology.

### 2.2.5 Compressed Air

An unconventional non-electric method of propelling cars that has received some media attention in recent years and is touted to be very sustainable and efficient is to use compressed air engines. These engines are quite similar to ICEs without a spark plug and the cylinders are driven exclusively by letting compressed air become decompressed. The air is stored at pressures of around 300 bar (or 4350 psi) in a carbon fibre tank lined with thermoplastic [43]. This offers very high strength for accident protection and in case of too severe an accident would split rather than fracture, thereby protecting the occupants of the car. A variety of mini-compact to compact cars sold by Motor Development International (MDI), a Luxembourg company, have tank sizes between 170-340l providing an urban range of around 180-200km [43] [44].

According to researchers at the University of California, Berkeley, the weight of compressed air required is only around a third of the weight of Li-ion batteries [45]. However, not only is the volume required for compressed air around twice as large as that of batteries but theoretical limitations of the compression and expansion process lead to a well-to-wheel efficiency that is between half and a third of that of Li-ion batteries. The comparatively low efficiency offering only small energy savings compared to conventional ICEV drivetrains, led the researchers to conclude that compressed-air cars are not financially competitive at present. Environmental competitiveness depends on the source of electricity but a compressed-air car powered by a coal-dominated mix was found to create more than twice as many GHG emissions per kWh than the equivalent ICEV.
2.3 Lithium-Ion Batteries

Given the identification of lithium-ion (Li-ion) batteries as the most promising and widely used energy storage technology for full-electric vehicles, this section outlines the findings of a deeper literature review on the current state-of-the-art of this technology.

Li-ion batteries are a class of lithium-based high specific energy batteries. This section will first give some background information on the components of Li-ion batteries and then focus on electrical properties of both individual cells and arrangements of cells into modules and battery systems.

2.3.1 Cell Anatomy

As can be seen in Figure 2.7, Li-ion batteries typically consist of an anode and a cathode with a separator between them, all dosed in an electrolyte solution. The anode typically consist of a layer of carbon that is connected to a copper current collector, while the cathode can be a variety of lithium-based materials that is typically attached to an aluminium current collector. During discharging, negative lithium-ions exit the negative anode, pass through the separator, and settle on the positive cathode. When charging, the ions flow in the opposite direction and re-intercalate into the carbon anode. The role of current collectors is to facilitate the exchange of electrons between the electrodes and the external circuitry.

Illustrated on a lithium cobalt oxide cathode, the reaction at the cathode is:

\[ \text{LiCoO}_2 \rightarrow \frac{1}{2} \text{Li}^+ + \frac{1}{2} e^- + \text{Li}_{0.5}\text{CoO}_2 \]  

(2.1)

At the anode the graphite then reacts with the lithium ions:

\[ \text{C}_6 + \text{Li}^+ + e^- \rightarrow \text{LiC}_6 \]  

(2.2)

In terms of material content, the negative anode in modern Li-ion batteries is typically made of carbon, specifically graphite which offers a higher voltage stability than other forms of carbon [47]. The electrolyte is usually made up of the organic solvents
Figure 2.7: Schematic construction of a Li-ion battery using a lithium cobalt oxide cathode.

Ethylene carbonate (C$_3$H$_4$O$_3$) or dimethyl carbonate (C$_3$H$_6$O$_3$) in which lithium salts such as lithium hexafluorophosphate (LiPF$_2$) are solved.

However, the cathode is where a lot of differentiation is seen between different Li-ion battery cells and associated manufacturers. Presently, the five dominant cathode materials of Li-ion cells are lithium cobalt oxide (LiCoO$_2$, or LCO), lithium manganese nickel cobalt oxide (LiNi$_{1/3}$Mn$_{1/3}$Co$_{1/3}$O$_2$, or NMC), lithium nickel cobalt aluminium oxide (LiNi$_{0.8}$Co$_{0.15}$Al$_{0.05}$O$_2$, or NCA), spinel lithium manganese oxide (LiMn$_2$O$_4$, or LMO) and lithium iron phosphate (LiFePO$_4$, or LFP).

LCO was one of the first cathode materials developed. It offers a relatively high specific energy and to this day remains commonly used in mobile electronics. However, the very high cobalt content leads to high material cost, which alongside a relatively limited cycle life and less safety tolerance as compared to newer chemistries, limits use in large-scale applications.

NMC has an identical structure to LCO, but the majority of cobalt is substituted with manganese and nickel. The result is a cathode that compared to LCO provides approximately the same energy density, but is cheaper and offers a better thermal stability and
associated safety [47]. NMC cells are used in various electric vehicles including the BMW i3 [49].

NCA is formed by combining LCO with LNO($\text{LiNiO}_2$), a particularly high specific energy cathode material that in pure form is limited by a very short cycle life. By adding aluminium, the cycle life is notably increased, while the specific energy reduces only slightly below that of pure LNO [48]. Compared to NMC, this chemistry has a relatively higher material cost and lower inherent safety, due to a relatively large remaining cobalt content and low thermal stability, respectively [47]. Nonetheless, several manufacturers including Tesla Motors have selected this chemistry for use in EVs [50].

LMO has a fundamentally different structure that allows it to charge and discharge at higher current rates [47]. Its downsides are limited energy density and low cycling life at higher temperatures, although particularly in terms of the latter there has been much recent progress [46]. To the knowledge of the author, no commercial electric car currently uses these batteries as of yet, but given the chemistry’s apparent potential it is seen as a contender for use [47].

Finally, LFP differs in structure yet again. Compared to the other chemistries, it offers outstanding safety properties. It also offers a high current rating capability, particularly at low temperatures and low material cost due to the absence of cobalt [46]. However, achieving an energy density that sits somewhat below those of other chemistries requires nanostructuring of the cathode material, which increases the processing cost [47]. LFP has been used by vehicle manufacturers including BYD [47].

An attempt to capture the battery trade-offs for the three cathode materials that have seen most uptake in EVs to date is provided in Figure 2.8.

### 2.3.2 Charge and Discharge Behaviour

Batteries are confined to be used within their safe operating region. At the very least, for Li-ion cells this is defined by an upper voltage which limits charging and a lower voltage which limits discharging. This is because the cell chemistries are stable only within a very strictly defined voltage range. Decreasing or increasing the voltage beyond minimum and maximum bounds, respectively, causes side reactions to occur that at best lead to
2.3 Lithium-Ion Batteries

Figure 2.8: Comparison of battery characteristics based on cathode chemistry [51]

accelerated ageing of the cell and at worst can cause very rapid failure with potential
safety implications. The state-of-charge is defined as the fraction of total charge capacity
in Ampere-hours that the cell can accept or provide when fully charging or discharging
in the safe operating region, respectively.

Illustrative charge and discharge curves for a 1Ah Li-ion battery cell are shown in
Fig. 2.9. At \( t = 0 \) the cell is fully charged, as is indicated by a state-of-charge (SOC) of
100%. The cell is initially discharged at 1A for one hour. As soon as a discharge current is
applied, the voltage at the terminals drops notably. This drop is due to internal resistance.
Under current load, this causes the voltage drop represented as the offset between the
ideal open-circuit voltage and terminal voltage. It should be noted here that the terms
“internal resistance” and “open-circuit voltage” are both somewhat misleading. This
is because the impedance contains a not insignificant reactive component, which leads
to a notable time delay between a cell being disconnected to form an open circuit and
the open-circuit voltage being measured at the terminals. Further discussion of this is
provided in Section 4.5. A further effect of this voltage drop is a drop in the power
output, as is indicated by the offset between the ideal and actual power curves shown.

As the discharging progresses, the open-circuit voltage reduces. As indicated in Fig.
2.9, the relationship between state-of-charge and open-circuit voltage is notably non-
linear and tends to have a steeper slope near both SOC extremes.

After one hour of discharging at a current of 1A, a cumulative charge of 1Ah has been
removed from the battery cell. This means that a cell initially storing 1Ah of charge, is
empty, or in other words its state-of-charge should in theory reach 0% at this time. In practice, however, the cell capacity, internal resistance, and associated energy efficiency are impacted by factors such as the magnitude of discharging current and the ambient temperature. This prevents the use of cumulative current or power output to determine the end-of-discharge. Instead, given it’s direct impact on the cell stability, the cell voltage is typically the core criterion that defines when discharging and charging need to conclude as discussed previously.

Following the conclusion of discharging, the 1Ah cell in Figure 2.9 is subsequently charged at 1A. As for discharging, the internal resistance again causes a voltage offset and a corresponding offset in power. The effect is that both voltage and input power provided to the battery cell by the charger need to be larger in magnitude than they
would be given an ideal cell without internal resistance.

As discussed previously, the cut-off point is again typically defined by a voltage limit. In the case of charging, however, what is frequently done is not a strict cut-off at maximum voltage, but rather a continuous lowering of current to maintain this voltage. This is because unlike discharging in which the current is inherently linked to the load, the charger providing power input can be controlled at will. By lowering the current, the voltage drop due to internal resistance decreases, allowing the open-circuit voltage of the battery to rise higher and the battery to store further charge without violating limits. This approach is referred to as constant current - constant voltage (CC-CV) charging.

### 2.3.3 Ageing Characteristics

Ageing processes in Li-ion batteries are inevitable. They begin immediately after manufacturing and continue until a cell has completely deteriorated.

The impacts caused by battery ageing are twofold. The most obvious aspect is a decrease in charge capacity of the cell. This means that the cell can provide less charge while discharging, and can accept less charge while charging. As the charge capacity is closely related to the energy of the cell (via the voltage curve), this impact is referred to as energy fade.

The second impact is a rise in the internal resistance of battery cells. As indicated in Section 2.3.2, an increased internal resistance causes a higher voltage drop, which results in increased heat dissipation losses and a decrease in the cell charge and discharge efficiency. As the voltage drop limits the power output a cell can provide during discharging without violating the minimum voltage limit, the term “power fade” is used to describe this impact.

### Cycle and Calendar Ageing

Viewed from a simplified electrical engineering perspective, Li-ion cell ageing can be divided into two processes: cycle ageing and calendar ageing.

Cycle ageing describes how battery cells age as a function of charge-discharge util-
isiation. The most common descriptor of battery ageing using in industry is the cycle life. This specifies how many cycles of a given sort a battery can withstand under certain conditions before its capacity decreases to a specific level, typically 80% of its initial capacity.

Generally, cycle ageing is accelerated by any of the following:

- Increased charge throughput per cycle
- Higher charging and discharge currents
- Extreme temperatures, both hot and cold
- Shorter periods of inactivity and resting

Figure 2.10 illustrates an example of a cycle ageing study [53]. In this study, a battery cell undergoes more than 2,500 cycles between a state-of-charge of 100% and a state-of-charge of 20%, corresponding to a depth-of-discharge of 80%. The left side of Fig. 2.10 shows the slow but steady reduction in cell capacity, while the right side shows the voltage curve during discharge after given numbers of cycles.

![Figure 2.10: Cycle ageing of a 45Ah cell undergoing 80% DOD at 20°C [53]](image)

While the cycle life is a widely used parameter, it fails to incorporate one specific aspect: that battery cells experience degradation even when the cell is not seeing any use at all. This characteristic is captured via calendar ageing or calendar life, its corresponding descriptor.

Calendar ageing tends to be accelerated by the following:

- A higher resting state-of-charge or associated open-circuit voltage.
2.3 Lithium-Ion Batteries

- Extreme temperatures, both hot and cold

An example of a calendar life study is provided in Figure 2.11 [53]. The left side shows the capacity fade for four cells, at different temperatures and float voltages. The temperature in particular is found to have a strong impact; the capacity of cells at 60°C reduces by 5% after less than a year, whereas the cells at 40°C only reach this state of degradation after around four years.

The right side of Fig. 2.11 demonstrates the power fade measured in the same study. The curves indicate strong impacts of both storage state-of-charge and temperature.

![Figure 2.11: Calendar ageing of 45Ah cells at different float voltages and temperatures](image)

**Underlying Chemical Processes**

Cycle and calendar ageing are useful quantifications of battery degradation. However, a deeper qualitative insight requires an understanding of the chemical processes that occur in the cells.

Fig. 2.12 illustrates the core chemical changes that occur in Li-ion cells throughout their life. They can be grouped into three main processes as described below. It should be noted that a number of other less significant ageing processes exist, including current collector dissolution and mechanical stresses within cells [54] [55].

**Initial SEI Growth** In the presence of carbon as found in the anode, the organic electrolyte used in Li-ion cells is not chemically stable. Particularly during the very first
Figure 2.12: Ageing processes occurring on the electrode-electrolyte interface [54]

cycle, and decreasing thereafter, some electrolyte decomposition occurs and its products including lithium are irreversibly absorbed by the anode. This absorption can occur in two ways. If the anode immediately sees very high potentials as are present in low states-of-charge, the electrolyte (i.e. solvent) can be absorbed into the anode and lead to undesirable exfoliation, which permanently damages the anode. However, if a lower potential is applied, then the donor solvent is absorbed to form a passivation film on the surface of the anode. This film is referred to as the solid electrolyte interface (SEI) and consists of a mixture of chemical compounds [56]. SEI formation is a metaphorical double-edged sword. It absorbs lithium otherwise available for energy transfer and contributes to the internal cell resistance. However, as it grows, its formation naturally slows and it also provides protection against exfoliation [46]. Therefore, the most desirable characteristic is to have a very thin, yet sturdy SEI.

From a practical perspective, this means battery manufacturers typically apply formation cycles to ensure the formation of a suitable SEI layer. The choice of electrolyte, electrolyte additives, and temperature during SEI formation all significantly impact the SEI growth and subsequent cell life [54] [57]. Furthermore, to avoid this process immediately reducing cell capacity due to reducing lithium reserves, surplus lithium donating cathode material is included in the battery during manufacturing. Finding the optimal
amount of surplus material is a key process required to reach high energy density and specific energy \[46\].

**SEI Repair** Once successfully formed, the SEI layer provides significant protection of the cell against further ageing if left at a steady-state. However, during battery cycling or high temperatures, the battery anode experiences substantial volume changes \[54\]. As the anode volume increases, the SEI film fractures and exposes non-passivated parts of the anode, leading further passivation to occur. Subsequent contraction of the anode increases the thickness of the SEI. This process of continued SEI repair with its associated growth in thickness accompanied by some SEI dissolution and precipitation is widely acknowledged as the main contributor to Li-ion cell degradation in terms of both energy and power fade \[54\] \[58\].

**Lithium Plating** Lithium plating is an adverse side process that can occur in Li-ion batteries under certain conditions. This occurs when, instead of intercalating into the carbon anode as is expected during charging, lithium deposits start forming on the electrode surface. This represents a significant problem as it not only irreversibly removes lithium from the cell, but it also forms dendrites that can pierce the separator and form a potentially catastrophic short-circuit \[59\].

Plating is likely to occur during overcharging when all intercalation sites have been filled, or in situations when more lithium reaches the electrode than can be intercalated \[54\]. The latter can be a result of very high charging rates in connection with, or separate to, slowed intercalation rates at low temperatures \[59\]. As a result, safe operation of Li-ion batteries to avoid plating includes strict avoidance of overcharging and in certain cases either a reduction in maximum charging rates at low temperatures or inclusion of a heating element to avoid low temperatures in the first place.

### 2.3.4 Cell Arrangement

While batteries can be manufactured to have different amounts of energy storage, the voltage output of cells with identical chemistry is always roughly the same. For Li-ion
batteries the voltage range is usually around 3-4 V, depending both on the cathode, anode and electrolyte materials used as well as the state-of-charge (SOC) of the battery. If a single very large capacity cell was used to power e.g. a 60 kW electric motor, then at the voltage of say 4V, the current would have to be 60/4= 15 kA. This would require a copper wire of more than 1cm² cross-sectional area to avoid wire melting and with its approximate resistance of 0.16 mΩ would lead to a voltage drop of more than 2V per metre of cable. This means that for a single metre of cable more than half the power fed into the cable would be wasted before reaching the motor. This example illustrates clearly why feeding a motor at the voltage of a single battery cell is not viable.

In order to reduce both the cable size and the voltage drop and power loss in the cable, cells are connected in series. As shown in Figure 2.13, the voltage of series connected cells becomes the sum of all cell voltages. The desired system voltage of around 300-400V is therefore achieved by connecting around 100 cells in series into what is often called strings of cells. However, depending on the size of the individual cells used, these 100 cells might not have sufficient power or energy storage to achieve the desired acceleration or range of the vehicle, respectively. Both these issues can be solved by placing several cells in parallel into what is often described as blocks of cells. The maximum current for parallel configurations is the sum of the maximum current of individual cells. Once the arrangement of cells into blocks and strings achieves all desired aspects of the vehicle, a range of controllers, a cooling system are added and together they are inserted into a solid case to form what is called the energy storage system.

The total energy storage (in kWh) is the sum of the energy storage of all individual cells. Energy storage is sometimes also given in the unit of Ampere-hours (Ah), which is calculated as the sum of Ah storage of cells in a single block. By multiplying this Ah value with the total voltage of the battery system, the total energy storage in kWh can be calculated.

There are a wide variety of ways in which a battery system consisting of a number \( k \) of cells with indexes \( 1 \ldots k \) could be structured theoretically.
Parallel Only  Cells are placed in parallel by interconnecting positive terminals of cells and separately interconnecting the negative terminals of all cells. If a system consists only of parallel connected cells with cell voltages and currents $v_k$ and $i_k$ respectively, then the system voltage is given by

$$v_{sys} = v_1 = \cdots = v_k,$$

and the system current $i_{sys}$ is

$$i_{sys} = \sum_k i_k.$$  \hspace{1cm} (2.3)

The voltage of a parallel-connected pack is thereby only as high as that of a single cells, requiring high current in order to transmit notable power.

Given cell internal resistances $r_k$, the cumulative internal resistance is given by

$$r_{sys} = \frac{1}{\frac{1}{r_1} + \frac{1}{r_2} + \cdots + \frac{1}{r_k}}.$$  \hspace{1cm} (2.4)

Under the assumption of identical internal cell resistance, i.e. $r_k = r^{all}$, this is found
to be

\[ r_{sys} = \frac{r^{all}}{k}. \] (2.6)

In this case, the energy losses due to internal resistance can be found to be

\[ p_{loss,sys} = i_{sys}^2 \times r_{sys} = \left( \frac{p_{sys}}{v_k} \right)^2 \times \frac{r^{all}}{k} \] (2.7)

where \( p_{sys} \) is the power input or output of the system.

It should further be noted that while the pack resistance due to internal cell resistance decreases with the number of parallel connected cells, resistances of pack-external connectors and wiring do not. The power loss due to a given resistance in external wiring \( r_{ext} \) becomes

\[ p_{loss,ext} = i_{sys}^2 \times r_{ext} = \left( \frac{p_{sys}}{v_k} \right)^2 \times r_{ext} \] (2.8)

**Series Only** Cells are placed in series by connecting the positive terminal of each cell to the negative terminal of the subsequent cell. If a system consists of only series-connected cells, then the system voltage \( v_{sys} \) is given by

\[ v_{sys} = \sum_k v_k, \] (2.9)

and the system current \( i_{sys} \) is

\[ i_{sys} = i_1 = \cdots = i_k. \] (2.10)

The cumulative resistance due to cells becomes

\[ r_{sys} = \sum_k r_k \] (2.11)

Under the assumption of identical internal cell resistance, i.e. \( r_k = r^{all} \), this is found to be

\[ r_{sys} = k \times r^{all} \] (2.12)
In this case, the energy losses due to internal resistance can be found to be

\[ p_{\text{loss,sys}} = i_{\text{sys}}^2 \times r_{\text{sys}} = \left( \frac{p_{\text{sys}}}{\sum_k v_k} \right)^2 \times k \times r_{\text{all}} \]  

(2.13)

where \( p_{\text{sys}} \) is the power input or output of the system.

The power loss due to a given resistance in external wiring \( r_{\text{ext}} \) becomes

\[ p_{\text{loss,ext}} = i_{\text{sys}}^2 \times r_{\text{ext}} = \left( \frac{p_{\text{sys}}}{\sum_k v_k} \right)^2 \times r_{\text{ext}} \]  

(2.14)

Under the assumption that the cell voltage \( v_k \) is uniform over all cells 1, 2, \ldots, \( k \), it is found that series-only systems have the same power loss due to internal resistance as a parallel-only system as found in Eq. 2.14. However, the power loss due to pack external resistances in series-system is \( 1/k \) of the power loss in a parallel connected system. To summarise, since resistive losses increase quadratically with current when transmitting energy to and from the pack, having a higher system voltage leads to significant energy loss in external circuitry. As a result, parallel-only connected packs are not used in high power applications such as electric vehicles.

However, series-connected packs also have a number of downsides. One issue is a direct result of cell currents being equal at all times. Without any additional provision, this means that energy capacity of the entire system, \( e_{\text{sys}} \) is limited by the cell with the smallest charge capacity:

\[ e_{\text{sys}} = v_{\text{sys}} \times \min_k \left( \int_i i_k \right) \]  

(2.15)

where \( t \) is the duration of discharge.

A further downside is that for a system with a fixed output voltage, the energy capacity of the pack can only be changed by re-engineering the system to take battery cells with a different capacity.

**Series-Parallel** An alternative to connecting all cells in series, which overcomes some of the limitations, is to form small blocks of parallel cells that are placed in series. If a system consists of a number \( s \) of series-connected blocks, with each block containing \( p \)
cells connected in parallel, then for cell voltages $v_{s,p}$ the system voltage is

$$v_{sys} = \sum_s v_{s,1} \cdots = \sum_s v_{s,p}. \quad (2.16)$$

For cell currents $i_{s,p}$, the system current $i_{sys}$ is

$$i_{sys} = \sum_p i_{1,p} \cdots = \sum_p i_{s,p}. \quad (2.17)$$

In this arrangement the capacity is limited by the weakest block of parallel cells:

$$e_{sys} = v_{sys} \times \min_s \left( \frac{\sum_p \int t_i_{s,p}}{p} \right) \quad (2.18)$$

Due to the law of large numbers, this leads to a larger capacity than if limited by a single cell, particularly for a large number of cells connected in parallel.

Compared to a series-only arrangement a downside of this arrangement is that failure of one cell can lead parallel connected cells to feed into the fault causing additional energy dissipation and potentially thermal runaway. It is therefore wise to fuse cells individually, which is feasible but adds to the complexity.

### 2.3.5 Balancing

As explained in Section 2.3.4, high energy transmission efficiency calls for a high number of cells connected in series within a battery pack. Each series blocks can contain one or more cells in parallel and, ignoring additional fusing requirements, multiple parallel-connected cells can effectively be considered as one larger cell.

Series-connected cells share all charging and discharge currents but can vary in voltage. Voltage imbalance in series-connected cells inevitably develops in cells during manufacturing as well as operation and leads to reduced useful string capacity and undesired irregular ageing. To counteract voltage imbalance in series-connected cells, systems are employed to draw energy from highly charged cells and/or supply energy to lower charged cells. Typically described as either cell balancing systems or cells equalisers,
2.3 Lithium-Ion Batteries

Figure 14: Resistive balancing system. ICE stands for individual cell equalizer (i.e. shunt resistor) [42]

An alternative cell shunting balancing system was proposed by Teofilo, Merritt, and Holandsworth (see Fig. 16) [45]. During charging, one operational amplifier and transistor per cell are used to bypass high-SOC cells and charge remaining cells. Teofilo et al tested the system on four 1.4Ah Li-ion cells achieving close to perfect balancing after around 20 full charge-discharge cycles. From a functionality point of view this is very similar to the method employed by Hopkins, Mosling, and Hung. However, by using more complex electronics such as operational amplifiers and transistors, the space requirement and weight associated with larger numbers of dc-dc converters can be significantly reduced.

Nishijima et al. were the first to propose a pulse-width modulation (PWM) controlled converter-based balancing system [46]. In their set-up, each set of two series-connected cells is balanced using PWM-controlled switches (see Fig. 17). The balancing current is related to the duty cycle of the PWM signal, which can be varied by the battery management system via inputs to two variable resistances. A demonstration showed that five 1.35Ah Li-ion cells with differences of 50% in the SOC could be balanced during either the charge and discharge process within three minutes. Like other active balancing methods, resistive losses are largely avoided. However, disadvantages include the requirement for an oscillator as well as high-frequency PWM devices to keep voltage ripple minimal.

Figure 2.14: Resistive balancing system. ICE stands for individual cell equaliser (i.e. shunt resistor) [60]

these systems form a large part of what is collectively described as the battery management system.

Bo Lindemark was among the first researchers to propose battery balancing in 1991. He suggested using current-shunting parallel resistors to largely bypass high-voltage cells during charging, letting current flow to low voltage cells (see Fig. 2.14) [60]. Resistors thereby effectively dissipate energy meant for fully-charged cells as heat so that subsequent low-SOC cells can continue charging. Demonstration on a 60-cell string of 150Ah lead-calcium batteries reduced cell voltage differences from ±0.2V to ±0.02V. The system also identified defective cells by their higher cell current. This design presented the first possibility to automatically re-balance cells during operation, avoiding the need for disconnection and manual measurement and balancing. Continuous battery balancing reduces risks of exceeding voltage boundaries, leading to improvements in battery life expectancy.

Hopkins, Hung and Mosling developed one of the first non-dissipative approaches to battery balancing between 1991 and 1993. As published first in [61] and in more detail in [62], they designed, modelled and demonstrated a balancing circuit using step-up DC-DC converters to bypass fully-charged cells (see Fig. 2.15). The core difference between this converter-based design and Lindemark’s resistive approach is that energy meant for high-SOC cells is actively redirected to low-SOC cells rather than dissipated and lost.
as heat. This increases system efficiency and balancing speed as low-charge cells receive both the energy meant for them as well as the energy transferred by the balancing system.

In recent years, a vast number of balancing systems for SOC and voltage balancing have been proposed with balancing methods based on inductors, capacitors, transformers and/or DC-DC converters [63–65]. However, only very few systems including the following have considered cell-to-cell differences in storage capacity.

Einhorn et al. proposed a balancing method for cells differing not only in SOC but also in nominal capacity [66]. Their system, shown in Fig. 2.16, uses a converter for each cell to transfer energy between the cell and the battery system terminals. A fully-charged demonstration system containing 12 cells with capacities of 20Ah ± 2Ah showed a 4% increase in available energy during a single discharge due to current being predominantly drawn from high-capacity cells. However, converter efficiencies of 80% led to losses of 20% of the balancing energy.

As it turns out, this loss can be avoided by taking a different approach to balancing altogether. In late 2011, Manenti et al. proposed a cell redundancy-based balancing system that uses two switches per cell to connect any given cell from a series-string (see Fig. 2.17) [67]. The system is slightly oversized so that at least one cell is disconnected at

![Figure 2.15: Converter-based active balancing system](image_url)

Figure 2.15: Converter-based active balancing system [61]
any point. By measuring all individual cell voltages or estimating cell SOCs during the charge or discharge process, the most charged or discharged cell is identified and disconnected, respectively. Advantages of this approach include using small switches instead of larger transformers or converters. Furthermore, a single underperforming or defective cell can be disconnected permanently until it can be replaced. However, the downside is that for each series-connected cell, a switch is also connected in series. While for small series-connection, such as the 6-cell system demonstrated in the paper, switch-associated losses represent less than 10%, 100-cell systems, as are required for EVs with a range of 150km, would have much higher losses making balancing very inefficient. The second major disadvantage is that any cell redundancy directly increases both the weight and cost of the system.
However, switch-based battery system methods hold some very unique opportunities. They fundamentally change the way battery balancing is conducted by using cells intermittently and thereby avoiding any flow of energy from one cell to another. This not only avoid cycling cells unnecessarily, but it also avoids energy passing through any auxiliary components which inevitably leads to a certain inefficiency.

Including switches within the main structure of battery packs further provides a source of isolation within the pack. In the context of electric vehicle energy flows as outlined in Section 2.1.2 the lack of isolation is a key reason for the necessity of a low-voltage battery as well as a DC-DC converter.

This review of the current state-of-the-art raises a particular research question which this thesis aims to answer. Specifically, can switched battery management system layouts be exploited not only to balance batteries, but be evolved further to avoid the need for a backup lead-acid battery, thereby increasing efficiency and reducing weight, space, and cost of the electric powertrain. As efficiency, weight, space and cost are all of parameters of key importance for electric vehicles, this research question is considered of significant importance for the research field of electric vehicles.
Chapter 3
Battery Modelling

Battery modelling is done for a variety of reasons and using a variety of approaches. Electrochemical models, also called physical models, simulate the chemical operation of the batteries, dealing with movement of active materials, material concentrations and chemical reactions taking place. These models are highly accurate, but also highly complex and at present still have some limitations in terms of what they can capture. Electrical circuit equivalent models are a simplification of physical models in that they lump various groups of reactions into approximately equivalent electric circuit components like voltage sources, resistors and capacitors. While some of the accuracy is lost in this process, currents, voltages and power flow are still replicated reasonably well and simulation is much faster than in physical models. Lastly, purely empirical numeric models can be used to describe certain processes, such as cell ageing based on cell external parameters such as temperature or operating time, but do not describe instantaneous battery behaviour.

In this thesis, modelling work was conducted with a very specific motivation. The goal was to understand how battery self-discharge and battery ageing contribute to the development of differences in state-of-charge and capacity in series-connected battery cells.

3.1 Related work

This section outlines the state-of-the-art of battery modelling and explains the choice of using equivalent circuit and empirical modelling methodologies in the conducted work.
3.1.1 Electrochemical Models

By describing specific physical reactions taking place inside a battery cell, electrochemical models represent the most detailed method of battery modelling.

Intercalation Models

The heart of any electrochemical model is its intercalation model. This model simulates the concentrations and potentials within a battery cell for a given current input, assuming certain physical characteristics of the cell anode, cathode, separator and electrolyte. The main model output is the voltage across the battery cell.

The electrochemical intercalation model is outlined here as background only, based on the work in [68] and [69]. For the purpose of the work in this thesis, only the ageing model described subsequently is directly relevant.

Considering only effects in the dominant direction of current flow, i.e. the axis directly connecting the anode and cathode that is perpendicular to the surface area of an ideally positioned separator, the full electrochemical intercalation model consists of six equations outlined hereafter (Eqs. 3.1-3.6).

The total current through the cell $I$ is the sum of currents in the solid particles $i_s$ and the electrolyte $i_e$. According to Ohm’s law, the electric potential of each solid electrode $\Phi_s$ is therefore found as:

$$\frac{\partial \Phi_s(x, t)}{\partial x} = \frac{i_e(x, t) - I(t)}{\sigma}$$  

(3.1)

where $\sigma$ is the effective electronic conductivity of the electrode and $x$ is the spatial dimension in which current flows.

The spatial derivative of the potential in the electrolyte $\Phi_e$ consists of two terms:

$$\frac{\partial \Phi_e(x, t)}{\partial x} = \frac{i_e(x, t) - I(t)}{\kappa} + \frac{2RT}{F} (1 - \xi_0^{l_t}) \times \left( 1 + \frac{d \times \ln f_{c/a}}{d \times \ln c_e(x, t)} \right) \frac{\partial \ln f_{c/a}}{\partial x}$$  

(3.2)

where $F$ is the Faraday constant, $R$ is the universal gas constant, $T$ is the cell temperature in Kelvin, $f_{c/a}$ is the electrolyte molar activity coefficient, $\kappa$ is the ionic conductivity of the electrolyte, and $\xi_0^{l_t}$ is the transference number of the cations with respect to the solvent.
velocity. In this equation, the first term is analogous to the solid electrode potential term, whereas the second term represents the voltage drop due to concentration gradients on the electrolyte.

Current in the electrolyte $i_e$ is driven by differences in electrolyte concentration $c_e$. The relationship between electrolyte current and the concentration can be calculated as follows:

$$\frac{\partial c_e(x, t)}{\partial t} = \frac{\partial}{\partial x} \left( D_e \frac{\partial c_e(x, t)}{\partial x} \right) + \frac{1}{F \epsilon_e} \frac{\partial (t_0^a i_e(x, t))}{\partial x} \quad (3.3)$$

where $D_e$ is the effective diffusion coefficient, $\epsilon_e$ is the volume fraction of the electrolyte, and $t_0^a$ is the transference number for the anion. The first term describes the contribution of limited diffusion rates on the concentration, whereas the second term describes the contribution of the current.

The electrode can be modelled to consist of particles that are roughly spherical. In this case, spherical diffusion is main factor impacting concentration $c_s[68,70]$. From Fick’s law of diffusion, the relationship between electrode current $i_s$ and concentration $c_s$ can be calculated as:

$$\frac{\partial c_s(x, r, t)}{\partial t} = \frac{1}{r^2} \frac{\partial}{\partial r} \left( D_s r^2 \frac{\partial c_s(x, r, t)}{\partial r} \right) \quad (3.4)$$

where $r$ is the radial dimension of the particles in the electrode, and $D_s$ is the diffusion coefficient.

Additionally, from conservation of charge of the molar flux of lithium $j_n$ at the electrode particle surface, it follows that:

$$\frac{\partial i_e(x, t)}{\partial x} = aF j_n(x, t) \quad (3.5)$$

where $a$ is the specific interfacial area, which is directly related to the volume fraction of the solid electrode material in the porous electrode.

Finally, molar flux is driven by the intercalation overpotential $\eta_s$ in the electrode. This leads to the Butler-Volmer equation:

$$j_n(x, t) = \frac{i_0(x, t)}{F} \left[ \exp \left( \frac{\alpha_a F}{RT} \eta_s(x, t) \right) - \exp \left( -\frac{\alpha_c F}{RT} \eta_s(x, t) \right) \right] \quad (3.6)$$
where $\alpha_a$ and $\alpha_c$ are transport coefficients for anodic and cathodic flow directions, respectively, and $i_0$ is the exchange current density. $i_0$ is a function of electrode and electrolyte concentrations, whereas $\eta_s(x,t)$ is a function of the electrode concentration, as well as the molar flux of lithium, electrode and electrolyte potentials. For full equations, refer e.g. to [69].

The resulting system consists of five governing partial differential equations and the additional Butler-Volmer equation. It can be solved using boundary conditions for concentration gradients as well as electric potentials of the two electrodes and the electrolyte.

Ageing Models

While the intercalation model captures the concentrations and potentials within the battery, an associated ageing model describes how these parameters influence battery ageing.

In electrochemical models, capacity fade is typically modelled as a side reaction [71], [72]. Using the Butler-Volmer rate expression, the side reaction current $i_k$ associated with each degradation mechanism $k$ can be described as:

$$i_k = i_{0,k} \left[ \exp \left( \frac{\alpha_{a,k} F}{RT} \eta_{s,k} \right) - \exp \left( \frac{\alpha_{c,k} F}{RT} \eta_{s,k} \right) \right]$$

(3.7)

For side reactions that are irreversible, this can be simplified to the Tafel expression:

$$i_k = i_{0,k} \left[ \exp \left( \frac{\alpha_{a,k} F}{RT} \eta_{s,k} \right) \right]$$

(3.8)

Further development led to specific expressions for two specific side reaction processes that have been observed in Li-ion [73]. For lithium deposition ageing, under the assumption that overpotential is low, the Tafel expression can be approximated linearly as follows:

$$i_{LD} = i_{0,k} \left( \frac{\alpha_a + \alpha_c}{RT} \right) \eta_s$$

(3.9)

For solid-electrolyte interface (SEI) layer growth, the rate of side reaction can be found
3.1 Related work

via the film thickness:

\[ i_{SEI} = \frac{L_{s-} a \rho F \delta}{M} \frac{\partial \delta}{\partial t} \]  

(3.10)

where \( L_{s-} \) is the negative electrode thickness, \( a \) is the interfacial electrode area per unit volume, \( \rho \) and \( M \) are the density and molecular weight of the SEI layer, respectively, and \( \delta \) is the SEI film thickness.

Ramadass et al. [58] amended the non-linearised Tafel equation model to additionally model power fade. They noted that due to SEI layer, the cell with have cell resistance increases \( R_p \) due to SEI products formed during cycling as follows:

\[ R_p(t) = \frac{\delta_{film}}{\kappa_p} \]  

(3.11)

where \( \delta_{film} \) is the SEI film thickness, and \( \kappa_p \) is the conductivity of the products formed.

Suitability for Unbalance Prediction

As described in the previous sections, state-of-the-art electrochemical modelling is capable of simulating capacity fade and resistance increase associated with the negative electrode. Including the equations describing solvent reduction and associated SEI layer growth, the full model consists of eight independent equations for the same number of dependent variables (concentrations and potentials at both electrodes, intercalation and solvent reduction rates, as well as lost and remaining charge capacities) [58].

However, while electrochemical models at their current state-of-the-art hold significant value, they also exhibit some shortfalls. Most models assume that battery ageing only occurs during charging. They only consider ageing reactions in the form of solvent degradation and SEI growth. And they assume that cell resistance is independent of state-of-charge and monotonically increasing with time. Each of these three assumptions has been shown not to hold in many cases (e.g. see [74], [53], and [75], respectively).

A further downside of a full electrochemical model is that it requires pre-determining values for 16 physical parameters for the electrodes as well as five parameters describing the solvent reduction reaction. Ramadass et al’s analysis found that relatively small variations in solvent parameters had a very significant impact on the simulated capacity loss.
so parameter accuracy is important [58].

The purpose of modelling in this thesis is to investigate how battery self-discharge and battery ageing contribute to the development of differences in state-of-charge and capacity. As such, two of the shortfalls are particularly critical. Firstly, by only considering ageing to occur during charging, the models are not suitable for capturing reversible self-discharge processes, which are known to occur during resting periods also [76]. Secondly, the large number of parameters coupled with high variable sensitivity make parameter estimation for one single cell a very cumbersome task requiring a large amount of high-accuracy testing. To evaluate differences in battery cells, one would need to conduct parameter estimation for a statistically significant number of cells. The excessive testing requirements led us to conclude this not to be a feasible option within the scope of this thesis.

While electrochemical model assumptions regarding charge-only degradation can be relaxed somewhat under suitable circumstances, the issues regarding parameter estimation were unavoidable. As a result, electrochemical modelling was considered not to be the ideal approach for the modelling work done in this thesis. Instead, two other options were investigated: equivalent circuit models and empirical models.

3.1.2 Equivalent Circuit Models

In equivalent circuit models, each series-connected cell is modelled as a collection of a number of components into what is called a Randles circuit. A voltage source represents the open-circuit voltage (OCV) as a function of the state-of-charge (SOC). A resistor is used to represent the purely passive part of the cell internal resistance. And the active part of the internal resistance is represented using one or more series-connected blocks of a resistor and a capacitor connected in parallel.

A number of publications have used equivalent circuit models to capture self-discharge behaviour in battery cells. Chen and Rincón-Mora, for example, proposed a Cadence-compatible model representing a mixture of Thevenin and runtime-based models [77]. While one part of the model calculates a voltage representing the state-of-charge as a function of cell capacity, a different part simulates the current flow through the cell. Sep-
3.1 Related work

Separating these processes decreases the amount of influence between various factors, which can decrease simulation time, but also requires creating characteristics (such as state-of-charge voltage), which are abstract and cannot be measured in a physical system. Reversible self-discharge is modelled as current through a static resistor, while capacity fade was modelled as a capacity loss process dependent on cycle number and time, without considering depth-of-discharge or current magnitudes.

Gould et al. [78] used a Randles circuit with a single RC block in which the capacitor was used to represent the open-circuit voltage. Reversible self-discharge was modelled via current flowing through a static resistor placed in parallel with the OCV capacitor. Capacity fade was included via an empirical model that assumed fixed cycling duration, allowing no flexibility in terms of cycling rates and pause durations.

Dubarry and Liaw use a similar approach to Gould et al., but model OCV using a controllable voltage source rather than a capacitor, which leads to more accuracy as the SOC-OCV relationship can be explicitly defined [79]. However, no reversible self-discharge or capacity fade were considered here.

This review of related work in equivalent circuit models highlighted their suitability for capturing cell-level behaviour including self-discharge processes. However, each of the approaches published prior to the work in this thesis had a given limitation regarding our purpose of modelling batteries including self-discharge on a cell-by-cell level. As a result, there was scope for creating a better equivalent circuit model and demonstrating its use in modelling reversible self-discharge in series-connected battery cells. This work is outlined in Section 3.2 and forms one contribution of this thesis.
Table 3.1: Factors considered in numerous publications on battery life cycle modelling

<table>
<thead>
<tr>
<th>Author</th>
<th>Temp</th>
<th>(I_{dch})</th>
<th>(I_{ch})</th>
<th>DOD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Zhou[80]</td>
<td>N</td>
<td>Y</td>
<td>N</td>
<td>N</td>
</tr>
<tr>
<td>Ng[81]</td>
<td>Y</td>
<td>N</td>
<td>N</td>
<td>Y(^a)</td>
</tr>
<tr>
<td>Nuhic[82]</td>
<td>Y</td>
<td>N</td>
<td>N</td>
<td>Y</td>
</tr>
<tr>
<td>Ecker[83]</td>
<td>Y</td>
<td>N</td>
<td>N</td>
<td>Y</td>
</tr>
<tr>
<td>Omar[84]</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y(^a)</td>
</tr>
</tbody>
</table>

\(^a\) Considers variations in the discharge cut-off point, but not in the charge cut-off point.

3.1.3 Empirical Models

Equivalent circuit models and electrochemical models are primarily intended to capture short-term behaviour of batteries in terms of individual charge and discharge processes. Compared to this, certain battery processes, including capacity and power fade, are at a much slower time-scale and the associated chemical reactions are in many cases less clear.

As a result of this mismatch in time-scales and complexity, most battery ageing models are based on trend analysis of measured data rather than fundamental process modelling. Empirical approaches use curve fitting to find general equations from discrete cycling measurement points. This reduces the complexity of model tuning notably. However, most empirical approaches focus on certain cells under a given range of conditions that entail only specific considered impact factors. This is done to limit the required amount of data and associated testing to a feasible volume.

Specific factors that are known to impact cycle life include, but are not limited to:

- Operating temperature
- Charging current
- Discharging current
- Depth-of-discharge in terms of both upper charging and lower discharging limit

Table 3.1 provides an overview of numerous battery prediction publications, listing the factors considered in each. Zhou et al. \[80\] for example conducted an ageing study...
of 18650-format LFP cells evaluating exclusively the impact of charging currents at rates of 5C, 10C, and 15C. Ecker et al. developed a life prediction model for pouch cells taking into account state-of-charge and temperature, but not charging or discharging currents [83]. And Ng et al. considered temperature, discharge current and depths-of-discharge, but do not consider charging currents or variations in the maximum state-of-charge [81].

The most encompassing empirically-based methodology was published by Omar et al. [84]. Their methodology uses separate models for four impact factors, all of which are modelled as independent from one-another. Their experimental validation confirmed this approach to produce good fit between the modelling results and experiments. However, their methodology representing the state-of-the-art has room for improvement in several areas:

- It considered that for each cycle charging ends and discharging begins at 100% SOC. This may frequently be undesirable as high SOCs can lead to notable degradation during both cycling [85] and storage [83].

- Our attempts at replicating the model found depth-of-discharge parameters that vary by several orders of magnitude from those published.

- The method of combining the various individual parameter models into a full model was demonstrated but not explained. It was based on fuzzy logic but is protected knowledge that the authors were not able to share (based on personal correspondence).

- The paper only predicted cycle life under static cycling conditions, in which cycling parameters such as currents and charging and discharging bounds do not change from cycle-to-cycle.

The shortfalls identified in the current state-of-the-art provide a clear scope for development of an improved empirically-based battery cycle life prediction. The resulting work, which is one of the contributions of this thesis, is outlined in Section 3.3.
3.2 Self-Discharge Model

3.2.1 Approach and Methodology

A standard way to model batteries is the Randles circuit. For low-frequency input, this consists of a resistor connected in series with a parallel RC circuit, which represent the polarisation resistance and limits in the electrochemical transport, respectively, as shown in Fig. 3.1. By adding in series a voltage source to represent the relationship of open-circuit voltage (OCV) and SOC, a single cell model is developed that can simulate both charge and discharge processes [79].

\[
V_{\text{cell}} = V_{\text{OCV}} + V_R + V_{\text{RC}} \tag{3.12}
\]

where \( V_{\text{OCV}} \) is the open-circuit voltage, and \( V_R \) and \( V_{\text{RC}} \) are the voltages across the resistive and RC elements, respectively. The polarity of \( V_R \) and \( V_{\text{RC}} \) here are defined such that both are positive during charge and negative during discharge.

The open-circuit voltage is linked to the state-of-charge of each cell \( \text{SOC}_t \). This can be found from the SOC at start of simulation \( \text{SOC}_{\text{start}} \) as follows:

\[
\text{SOC}_t = \text{SOC}_{\text{start}} - \frac{C_{\text{discharged}}}{C_{\text{remain}}} \times 100 \tag{3.13}
\]

where \( \text{SOC}_{\text{start}} \) and \( \text{SOC}_t \) are calculated as integer percentage points. \( C_{\text{remaining}} = C_{\text{start}} - C_{\text{ISD}} \) is the remaining capacity of the cell at time \( t \) after a given irreversible self-discharge capacity loss \( C_{\text{ISD}} \). \( C_{\text{discharged}} \) is the net capacity discharged from the cell since simulation start.

For the purpose of observability of mixed variables, this was implemented in the simulation model as:

\[
\text{SOC}_t = \frac{\text{SOC}_{\text{start}}}{100} \times C_{\text{start}} \times \frac{C_{\text{remain}}}{C_{\text{start}}} - \frac{C_{\text{discharged}}}{C_{\text{remain}}} \times 100 \tag{3.14}
\]

where \( C_{\text{start}} \) is the cell capacity at the start of experiment.

Li-ion cells have been shown to lose a certain amount of charge during storage through
3.2 Self-Discharge Model

so-called leakage currents of two different kinds \[76\]. The first type of leakage current oc-
curs due to reversible lithium-consuming reactions in the electrolyte, which reduces the
stored charge but not the capacity of the cell. The second type of leakage current oc-
curs due to irreversible lithium-consuming reactions in the electrodes, which reduces not
only the stored charge but also the capacity of the cell. These two types of self-discharge
will hereafter be referred to as reversible and irreversible self-discharge, or RSD and ISD,
respectively. In most electric circuit equivalent based battery models, RSD is not con-
sidered. An exception to this is \[86\], where RSD is incorporated as a lump resistance in
parallel to the capacitor representing the OCV. ISD represents capacity fade, which we
do not consider further in this section but instead focus on specifically in Section 3.3.

![Graph showing reversible self-discharge current rate at 4.1V cell voltage as an exponential function of temperature.]

Figure 3.2: Reversible self-discharge current rate at 4.1V cell voltage as an exponential function of temperature.

**Temperature Dependency**

The proposed approach is to represent RSD as a current source that is controlled as a
function of the cell voltage and temperature. Very limited empirical data is available
in the literature regarding long-term self-discharge of Li-ion cells over a range of cell
temperature and cell voltages or SOCs. Reference \[76\] provides data for two different
temperatures (293.18K and 296.08K) at various cell voltages. Based on steady-state data
at 4.1V for both temperatures and assuming \( RSD = 0 \) for \( T = 0K \), we approximate
self-discharge at 4.1V to grow exponentially with cell temperature (see Fig. 3.2). The
Figure 3.3: Reversible self-discharge current rate as a piecewise linear function of cell voltage at various temperatures.

Voltage-dependency is then incorporated as a linear approximation of the steady-state data in [76] (see Fig. 3.3). This leads to our cell RSD function $RSD_C$ in amperes:

$$RSD_C = \max\left\{0, \left[(V_{OC} - 3.4V) \times 7.686 \times e^{0.01553 \times T_C - 5.38}\right] \times 10^{-8}\right\}$$ (3.15)

where $V_{OC}$ is the cell open-circuit voltage (OCV) and $T_C$ is the cell temperature. We believe this to be the best possible assumption given the limited data available at present; with further data becoming available we will adjust and improve this model accordingly.

For our preliminary simulations presented here, we have assumed a very simple temperature profile:

$$T_C = \begin{cases} 
293.15K, & \text{if } I < \frac{C}{10} \\
303.15K + \Delta T_C, & \text{if } I \geq \frac{C}{10}
\end{cases}$$ (3.16)

where $T_C$ is the cell temperature, $I$ the absolute current through a three-cell string (i.e. both charging and discharging), and $\Delta T_C$ is the operating cell temperature offset for cell C. The operating cell temperature offset, which is the difference between the temperature of an individual cell and the average cell temperature during standard operation, represents our main simulation variable.

Our resulting Simulink single cell model can be seen in Fig. 3.5. ISD has already...
Figure 3.4: Simulink system model containing 3 cell models as well as a current source for charging and discharging.

been implemented in the model for future use, but for the simulation described here it has been configured to have negligible impact. Fig. 3.4 shows our system model, which includes the three series-connected cells as well as a current source to control charging and discharging.

Simulation Parameters

For each simulation a period of 30 days was chosen, as this represents a sufficiently long period over which voltage divergence can occur but a sufficiently short period so that ageing and ISD can reasonably be neglected. Throughout this timespan, the three-cell string undergoes one complete charge-discharge cycle per day, where discharging occurs at a rate of 1C and charging occurs at C/4. The charging and discharging processes both follow constant-current regimes, whereby the process is terminated when either an upper (4.2V) or lower (2.7V) boundary is crossed by the average cell voltage in the string.
Figure 3.5: Simulink cell model containing voltage source, series resistor, RC block and both reversible and irreversible self-discharge sources.

During times when the current is switched off, the control system reconnects the string once every two hours, only to disconnect after a timespan of 1s assuming the voltage boundary is crossed again. This control method was chosen to allow future implementation of varying charge and discharge currents, where reconnection occurs if the voltage drop over the polarisation resistance decreases sufficiently.

Figure 3.6: Estimation of open-circuit voltage profile using 60s pause method.

Cells were simulated to have capacities of 1.25Ah as information on temperature- and voltage-dependent self-discharge rates for this size was available, unlike for larger-
capacity cells. The implemented SOC-OCV curve, which for Li-ion cells is typically capacity-independent, was gained from testing commercially available 0.9Ah cells using the pause estimation method suggested in [87] as shown in Fig. 3.6.

Using these general parameters, we then ran three simulations to illustrate the impact of different operating temperatures on cell imbalance. In the first simulation we set $\Delta T_1 = 2^\circ C$, $\Delta T_2 = 0^\circ C$, and $\Delta T_3 = -2^\circ C$. According to [88] this temperature gradient is a reasonable assumption for practical application where cells near the edges of the battery system have better cooling than cells inside. We also conducted a second simulation to evaluate the impact of more significant temperature gradients, which could be the result of either cooling system malfunction or inconsistent cell degradation leading to particularly high heat generation in some of the cells. For this simulation we set $\Delta T_1 = 30^\circ C$, $\Delta T_2 = 20^\circ C$, and $\Delta T_3 = 10^\circ C$.

![Figure 3.7: Terminal voltage of cell 2 over initial 27h of simulation](image)

3.2.2 Simulation Results

Fig. 3.7 illustrates the voltage curve of cell 2 during standard operation for slightly more than one full day. Within the first hour, the battery discharges until the string reaches an average terminal voltage of 2.7V. At this point the discharging process terminates and the voltage rises notably due to the reduction in voltage drop across the polarisation resistance. Around 12 hours after the beginning of the discharge process, the charge process starts and continues for approximately 4h until the maximum voltage boundary is reached. At times when the string is neither charging nor discharging, two-hourly
temporal reconnections occur for reasons discussed previously.

The resulting terminal voltage divergence between the warmest cell (cell 1) and the coldest cell (cell 3) for the three simulations is shown in Fig. 3.8. After 30 days with a reasonably standard 2C temperature variation among cells during operation, and no variation during pauses, the coldest cell has a terminal voltage that is around 0.9mV higher than the warmest cell. The larger temperature gradient, as could be caused by various malfunctions, increases maximum final voltage differences to around 5.5mV. The underlying SOC differences between the warmest and coldest cells developed over the 30-day simulations are 0.003% and 0.020%, respectively. In all cases the voltage differences are much larger after discharging than charging. This is due to the OCV- SOC curve, which is steeper at very low SOC values than at very high SOC values. The higher the gradient, the more significant the difference in cell voltage caused by a given difference in SOC.

3.2.3 Discussion

To put these results into context, consider the effects of over-discharging described in [8]. 15 days storage at an OCV of 2.0V led to a 2% decrease in cell capacity and a 10% increase
3.2 Self-Discharge Model

in cell thickness. Assuming a rated voltage of 2.7V, cell voltages of 2.0V can be reached with a voltage divergence of 1.4V if the discharging of a two-cell string is stopped when the average voltage crosses the minimum boundary.

Our simulation results suggest that steady-state RSD has a very low impact on cell imbalance. Under the condition of malfunction-typical temperature differences, a post-discharge voltage difference of 0.7V would be reached after approximately 10 years of operation. Given that the design life of battery systems of 8-10 years and the low likelihood of continuous malfunction-typical temperatures, these results suggest that temperature dependent RSD alone does not appear to warrant a need for balancing systems. This limits the direct impact of our simulation results for quantitative understanding and operation of balancing systems.

However, in the preliminary simulations presented here, a number of important factors has not been accounted for, which include:

- cell imbalances at the beginning of life, which can be of significant magnitude [89];
- reversible self-discharge rates during and after operation, which are higher than at steady-state [76]; and
- the impact of ageing and resulting capacity degradation on cell imbalance.

While these factors will need to be considered in future work to broaden the applicability of the model, our work has introduced a preliminary methodology for simulating the impact of temperature-dependent steady-state reversible self-discharge on cell imbalance.
3.3 Battery Ageing Model

3.3.1 Introduction

As outlined in the literature review in Section 3.1.3, there is scope for an improved battery ageing model that can take into account a wide variety of degradation factors. Specifically, the goal is to:

1. Develop and demonstrate an empirically-supported model of how battery cycle life varies with interdependent average state-of-charge and depth-of-discharge.

2. Present a reproducible framework for combining numerous independent cycle life models considering different impact factors into a unified multi-factor cycle life model.

3. Develop and demonstrate a technique for enabling battery life prediction models to assess battery usage with dynamically changing cycling parameters.

3.3.2 Methodology

This section presents the combined cycle life algorithm, with following sections describing models for individual ageing factors for Li-ion batteries.

While the underlying methodology is valid for battery cells of any chemistry, the individual factor models and curve fitting are chemistry-dependent. The limited availability of suitable published Li-ion cell ageing data at present restricts us to taking a chemistry-agnostic approach here, but in future work this model is to be adjusted for specific Li-ion chemistries.

At the heart of the chosen approach, and as suggested in [84], is the assumption that the impacts that certain environmental and operational factors on Li-ion battery cycle life are, or can be approximated as being, independent from one-another. Based on this independence assumption, it follows:

$$\frac{CL(x_1, \ldots, x_k)}{CL(x_{1,nom}, \ldots, x_{k,nom})} = \frac{CL(x_1)}{CL(x_{1,nom})} \times \cdots \times \frac{CL(x_k)}{CL(x_{k,nom})}$$

(3.17)
where $CL$ is the predicted cycle life to a certain limit of degradation under given cycling parameters, $x_k$ is the $k$th cycling parameter, and degradation impact factor, to be considered. In the case of interdependent ageing factors, the relevant factors need to be jointly included in one fraction on the right hand side. The index $nom$ refers to nominal cycle life and cycling parameters, as found for example in a battery data sheet or gained from a cycling experiment for a single set of cycling parameters.

$$CL(x_1 \cdots x_k) = CL(x_{1,nom} \cdots x_{k,nom}) \times \frac{CL(x_1)}{CL(x_{1,nom})} \times \cdots \times \frac{CL(x_k)}{CL(x_{k,nom})}$$ (3.18)

In the case of Li-ion battery ageing, among the most important impact factors are the operating temperature $T$, charging current $I_{ch}$, the discharging current $I_d$, as well as the minimum and maximum state-of-charge boundaries [85]. The following sections discuss and describe the development of impact factor models for these factors. The state-of-charge boundaries are transformed into depth-of-discharge $DOD$ and average state-of-charge $SOC_{av}$.

The combined Li-ion battery life cycle model, used in latter analysis and case studies, is formed by taking the product of the normalised individual models (Eqns. (3.23), (3.24), (3.25), and (3.40)) and the nominal cycle life:

$$CL(T, I_d, I_{ch}, SOC_{av}, DOD) = CL_{nom} \times nCL(T) \times nCL(I_d) \times nCL(I_{ch}) \times nCL(SOC_{av}, DOD)$$ (3.19)

where $nCL$ is each associated normalised cycle life fraction, corresponding to terms on the right side of Eq. (3.17). This provides the underlying framework for predicting the cycle life of a given battery cell based on a single data cycle life data point. This data point can either come from manufacturer specifications, or from testing of a cell under a single set of cycling conditions.

**Battery Currents and Temperature**

For charging current, discharging current and working temperature of the cell, modified versions of the model published in [84] are used. In this model, cycle life is captured as a
Table 3.2: Values for tuning coefficients of models of Li-ion degradation impact factors. Values for coefficients $a \cdots p$ are as published in [84]. Coefficients $q_0 \cdots v_0$, and $q \cdots v$ are deduced in Section 3.3.2.

<table>
<thead>
<tr>
<th>Variable</th>
<th>a</th>
<th>b</th>
<th>c</th>
<th>d</th>
<th>e</th>
<th>f</th>
<th>g</th>
<th>h</th>
</tr>
</thead>
<tbody>
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<td>1.95</td>
<td>67.51</td>
<td>2070</td>
<td>4464</td>
<td>-0.1382</td>
<td>-1519</td>
<td>-0.4305</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Variable</th>
<th>m</th>
<th>n</th>
<th>o</th>
<th>p</th>
<th>q_0</th>
<th>r_0</th>
<th>s_0</th>
<th>t_0</th>
</tr>
</thead>
<tbody>
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<td>Value</td>
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<td>-0.6531</td>
<td>321.4</td>
<td>0.03168</td>
<td>1806</td>
<td>-160.8</td>
<td>207.7</td>
<td>0.7901</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Variable</th>
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<th>v_0</th>
<th>q</th>
<th>s</th>
<th>t</th>
<th>u</th>
<th>v</th>
</tr>
</thead>
<tbody>
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<td>1471</td>
<td>214.3</td>
<td>0.6111</td>
<td>0.3369</td>
<td>-2.295</td>
</tr>
</tbody>
</table>

third order polynomial function of temperature:

$$CL(T) = aT^3 - bT^2 + cT + d$$

(3.20)

where $a$, $b$, $c$, and $d$ are coefficients from fitting of experimental data on lithium iron phosphate based cells with values shown in Table 3.2. Note that the experiments in [84] used short-term cycling rather than as a simple constant current discharge, which is assumed here to have negligible impact.

The published model further approximates cycle life as a second-order exponential function of both discharging and charging current, respectively given as:

$$CL(I_d) = e \times \exp(f I_d) + g \times \exp(h I_d)$$

(3.21)

$$CL(I_{ch}) = m \times \exp(n I_{ch}) + o \times \exp(p I_{ch})$$

(3.22)

where $I_d$ and $I_{ch}$ are the discharging and charging current, respectively, and $e$, $f$, $g$, $h$, $m$, $n$, $o$, and $p$ are fit coefficients, the values of which are also listed in Table 3.2.

Eq. (3.19) requires each of the published models to be normalised. This normalisation is done as follows:

$$nCL(T) = \frac{aT^3 - bT^2 + cT + d}{aT_{nom}^3 - bT_{nom}^2 + cT_{nom} + d}$$

(3.23)

$$nCL(I_d) = \frac{e \times \exp(f I_d) + g \times \exp(h I_d)}{e \times \exp(f I_{d, nom}) + g \times \exp(h I_{d, nom})}$$

(3.24)
where $nCL$ represents the normalised cycle life for each respective impact factor, $T_{nom}$, $I_{d,nom}$, and $I_{ch,nom}$, are nominal working temperature, nominal discharging current, and nominal charging current, respectively, as specified by the manufacturer for a given specified cycle life.

**State-of-Charge and Depth-of-Discharge**

By the nature of the coupling between the average state-of-charge, $SOC_{av}$, and depth-of-discharge, $DOD$, the respective impacts on cycle life are intuitively likely to be notably interdependent. For example, assume the life of a battery cell cycling between 40-60% (i.e. $SOC_{av} = 50\%$, and $DOD = 20\%$) is double that of a cell cycling from 30-70% ($SOC_{av} = 50\%$, and $DOD = 40\%$). This does not necessarily mean that a cell cycling between 10-30% SOC ($SOC_{av} = 20\%$, and $DOD = 20\%$) also has double the life of a cell cycling between 0-40% ($SOC_{av} = 20\%$, and $DOD = 40\%$). In fact, this is unlikely to give similar ageing, as discussed subsequently.

As a result an experimental dataset is required, in which both $DOD$ and $SOC_{av}$ are varied independently. Such a dataset was recently published by Ecker et al. [85]. It contains cycle life measurements for average $SOC$ and $DOD$ ranging from 10-90% and 10-100%, respectively. Obviously, the closer $SOC_{av}$ is to either 0 or 100%, the lower the maximum $DOD$ can be (a cell with an $SOC_{av}$ of 10% can have at most a $DOD$ of 20%, corresponding to cycling between 0-20% SOC).

Once digitised, a suitable fitting function is required for the dataset. [85] indicates that the cycle life of batteries decreases for cycling in both high and low $SOC$ regions, while in mid-$SOC$ regions less degradation occurs. This suggests a second-order polynomial function related to average $SOC$ as a potentially suitable approach. The data further illustrates that as $DOD$ increases, the cycle life reduces non-linearly. Having incorporated $SOC_{av}$ as a second-order polynomial, a logical approach is to incorporate $DOD$ as a multi-order polynomial also. Given the $DOD$ and $SOC_{av}$ are expected to be interdependent as
discussed previously, there will also be one or more terms containing both variables.

Taking a second-order approach for \(DOD\) and \(SOC_{av}\), the function to be fitted becomes:

\[
CL^*(DOD, SOC_{av}) = q_0 + r_0 \cdot DOD + s_0 \cdot SOC_{av} + t_0 \cdot DOD^2 + u_0 \cdot DOD \cdot SOC_{av} + v_0 \cdot SOC_{av}^2
\]  

where \(CL^*\) is the equivalent cycle life, and \(SOC_{av}\) and \(DOD\) are the average state-of-charge and depth-of-discharge over each cycle, respectively. Constants \(q_0, r_0, s_0, t_0, u_0,\) and \(v_0\) are the fit coefficients. Curve fitting using the least-squares fitting method via the Matlab Curve Fitting Tool found these coefficients to have the values listed in Table 3.2.

As shown in left and centre of Fig. 3.9, this leads to a reasonably good fit, characterised by R-square and Root Mean Square Error values of 0.767 and 1220, respectively. Note that the figure shows all of the curve within the \(SOC_{av}\) and \(DOD\) range for which the cycle life is positive, including infeasible combinations of \(DOD\) and \(SOC_{av}\). However, the fit has one problematic aspect. As shown in Fig. 3.9c, the maximum equivalent cycle life over \(SOC_{av}\) actually increases slightly when increasing \(DOD\) from around 85% upwards. This goes against the trend seen in experiments (e.g. [85]). A local maximum at the 100% \(DOD\) boundary is problematic for use in optimisation of battery management as it would encourage batteries to be cycled to its maximum limits, leading in practice to particularly strong degradation.

One approach to avoid this is to force the cycle life to have its minimum over \(DOD\)
at 100% DOD at all SOC$_{av}$ points. This is done by determined the relationship between the coefficients at the local minimum by partially differentiating the original two by two order polynomial function with respect to the DOD:

\[
\frac{\partial CL_2(DOD, SOC_{av})}{\partial DOD} = r_1 + u_1 * SOC_{av} + 2 * t_1 * DOD
\] (3.27)

To find the local minimum, this is set to zero:

\[
0 = r_1 + u_1 * SOC_{av} + 2 * t_1 * DOD
\] (3.28)

We then need to solve for one coefficient, e.g. $r_1$:

\[
r_1 = -2 * t_1 * DOD - u_1 * SOC_{av}
\] (3.29)

Finally, we set the DOD to 100, as this is where we want the minimum to be:

\[
r_1 = -200 * t_1 - u_1 * SOC_{av}
\] (3.30)

The resulting formula for $s$ can now be inserted into our original quadratic equation with two variables (Eq. 3.26), to form our new fit equation:

\[
CL_3(DOD, SOC_{av}) = q_1 + (-200 * t_1 - u_1 * SOC_{av}) * DOD + s_1 * SOC_{av} + t_1 * DOD^2 + u_1 * DOD * SOC_{av} + v_1 * SOC_{av}^2
\] (3.31)

Rearranging:

\[
CL_3(DOD, SOC_{av}) = q_1 - 200 * t_1 * DOD - u_1 * SOC_{av} * DOD + u_1 * DOD * SOC_{av} + s_1 * SOC_{av} + t_1 * DOD^2 + v_1 * SOC_{av}^2
\] (3.32)

It is found that this approach leads the SOC$_{av}$-DOD interdependence factor to cancel out. This is undesirable as we explicitly are looking to preserve interdependency. In fact,
it is very logical that this approach removes interdependence considering we force all 
SOC\textsubscript{av} values to have fixed minimum at DOD = 100, allowing no interdependence.

A different approach, which is found to lead to a more suitable result, is to specify 
that the minimum only falls at a specific single point where DOD=100%, thereby allowing 
flexibility at all other points. A logical point given its location approximately in the 
middle of the viable SOC\textsubscript{av} region is where the cycle life has its maximum with respect 
to SOC\textsubscript{av} at 100% DOD (See Fig. 3.9). This point can be found by partially differentiating 
the cycle life from Eq. (3.26) with respect to the SOC\textsubscript{av} and setting to zero:

\[ \text{SOC}_{\text{av,100\% max}} = \frac{-s - 100 \times u}{2 \times v} \]  \hspace{1cm} (3.33)

It is at this maximum point over the SOC that we want the minimum over DOD to 
occur. Therefore inserting this SOC\textsubscript{av} value into Eq. (3.26) and setting DOD = 100:

\[ r = -200 \times t - u \times \frac{-s - 100 \times u}{2 \times v} = \frac{u}{2 \times v} \times (s + 100 \times u) - 200 \times t \]  \hspace{1cm} (3.34)

Reinserting into our original fitting function in Eq. (3.26), gives:

\[ \text{CL}(DOD, \text{SOC}_{\text{av}}) = q + \left( \frac{u}{2 \times v} \times (s + 100 \times u) - 200 \times t \right) \times DOD + s \times \text{SOC}_{\text{av}} \]

\[ + t \times DOD^2 + u \times DOD \times \text{SOC}_{\text{av}} + v \times \text{SOC}_{\text{av}}^2 \]  \hspace{1cm} (3.35)

Recomputing the fit coefficients for this function using least-squares fitting gives the 
coefficient values listed in Table 3.2. It results in the function shown in Fig. 3.10.
3.3 Battery Ageing Model

slightly worse R-square value of 0.7634, and slightly improved Root Mean Square Error of 1188 indicates that the imposed constraint does not significantly degrade the quality of fit.

For the fitted coefficient, the proposed function can analytically be shown to produce no local minimum over $DOD$ within the viable region characterised by the following four criteria:

\begin{align*}
0\% & \leq \text{SOC}_{av} \leq 100\% \quad (3.36) \\
0\% & \leq DOD \leq 100\% \quad (3.37) \\
DOD & \leq 2 \times \text{SOC}_{av} \quad (3.38) \\
DOD & \leq 2 \times (100 - \text{SOC}_{av}) \quad (3.39)
\end{align*}

The result is a model that predicts the normalised battery cycle life not just as a function of depth-of-discharge but also taking into account the average state-of-charge over a cycle.

Finally, the function in Eq. (3.35) can be normalised as follows:

\begin{equation}
\text{nCL}(\text{SOC}_{av}, DOD) = \frac{\text{CL}_4(DOD, \text{SOC}_{av})}{\text{CL}_4(DOD_{nom}, \text{SOC}_{av,nom})} \quad (3.40)
\end{equation}

**Proof of Non-Existence of Internal Minima**

To verify that this function does not lead to any minima within the viable $\text{SOC}_{av}$-$DOD$ region, it needs to be evaluated whether minima can fall on any feasible points in the $\text{SOC}_{av}$-$DOD$ region, which are defined by four criteria.

The first criterion is that the $\text{SOC}_{av}$ stays within its reasonable bounds

\begin{equation}
0\% \leq \text{SOC}_{av} \leq 100\% \quad (3.41)
\end{equation}
The second criterion is that the DOD stays within its reasonable bounds

\[ 0\% \leq \text{DOD} \leq 100\% \]  
(3.42)

The third criterion is that when discharging, the DOD is small enough not to reach less than 0% of the SOC_{av} at its lowest point in each cycle:

\[ \text{DOD} \leq 2 \times \text{SOC}_{av} \]  
(3.43)

The fourth and final criterion is that when charging, the DOD is small enough not to reach more than 100% of the SOC_{av} at its highest point in each cycle:

\[ \text{DOD} \leq 2 \times (100 - \text{SOC}_{av}) \]  
(3.44)

To compare against these criteria, we first need to recompute the DOD-SOC_{av} relationship for the CL minima over DOD. We therefore partially differentiate our resulting function (Eq. 3.35) with respect to DOD and set it equal to zero:

\[ \frac{\partial CL_4(\text{DOD}, \text{SOC}_{av})}{\partial \text{DOD}} = \frac{u}{2 \times v} (s + 100u) - 200t + 2t \times \text{DOD} + u \times \text{SOC}_{av} = 0 \]  
(3.45)

Solving for DOD:

\[ \text{DOD} = \frac{\frac{u}{2v} (s + 100u) - 200t + u \times \text{SOC}_{av}}{-2t} \]  
(3.46)

\[ \text{DOD} = 100 - \frac{u}{4tv} (s + 100u) - \frac{u}{2t} \text{SOC}_{av} \]  
(3.47)

From Fig. 3.10 we know that the minima tend to fall near the upper DOD bound. We will therefore first test the second criterion in regards to the upper bound:

\[ \text{DOD} \leq 100\% \]  
(3.48)
3.3 Battery Ageing Model

Substituting DOD from Eq 3.47:

\[ 100 \geq 100 - \frac{u}{4tv} (s + 100u) - \frac{u}{2t} \text{SOC}_{av} \]  
(3.49)

\[ \frac{u}{4tv} (s + 100u) \geq - \frac{u}{2t} \text{SOC}_{av} \]  
(3.50)

From our recalculated fit coefficients, we know that both \( u \) and \( t \) are positive. Therefore:

\[ \frac{1}{2v} (s + 100u) \geq - \text{SOC}_{av} \]  
(3.51)

\[ \text{SOC}_{av} \geq - \frac{1}{2v} (s + 100u) \]  
(3.52)

Substituting the fit values finds that the upper bound of criterion 2 is fulfilled only when:

\[ \text{SOC}_{av} \geq \frac{-1}{2} \ast (-2.295) \ast (214.3 + 100 \ast 0.3369) \approx 54.03\% \]  
(3.53)

Given that the only potential points where minima may fall into the valid region are above 50% \( \text{SOC}_{av} \), we next choose to evaluate criterion four (Eq 3.44). Again substituting DOD from Eq 3.47:

\[ 2 \ast (100 - \text{SOC}_{av}) \geq \text{DOD} \]  
(3.54)

\[ 200 - 2 \ast \text{SOC}_{av} \geq 100 - \frac{u}{4tv} (s + 100u) - \frac{u}{2t} \text{SOC}_{av} \]  
(3.55)

\[ \left( \frac{u}{2t} - 2 \right) \ast \text{SOC}_{av} \geq -100 - \frac{u}{4tv} (s + 100u) \]  
(3.56)

From the recalculated fit values, we know that:

\[ \frac{u}{2t} - 2 < 0 \]  
(3.57)
Therefore:

\[
SOC_{av} \leq \frac{100 + \frac{u}{100} (s + 100u)}{2 - \frac{u}{100}}
\]  

(3.58)

Substituting the fit values finds that criterion four is only fulfilled if:

\[
SOC_{av} \leq \frac{100 + \frac{0.3369}{4 \times 0.6111} (s + 100u)}{2 - \frac{0.3369}{2 \times 0.6111}} (214.3 + 100 \times 0.3369) \approx 49.36\%
\]  

(3.59)

By evaluating this outcome alongside Eq. 3.53, we know that no minima falls within the feasible \(SOC_{av}-DOD\) region.

**Verification of the Developed Model**

To ensure the developed \(DOD-SOC_{av}\) cycle life model is in line with expected results, it is compared to the \(DOD\) cycle life model based on [84]. Neither this model, nor associated data, was previously used to fit our model. Given difficulties in replicating the model’s cycle life results directly using the published coefficients, the original data points are used to refit an exponential function as proposed, against which our model can then be compared. Least-squares fitting finds the model as:

\[
CL^+ = i \times \exp(j \times DOD)
\]  

(3.60)

with coefficients \(i\) and \(j\) having values of 67560 and -0.03223, respectively. As illustrated in Figure 3.11, this approach led to a very good fit with a degree of freedom adjusted R-square value of 0.9894.

Fig. 3.12 illustrates the comparison between this previously proposed \(DOD\)-only cycle life model and our \(DOD-SOC_{av}\) model. The closeness of results depends on both the \(SOC_{av}\) value chosen in our model, as well as the \(DOD\) region considered. The curve for \(SOC_{max} = 100\%\), which corresponds to the conditions at which the \(DOD\)-only data was collected, is a reasonable fit only above 70\% \(DOD\). This is because this choice of \(SOC\) represents the boundary case of feasible \(SOC-DOD\) behaviour (100\% \(SOC\) is reached during very cycle) at which curve fitting seems to have its issues. With \(SOCs\) away from the edges, either by limiting \(SOC_{max}\) to 80\%, or by fixing the average \(SOC\) to 50\%, the result-
Figure 3.11: Relationship between cycle life and depth-of-discharge from [84] with fitted single order exponential function.

Fitting curves resemble the previously proposed model notably more closely. The remaining mismatch is presumed to be the result of differences in the battery cells used for the experiments.

Table 3.3: Parameter limits of data points used for model fitting

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Minimum value</th>
<th>Maximum value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Temperature</td>
<td>-18°C</td>
<td>40°C</td>
</tr>
<tr>
<td>Discharge Current</td>
<td>1C</td>
<td>15C</td>
</tr>
<tr>
<td>Charge Current</td>
<td>C/8</td>
<td>4C</td>
</tr>
<tr>
<td>Average SOC³</td>
<td>10%</td>
<td>95%</td>
</tr>
<tr>
<td>DOD³</td>
<td>5%</td>
<td>100%</td>
</tr>
</tbody>
</table>

³ Only part of the SOC-DOD region is feasible; see Eq. 3.36-3.44
Figure 3.12: Verification of normalised cycle life models. The DOD-only model based on [84] does not consider SOC. Our model considers SOC.

### 3.3.3 Static Case Study: Smartphone

To demonstrate the value of the static cycle life model developed thus far, we illustrate its use on a case study centred around smartphones. One of the suppliers of smartphone battery cells is Panasonic. Its NCA103450 battery, for example, is a prismatic Li-ion cell with a nominal capacity of 2350mAh, almost perfectly matching the 2300mAh offered by the batteries of Google 2013 Nexus 5 smartphone [90, 91]. The cell uses NCA cathodes, similar to those found in Tesla Motors electric vehicles.

Assuming one hour each of calling, browsing, and video watching per day, a new Nexus 5 battery has been shown to last 40 hours [92]. Under this assumption, a user has a wide range of charging options. We consider the following:

1. The battery is charged fully every 24 hours.
2. The battery is charged until full whenever it reaches a state-of-charge of 10%.
3. The battery is charged every 24 hours but only to the optimal level as determined as optimal by our battery ageing algorithm.

The obvious question is: what is the comparative battery life for each of these three charging options?
3.3 Battery Ageing Model

Using the developed life cycle prediction methodology, finding the answer to this question is quite straightforward. First, the nominal cycle life parameters of the cells need to be considered. The specifications listed in Table 3.4 are supplied by Panasonic in their associated data sheet [91].

Table 3.4: Battery cell specifications from Panasonic NCA103450 data sheet

<table>
<thead>
<tr>
<th>Manufacturer spec</th>
<th>Variable</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nominal capacity (Ah)</td>
<td>$N/A$</td>
<td>2.35</td>
</tr>
<tr>
<td>Nominal cycle life</td>
<td>$CL_{\text{nom}}$</td>
<td>649$^a$</td>
</tr>
<tr>
<td>Measured at temp (deg C)</td>
<td>$T_{\text{nom}}$</td>
<td>25</td>
</tr>
<tr>
<td>Discharge current (C)</td>
<td>$i_{d,\text{nom}}$</td>
<td>1</td>
</tr>
<tr>
<td>Charging current (C)</td>
<td>$i_{ch,\text{nom}}$</td>
<td>0.7</td>
</tr>
<tr>
<td>Depth-of-discharge (%)</td>
<td>$DOD_{\text{nom}}$</td>
<td>100%</td>
</tr>
<tr>
<td>Average SOC (%)</td>
<td>$SOC_{\text{nom}}$</td>
<td>50%</td>
</tr>
</tbody>
</table>

$^a$ The cycle life was determined by digitising the cycle life graph, and linearly scaling forward the degradation seen at 100-500 cycles until the capacity falls below 80% of 2.35Ah.
Table 3.5: Smartphone cycling scenarios and cycling life outcomes

<table>
<thead>
<tr>
<th></th>
<th>Full charge from 10% SOC</th>
<th>Daily full charge</th>
<th>Daily optimal charge</th>
</tr>
</thead>
<tbody>
<tr>
<td>$i_d (C)$</td>
<td></td>
<td>0.025</td>
<td></td>
</tr>
<tr>
<td>$i_{ch} (C)$</td>
<td></td>
<td>0.7</td>
<td></td>
</tr>
<tr>
<td>$T (dC)$</td>
<td></td>
<td>25</td>
<td></td>
</tr>
<tr>
<td>$DOD (%)$</td>
<td>90</td>
<td>60</td>
<td></td>
</tr>
<tr>
<td>$SOC_{av}$</td>
<td>55</td>
<td>70</td>
<td>51.09</td>
</tr>
<tr>
<td>$CL_{equiv}$</td>
<td>963</td>
<td>1359</td>
<td>4040</td>
</tr>
<tr>
<td>$CL_{actual}$</td>
<td>1070</td>
<td>2265</td>
<td>6733</td>
</tr>
<tr>
<td>Life (years)</td>
<td>4.88</td>
<td>6.20</td>
<td>18.4</td>
</tr>
</tbody>
</table>

Assuming discharging at a steady rate, the current draw during its 40-hour battery life is:

$$I = \frac{2350 Ah}{40 h} = 58.75 mA$$ \hspace{1cm} (3.61)

Or:

$$I = \frac{58.75 mA}{2350 Ah} = 0.025 C$$ \hspace{1cm} (3.62)

The standard charging current is assumed to be 0.7C, which roughly falls in line with the Nexus 5 charger rating of 1.8A, or $1.8 A / 2.3 Ah = 0.78 C$.

The depth-of-discharge for the profiles assuming daily recharging is found to be:

$$DOD_{daily} = \frac{24 h}{40 h} = 60\%$$ \hspace{1cm} (3.63)

The cycle life can then be estimated using our prediction methodology for the three types of use cases discussed previously, as defined by the parameters as listed in the upper part of Table 3.5.

As indicated in the final three rows of Table 3.5, the predicted cycle lives differ significantly. For the given assumptions, the smartphone battery is predicted to last around six years for daily full charging, versus five years for full charging only whenever 10% SOC is reached. However, an optimal daily charge approach, which is determined as having an average SOC of 51% (i.e. cycling between 21-81% SOC) more than doubles the expected life of the battery.

It should be noted that several of the assumptions mean that the predicted lifetimes
are slightly optimistic. These include that battery cells always discharge at a steady rate and continuously operate at exactly 25°C working temperature. Better tailored assumptions would be likely to allow more accurate cycle life predictions. Nevertheless, it is clear that a strategic charging system has the potential to dramatically increase the expected lifetime of the battery.

### 3.3.4 Modelling of dynamic cycles

The methodology presented thus far is able to predict the battery lifespan for all scenarios in which an identical charge-discharge cycle is repeated over the full life of the battery. However, in most applications, the cycles change dynamically over time. In electric vehicles, for example, the current input and output needs to change dynamically to provide timely vehicle acceleration and regenerative braking, respectively. And even in a less variable application such as energy storage of surplus renewable generation, day-to-day variations in surplus generation lead to a variability in the cycling depth-of-discharge.

**Rainflow Counting**

To allow dynamic cycling, we have extended the prediction methodology using an approach called rainflow counting. This process combines a data set with non-uniform fluctuations in at least one variable into numerous data sets of uniform fluctuations by prioritising the most extreme fluctuations and discretising. In effect, rainflow counting

![Rainflow Counting Diagram](image)

**Figure 3.13**: Rainflow counting algorithm illustrated on two profiles. Left and right shows the profiles before and after counting a local cycle, respectively.
screens a series of data for subsequent local maxima and minima indicating local cycle loops. Once found, these loops are recorded and removed from the data until the remaining loops become ever larger. It thereby preserves the most significant peaks and troughs to be considered last. The method is traditionally used for predicting material fatigue but has also been proposed for the prediction of battery ageing (e.g. [82]). In many battery applications such as electric cars with regeneration capability, batteries see notable short-term fluctuations in their state-of-charge, while at the same time following overall charge or discharge profiles. Previous experimental research has shown that deep cycling causes the most significant degradation whereas smaller cycles are less significant (e.g. [85]). As a result, rainflow counting is very suitable for modelling battery ageing.

Rainflow counting can be done in the form of either three- or four-point algorithms, which have been shown to be mathematically identical [93]. The three-point algorithm is faster as it only considers the two cycling ranges existing between three points in each iteration, as apposed to four points and three ranges for the four-point method. However, the three-point method requires an initial prearrangement of the data in order to start at either the global maximum or minimum. This inhibits real-time use of the method. To avoid this limitation, we have opted for the four-point approach.

The four-point rainflow counting method works as follows. It takes as input a set of data containing only the turning points. It then steps through this data from start to end, evaluating four turning points at a time. For each set of four points \( P_0, ..., P_3 \), three
associated ranges are calculated:

$$R_k = |P_k - P_{k-1}|$$ (3.64)

where $k \in 1, 2, 3$. For a given set of four points, a local cycle is identified when the middle range has a smaller magnitude than the two outside ranges:

$$(R_k \geq R_{k-1}) \cap (R_{k-2} \geq R_{k-1}) = 1$$ (3.65)

Following identification of a local cycle, the associated points $P_1$ and $P_2$ are recorded and removed from the dataset, and the algorithm continues. As shown in Fig. 3.13, this identification and removal approach works both when a local maximum is followed by a local minimum, and vice versa. Once the end of the data set is reached, the remaining cycles are accounted for through sequential repetition of the remaining points and rerunning the algorithm. When the end is reached the second time, all cycles have been accounted for. A more in-depth explanation of the algorithm as well as the pseudocode used as the basis for our programming code can be found in [93].

Dynamic Cycling Limits

Rainflow counting can be used to deal with variability in individual factor2 or multiple interlinked factors. An example of two interlinked factors, which we use in the demonstration case study in Section 3.3.5, are the maximum and minimum SOC points. As mentioned previously, variability in the depth-of-discharge of a battery is unavoidable for battery systems that are used to support the variable output from renewable generation, e.g. from solar and wind.

Combining Multiple Independent Factors

If only a single independent variable is considered (such as the temperature, or the charging current), the distribution will be one-dimensional. If multiple independent factors are considered to vary simultaneously, then this can be taken into account by recording not
Figure 3.15: Top left: Cycle distribution after rainflow counting; the points represent individual cycles and the colour map indicates frequency of 5x5% sections. Top right: Fractional battery degradation per cycle for each 5x5% section. Bottom centre: Fractional degradation associated with each section for year-long profile.

only cycles to be removed but also the other varying factors. Subsequently the cycles are then discretised in further dimensions (one for each varying independent factor), and the ageing map need to be conducted in an equally multi-dimensional form to allow matching up of cycles with corresponding ageing.

3.3.5 Dynamic Case Study: Storage for Domestic PV

To illustrate this algorithm, we have chosen to focus on the application of Li-ion battery storage for households that have solar panels. In countries where the feed-in tariff for solar generation has dropped below the typical electricity price, households are incen-
tivised to store surplus energy generated for subsequent use. The authors have previously conducted initial simulations to evaluate under which conditions battery storage becomes cost-effective in this context [8]. Here, we will use a randomly-selected simulation profile from the aforementioned paper to demonstrate the proposed ageing model.

Table 3.6: Domestic PV and storage assumptions. Top: application-specific cycling parameters; bottom: nominal battery parameters.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Battery capacity</td>
<td>5 kWh</td>
</tr>
<tr>
<td>Operating temperature</td>
<td>25°C</td>
</tr>
<tr>
<td>Charge current</td>
<td>0.5C</td>
</tr>
<tr>
<td>Discharge current</td>
<td>1C</td>
</tr>
<tr>
<td>Maximum SOC</td>
<td>Dynamic (from profile)</td>
</tr>
<tr>
<td>Minimum SOC</td>
<td>Dynamic (from profile)</td>
</tr>
<tr>
<td>Nominal battery life</td>
<td>1200 cycles</td>
</tr>
<tr>
<td>@ Temperature</td>
<td>25°C</td>
</tr>
<tr>
<td>@ Charge current</td>
<td>0.5C</td>
</tr>
<tr>
<td>@ Discharge current</td>
<td>1C</td>
</tr>
<tr>
<td>@ Depth-of-discharge</td>
<td>80%</td>
</tr>
<tr>
<td>@ Average SOC</td>
<td>60%</td>
</tr>
</tbody>
</table>

Assumptions

The battery profile considers a 5kWh battery installed alongside an Australian household with a 2.5kWp solar panel. The battery operation is optimised from a value-generating perspective that takes into account the electricity and feed-in price, but not the cost associated with battery degradation. It should also be noted that the battery was assumed to be limited to a DOD of 80% as is frequently done to avoid premature battery degradation. A five-day subset of the profile is shown in Fig. 3.14.

For this case study we have chosen the maximum and minimum state-of-charge to vary dynamically from cycle-to-cycle. The operating temperature, as well as the charge and discharge currents, are assumed to be fixed and have the values given in Table 3.6. The turning points fall at the times when the battery current changes direction. That is, the battery transitions either from charging to discharging, or vice versa.
Cycling Frequency

The first step is extracting the turning points from the data set. Next, the 4-point rainflow counting algorithm described in Section 3.3.4 is applied. The counted cycles are then discretised into segments, which we have chosen to be 5% $SOCA_{av}$ by 5% $DOD$.

The top left side of Figure 3.15 illustrates the cycle results. All individual extracted cycles are represented as points, whereas the colour map indicates the frequency of each discretised segment occurring in the one-year profile. It can be seen that by far the most frequent cycle is the maximum allowed battery cycle of 80% $DOD$ and 50% $SOCA_{av}$, corresponding to cycling between the boundaries 10% and 90% SOC.
Degradation

To calculate degradation, the cycling frequency matrix has to be matched with a matrix containing degradation per cycle for each segment. A matrix of cycle lives is found by evaluating ageing using the methodology presented in Section 3.3.2 for the assumptions valid for each individual segment. This is converted to a matrix of degradation per cycle with elements $D_k$ as follows:

$$D_k = \frac{1}{CL_k}$$

(3.66)

The resulting degradation map is shown on the top right side of Figure 3.15. It shows the analogous trend to Figure 3.10 in that the degradation per cycle increases with both increasing depth-of-discharge and when moving towards either extreme of the state-of-charge region.

The predicted battery degradation for the year-long data set can now be found by multiplying each sector frequency with its related degradation per cycle. This leads to the desired annual degradation matrix illustrated in Figure 3.15 bottom centre. The resulting degradation trends are similar to the frequency map, which is to be expected as many cycles of one type are likely to cause a notable degradation. By accumulating all points on the map, the total degradation over the year can be found. Assuming the profile is repeated year-after-year and that degradation occurs linearly, this can be used to estimate the lifetime of the battery cells until the capacity has reduced to a specific point. The results for the domestic PV with storage case study are listed in Table 3.7.

Table 3.7: Degradation result for storage alongside domestic PV generation

<table>
<thead>
<tr>
<th>Degradation over one year</th>
<th>2.19%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lifetime to 70%</td>
<td>13.72 years</td>
</tr>
</tbody>
</table>

3.3.6 Discussion

The empirical life cycle prediction work developed a simple, yet powerful, methodology for predicting battery degradation rates and life spans that takes into account multiple impact factors. The significant increase in life found during the mobile phone case study
demonstration of the static model suggests opportunities for charging solutions that improve battery management without requiring any user input or change in behaviour. The resulting methodology provides a basis for conducting evaluations of battery life and optimisation of battery management for any battery-related applications.

Three specific advancements were made in this work to the underlying state-of-the-art model:

1. An empirically-supported model of how battery cycle life varies with interdependent average state-of-charge and depth-of-discharge was developed and demonstrated.

2. A reproducible framework for combining numerous independent cycle life models considering different impact factors into a unified multi-factor cycle life model was presented.

3. A technique for enabling battery life prediction models to assess battery usage with dynamically changing cycling parameters was developed and demonstrated.

Future work to be done on this model is to extend the validation of the impact factor models against further experimental data. In particular, the individual factor models need to be evaluated for different cell chemistries to ensure suitability. Further factors should also be considered for inclusion in the methodology. One obvious such factor is the impact of resting periods between cycles, which over short times can lead to recovery effects but over long periods must include elements of calendar ageing.

3.4 Conclusions

The modelling work in this thesis developed two different models investigating two respective aspects of battery cell differences: state-of-charge differences due to self-discharge and capacity differences due to battery ageing.

Given the weakest link characteristic in series-connected battery packs, non-uniform battery ageing is not desirable as the cell with the lowest capacity will limit the entire series-string. Non-uniform self-discharge leading to state-of-charge differences is not as
critical as it can be reversed using cell balancing systems. Balancing, however, brings with it its own challenges and inefficiencies as discussed in more detail in Chapter 5.

In both cases, operating temperature and state-of-charge are found to have strong impacts. This highlights the importance of both good thermal management and cell equalisation in multi-cell battery packs. By maintaining a uniform temperature profile across individual battery cells in a pack, thermal management ensures even self-discharge and battery ageing, thereby preventing a myriad of issues. Cell equalisation for its part counteracts reversible self-discharge and thereby keeps individual cells from entering high or low state-of-charge regions, thereby similarly avoiding uneven reversible self-discharge and permanent ageing in individual cells.
Chapter 4

Experimental Study of Li-Ion Cells

Introduction to Chapter 4

The modelling in Chapter 3 identified two processes, reversible self-discharge and capacity fade, which over time can cause cell-to-cell differences in state-of-charge and charge storage capacity, respectively. However, these processes do not account for discrepancies between in batteries at the beginning of life caused by inevitable variations in manufacturing processes.

There are many different cell manufacturers that offer a wide variety of battery cells to both corporate and personal customers. Unfortunately, reliable information on the physical dimensions and electrical characteristics can be difficult to obtain for many cells. High-end suppliers commonly provide data sheets that contain technical product information including factors such as size, weight, capacity, voltage profile and cycle life, as well as some limited measurement data to support these numbers. Low-cost products are frequently supplied only with a nominal capacity rating, without any measurement data. Where available, the ratings are typically based on in-house testing without independent verification. As a result, adequately investigating the cell-to-cell differences in the beginning of life required experimental testing of batteries.
4.1 Related Work

4.1.1 Physical parameters

Not all important aspects of batteries are related to the electrical performance. Additional important characteristics of battery cells include the physical size, weight and shape. Commercial Li-ion batteries come in many shapes and sizes \[48\]. The most common Li-ion battery format is termed ‘18650’, and denotes cylindrical cells with a diameter of 18mm and a length of 65mm. Originally intended for use in laptops, the resulting economy of scale of 18650-format cells has led to adoption in other applications including many power tools, electric bicycles and Tesla Motors’ electric cars. The widespread use, as well as the predefined format against which actual sizing can be compared, make 18650 cells particularly interesting for study. For any application offering flexibility regarding the shape of the battery, the physical parameters should be compared in direct correspondence with the electrical performance. Specifically, choosing cells represents a trade-off between high capacity, charge and discharge capabilities, low weight and size, as well as cost.

4.1.2 Capacity Measurement

Important short-term electrical characteristics include maximum and minimum voltage limits, maximum charge and discharge current capabilities, the capacity of the cell at the beginning of life for different charging and discharging rates and temperatures as well as the output voltage for different currents and states-of-charge. Table 4.1 summarises findings of a range of initial capacity tests of 18650 cells published in the literature. The results show that the measured capacity of commercial 18650 cells can deviate somewhat from the nominal capacity. Note that the rate in the table is the C-rate, a normalised current parameter that is calculated by dividing the applied discharge current by the cell capacity. As an example, discharging a 1.9Ah cell at a current of 0.95A corresponds to a C-rate of $1/2 \ C$, which is typically shortened to C/2.
4.1 Related Work

Table 4.1: Initial Capacities of Commercial 18650-Format Cell Capacity Studies in Literature

<table>
<thead>
<tr>
<th>Author</th>
<th>Cell Type (Quantity)</th>
<th>Nominal Cap.</th>
<th>Capacity\textsuperscript{a}</th>
<th>Spread\textsuperscript{b}</th>
<th>@ Rate</th>
<th>@ Temp\textsuperscript{c}</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dubarry \textsuperscript{[94]}</td>
<td>Unknown (10)</td>
<td>1.9Ah</td>
<td>99.4%</td>
<td>0.2%</td>
<td>C/2</td>
<td>23°C</td>
</tr>
<tr>
<td>Dubarry \textsuperscript{[94]}</td>
<td>Unknown (10)</td>
<td>1.9Ah</td>
<td>102.6%</td>
<td>0.2%</td>
<td>C/25</td>
<td>23°C</td>
</tr>
<tr>
<td>Ecker \textsuperscript{[85]}</td>
<td>Sanyo UR18650E (2)</td>
<td>2.05Ah</td>
<td>97.9%\textsuperscript{d}</td>
<td>1.2%\textsuperscript{d}</td>
<td>C/4</td>
<td>35°C</td>
</tr>
<tr>
<td>Ecker \textsuperscript{[85]}</td>
<td>Sanyo UR18650E (2)</td>
<td>2.05Ah</td>
<td>97.5%\textsuperscript{d}</td>
<td>2.8%\textsuperscript{d}</td>
<td>C/4</td>
<td>50°C</td>
</tr>
<tr>
<td>Mulder \textsuperscript{[48]}</td>
<td>Unknown\textsuperscript{f} (5)</td>
<td>2.3Ah</td>
<td>93.5%</td>
<td>0.4%\textsuperscript{f}</td>
<td>1C</td>
<td>23°C</td>
</tr>
<tr>
<td>Mulder \textsuperscript{[48]}</td>
<td>Unknown\textsuperscript{f} (5)</td>
<td>2.5Ah</td>
<td>97.2%</td>
<td>1.2%\textsuperscript{f}</td>
<td>1C</td>
<td>23°C</td>
</tr>
<tr>
<td>Reichert \textsuperscript{[95]}</td>
<td>A123 APR18650-M1A</td>
<td>1.1Ah</td>
<td>102.0%\textsuperscript{g}</td>
<td>2.8%\textsuperscript{g}</td>
<td>1C</td>
<td>20°C</td>
</tr>
<tr>
<td>Reichert \textsuperscript{[95]}</td>
<td>Samsung ICR18650-Z6F</td>
<td>2.6Ah</td>
<td>100.3%\textsuperscript{g}</td>
<td>1.18%\textsuperscript{g}</td>
<td>1C</td>
<td>20°C</td>
</tr>
<tr>
<td>Stiaszny \textsuperscript{[96]}</td>
<td>Unknown (6)</td>
<td>2.0Ah</td>
<td>101.5%\textsuperscript{h}</td>
<td>7.3%\textsuperscript{h}</td>
<td>C/2</td>
<td>23°C</td>
</tr>
<tr>
<td>Stiaszny \textsuperscript{[96]}</td>
<td>Unknown (6)</td>
<td>2.0Ah</td>
<td>95.5 %\textsuperscript{h}</td>
<td>≤ 1.3%\textsuperscript{h}</td>
<td>1C</td>
<td>23°C</td>
</tr>
</tbody>
</table>

\textsuperscript{a} Average of measured cell capacities. \textsuperscript{b} Difference between maximum and minimum unless otherwise specified. \textsuperscript{c} Room temperature was assumed to be equivalent to 23 °C. \textsuperscript{d} Approximation from the non-normalised curves in Figs. 19a, 20a, 21a and 22a of reference [85]. \textsuperscript{e} Specified as cylindrical cells, which given the capacity are likely either 18650 or slightly larger 26650 cells. \textsuperscript{f} Standard deviation value, as individual values are not published. \textsuperscript{g} Approximation from the zero-cycle points in Figs. 8, 9, 14 and 15 of reference [95]. \textsuperscript{h} Approximation from the zero-cycle points in Fig. 5 of reference [96].

4.1.3 Capacity Fade Measurement

In the long-term, the performance of battery cells in practical applications is a factor of how little the capacity and the resistance changes as an interdependent function of both time and cycling. Of particular interest for the work in this thesis is how the cell-to-cell variations in multiple battery cells of the same make, or at least of identical formats, develop during cycling.

Paul \textit{et al.} tested an automotive battery pack consisting of 96 cylindrical 4.4Ah LiFePO\textsubscript{4} cells \textsuperscript{[97]}. The cells underwent a hybrid-typical driving profile making up an energy throughput of 140kWh, corresponding to around 100 full cycles. At the beginning of the experiment, the charge capacity spread among the cells in the pack was measured to be around 4.5% of nominal capacity. Over the first 15 equivalent full cycles, the deviation decreased to about half. Following this, however, it began to increase again and by the end of the experiment had reached over 11% of nominal charge capacity.

Baumhöfer \textit{et al.} conducted testing on 48 Sanyo UR18650E cells offering a mean capacity of 1.85Ah. At the beginning of life the cell spread was approximately 1.5%. Cycling between SOC boundaries of approximately 80-20%, first saw a slow increase in spread
to around 7% of nominal over 950 full equivalent cycles and then an increase to 24% of nominal over a further 650 cycles. This specific data set is shown in Fig. 5.15 as it is used as a baseline for testing in Chapter 5.

Collectively, these papers highlight a trend of increased cell-to-cell capacity variations during battery use. However, prior to the work conducted in this thesis, it was not known how these trends differ across the full spectrum of commercial battery cells from premium cells to low-cost products.

4.1.4 Cell Impedance Measurement

The cell impedance, frequently called internal resistance, of a battery cell defines the energy losses within a battery cell for a specific current, and thereby the maximum power a battery cell can safely accept or provide without overheating. The widely used terminology of internal resistance is misleading as battery cells are not purely resistive and have reactive elements inside them. We will therefore opt to use the terminology of cell impedance here. The cell impedance is further known to vary significantly with both cell state-of-charge and operating temperature, necessitating multiple measurements per cell in order to assess cell suitability for a specific application [75]. There are two predominant methods used to test cell impedance: pulse testing, and electrochemical impedance spectroscopy.

In pulse testing, a cell begins at rest and is then subjected to a multi-second pulse before returning to rest [75]. A constant current pulse is used most commonly, although constant voltage or constant power pulses are also feasible [98]. Typically this is either a charging pulse, a discharging pulse, or one of each with a break in-between. The cell impedance can be calculated both at the onset and offset of a pulse.

Assuming a discharging pulse at constant current $I_{\text{pulse}}$, the internal impedance $Z_{\text{cell}}$ can be found via Ohm’s law as follows:

$$Z_{\text{cell}} = \frac{V_{\text{rest}} - V_{\text{pulse}}}{I_{\text{pulse}}} \quad (4.1)$$

where $V_{\text{rest}}$ is the cell voltage measured at rest either before or after the pulse and $V_{\text{pulse}}$
is the cell voltage during the pulse.

Due to the reactive effects of the battery cell, the timing of the voltage measurements determines what aspect of the impedance is measured. At the current onset or offset, the resistive part of the impedance has an immediate effect. Conversely, limitations in charge transfer and diffusion have a capacitative element and therefore are associated with a certain time constant, which leads the voltage to change over time.

Electrochemical impedance spectroscopy is a method of cell impedance measurement that avoids issues with measurement timing by shifting analysis into the frequency domain. Instead of a steady state pulse, the battery cell is subjected to sine-wave signals, typically in terms of voltage. By conducting testing over a broad range of frequencies potentially from partial hertz to hundreds of kilohertz, the time constants of electrochemical processes within the battery cell are analysed [75].

Figure 4.1 illustrates the output of EIS measurement in a Nyquist plot. For each frequency, the real part of the impedance is plotted against the imaginary part of the impedance. The resulting trace provides insight into the makeup of the battery. At very high frequencies, the plot is dominated by inductive parameters typically associated with cabling. At very low frequencies, the plot is dominated by capacitive parameters inside the cell. The region of predominant interest lies in-between.

![Figure 4.1: Nyquist plot illustrating results of electrochemical impedance spectroscopy of a Panasonic NCR18650A cell.](image)
The value of the real axis at the point where it is crossed by the plot denotes the value of the standard series resistance in the electrochemical circuit model. This corresponds to the impedance corresponding to the immediate voltage drop for pulse measurements, usually occurs at frequencies around 1kHz, and is the point that most clearly allows comparison between cells [98]. At frequencies slightly lower than this, up to two semi-circles occur. If two are present, then the higher frequency semi-circle represents chemical processes in the solid-electrolyte interface and the lower frequency semi-circles represents the charge transfer. The semi-circles can in some cases however also be sufficiently closely lumped to seem as one, as is the case in the example shown in Fig. 4.1 approximately between 876 and 1Hz. Finally, the upwards tail at the end of the curve is related to the intercalation reaction [75].

Pulse testing is frequently used to investigate cell suitability at high-power applications where high-frequency sine-signal generation represents a technically challenging and expensive endeavour. For general purpose applications, however, electrochemical impedance spectroscopy provides deeper insight into cell behaviour and is therefore recognised as the state-of-the-art [75]. As such, electrochemical impedance spectroscopy was chosen as the cell impedance testing approach for the cell-level experimental work conducted as part of this thesis.

4.2 Testing Methodology

We conducted testing for five types of 18650-format Li-ion cells made by three different manufacturers: Panasonic, Sanyo and UltraFire (shown in Fig. 4.2). The testing includes initial weight, size, capacity and electrochemical impedance spectroscopy (EIS) measurements, between 40 and 80 full ageing cycles, and final capacity and EIS measurements. Four battery cells of each type were tested, although for cycle ageing these were split into two sets of two cells per type, which were exposed to different depths-of-discharge.

This testing methodology is designed as a repeatable experiment for batteries used across a broad spectrum of potential applications. Nonetheless, it yields key aspects that are critical in electric vehicle battery systems, including specific energy, energy density,
cell impedance, cell capacity and variation, and cell ageing. Due to the broad spectrum of cells tested, it was considered that using electric vehicle typical drive cycles for cycle ageing could impede comparability. To avoid this, standard constant charge and discharge profiles were implemented in this work.

Figure 4.2: Tested cells, from left to right: UltraFire TR18650 4200mAh (UF4.2), UltraFire TR18650 4900mAh (UF4.9), Sanyo UR18650FM (San2.6), Panasonic NCR18650A (Pan3.1) and Panasonic NCR18650B (Pan3.4).

4.2.1 Testing procedures

The testing procedure for each cell consisted of six stages as shown in the scheme presented in Fig. 4.3. In the first stage the capacity of cells at beginning-of-life was measured over eight charges and discharges. A constant current, constant voltage (CC-CV) process was applied for charging. In the first stage a constant current of 1A was applied until the cells reached the maximum voltage of 4.2A. Once this voltage was reached, the current was progressively reduced in such a way that the terminal voltage remained equal despite further charging. When the current reached a nominal minimum value set at 50mA, the charging process terminated. Discharge was conducted as a pure constant current process at 1A. For the first five cycles all cells were discharged to 2.8V. For the sixth to eighth cycle, the Panasonic cells were discharged to 2.5V, while the remainder
were discharged to the same 2.8V as previously. This was done to allow comparability between different cells, while also enabling an evaluation of the additional capacity offered by the lower minimum limit of 2.5V specified for the Panasonic cells. The approach of using CC-CV for charging and CC for discharging is frequently chosen for testing. CC discharging is chosen because many applications for batteries are unable to operate at a reduced power throughput as is required for a constant voltage discharging stage.

The second stage consisted of testing focussed on the dimensions and weight of the cells. This was done in order to enable comparisons of the energy density (energy per unit volume) and specific energy (energy per unit weight) between different cells. Due to the weight and size constraints in mobility applications, energy density and specific energy are among the most crucial parameters.

The third and final step of the initial testing was to conduct electrochemical impedance spectroscopy (EIS). For this testing method, alternating voltages with a range of frequencies are applied consecutively in order to determine the impedance behaviour of battery cells. Based on the interesting regions identified in [75], we selected the frequency range of 0.1Hz and 100 kHz.

The fourth step focussed on the ageing of cells. Of the four cells of each type, two cells underwent the same full cycles between voltage limits of 2.8 to 4.2V as were used for the initial capacity tests. The two remaining cells of each type instead underwent partial cycles following the same current limits as for the full cycle test but between a narrower voltage range of 3.2 to 4.0V. To provide comparability, each tenth cycle of the partial ageing was conducted as a full cycle. This division of the ageing process into partial and full cycles was done in order to evaluate the performance of cells in certain real-life applications where full cycles are not always required and the associated increased ageing near the voltage boundaries can be avoided. To incorporate the effect of limited charging time, the constant voltage charging stage of the comparison cycles terminated when the current had either reduced to 50mA or one hour of time had passed.

Following the cycle ageing, the cells remained at a resting state for a duration of several days to several weeks depending on when the respective cycles had concluded. The fifth stage was then to conduct a final capacity test, which was identical to the initial
4.2 Testing Methodology

The sixth and final stage of the testing was a second EIS analysis of all cells.

![Testing procedures diagram](image)

Figure 4.3: Testing procedures

4.2.2 Experimental Set-Up

The initial and final capacity testing as well as the ageing studies were conducted using a MACCOR 4000 Series multi-channel battery cycler. Battery cells were connected using commercially available 18650 battery holders, which had their coils removed and wires replaced in order to decrease the connector resistance. Furthermore four-terminal sensing was used to minimise the measured voltage drop due to applied currents. For safety purposes, cells being cycled were placed into sand-filled containers. This allows any electrolyte leakage to be contained and provides a heat-tolerant surface. The testing set-up for two cells is shown in Fig. 4.4. Note that voltage measurements are taken directly from the surface of the cells, whereas the currents are applied via the replaced wires.

Electrochemical impedance spectroscopy was conducted using a BioLogic VMP3. The cells were attached in exactly the same fashion as during the capacity testing described
Figure 4.4: Cell testing set-up for capacity and ageing tests

above.

The length was measured using a vernier calliper with doubly folded sheets of paper used as electrical insulation on the terminals, the thickness of which was subsequently subtracted from the measurements. For measuring the diameter, a digital micrometer screw gauge was used to determine the thickest point of the cell. For most cells this point was near the positive terminal with the exception of the UltraFire 4200mAh cells for which it was located near the negative terminal. The weight was measured using a Mettler AE 260 DeltaRange balance.

Regarding the tested cells, it should also be noted that there exists some uncertainty regarding the manufacturer of the UltraFire cells. On online marketplaces in Australia and several other countries, UltraFire-branded cells make up the majority of highly-ranked search results for 18650 cells. This suggests a high number of sales of these cells. However, on several forums and webpages it has been suggested that some UltraFire-branded cells may be made by manufacturers other than the original UltraFire company itself. Given this uncertainty regarding the manufacturer, the UltraFire cells should there-
fore be regarded more as an example of a generic, low-cost products rather than a specific type and brand of cells.

4.3 Initial Testing

4.3.1 Physical Dimensions and Weight

In order to compare the specific energy (energy per unit weight) and energy density (energy per unit volume) of the cells, both the physical dimensions and the weight of the cells had to be determined. Measuring the physical dimensions further provided feedback regarding how closely manufacturers were following the 18650 format, which specifies cells to have an 18mm diameter and 65mm length.

The results are listed in Table 4.2. All cells tested exceeded the nominal diameter of 18mm and all but the San2.6 cells exceeded the nominal length of 65mm. All cells remained within 1.6% of the specifications with the exception of Pan3.4 cells, which exceeded the diameter and length by 3.2% and 3.6%, respectively. This is a significant deviation from the specified standard and needs to be considered by designers of large battery packs with several tens to thousands of cells. It also has a notable impact on the energy density of the cells, which will be discussed in the following section.

4.3.2 Initial Capacity Results

Table 4.2 also shows the results of the initial testing of the cells. In the initial testing regime, the Panasonic and Sanyo cells all achieved over 92% of their rated charge capacity. The UltraFire cells on the other hand perform much worse, with the 4.2Ah and 4.9Ah cells only achieving 18% and 12% of their rated charge capacity, respectively. The slight differences between the rated and measured values of the Panasonic and Sanyo cells can reasonably be viewed as a product of minor variations in the applied charge and discharge cycles. In fact, the Panasonic cells are rated to be discharged to a lower voltage cut-off of 2.5V, which was found to increase their charge capacity by a further 3%. Furthermore, continuing CV charging to a lower current cut-off, discharging at a lower rate
Table 4.2: Initial Capacities and Physical Dimensions

<table>
<thead>
<tr>
<th></th>
<th>Pan3.1</th>
<th>Pan3.4</th>
<th>San2.6</th>
<th>UF4.2</th>
<th>UF4.9</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nom. Charge Capacity (mAh)</td>
<td>3100</td>
<td>3400</td>
<td>2600</td>
<td>4200</td>
<td>4900</td>
</tr>
<tr>
<td>Meas. Charge Capacityb (mAh)</td>
<td>2862 (2961)</td>
<td>3166 (3267)</td>
<td>2480</td>
<td>757.1</td>
<td>579.4c</td>
</tr>
<tr>
<td>Meas. Charge Capacityb (%)</td>
<td>92.3 (95.5)</td>
<td>93.1 (96.1)</td>
<td>95.4</td>
<td>18.0</td>
<td>11.8c</td>
</tr>
<tr>
<td>Meas. Energy Capacity (Wh)</td>
<td>10.19 (10.61)</td>
<td>11.33 (11.78)</td>
<td>9.25</td>
<td>2.74</td>
<td>1.96</td>
</tr>
<tr>
<td>Measured Weight (g)</td>
<td>44.66</td>
<td>46.70</td>
<td>45.62</td>
<td>32.24</td>
<td>37.98</td>
</tr>
<tr>
<td>Measured Lengthc (mm)</td>
<td>65.08</td>
<td>67.34</td>
<td>64.96</td>
<td>65.74</td>
<td>65.44</td>
</tr>
<tr>
<td>Measured Diameterc (mm)</td>
<td>18.28</td>
<td>18.57</td>
<td>18.28</td>
<td>18.27</td>
<td>18.22</td>
</tr>
<tr>
<td>Specific Energy (Wh/kg)</td>
<td>228.3 (237.6)</td>
<td>242.6 (252.3)</td>
<td>202.8</td>
<td>84.8</td>
<td>51.6</td>
</tr>
<tr>
<td>Energy Density (Wh/l)</td>
<td>596.9 (621.3)</td>
<td>621.3 (646.2)</td>
<td>542.6</td>
<td>158.7</td>
<td>114.8</td>
</tr>
<tr>
<td>Cost per Cell (AU$)</td>
<td>11.48</td>
<td>13.48</td>
<td>5.31</td>
<td>1.45</td>
<td>1.63</td>
</tr>
<tr>
<td>Cost/Meas. Capacity ($/kWh)</td>
<td>1125.9 (1081.8)</td>
<td>1189.7 (1144.0)</td>
<td>574.1</td>
<td>530.1</td>
<td>831.7</td>
</tr>
<tr>
<td>Cost/Meas. SE ($kg/kWh)</td>
<td>50.29</td>
<td>55.56</td>
<td>26.19</td>
<td>17.09</td>
<td>31.59</td>
</tr>
</tbody>
</table>

aUnless state otherwise, all values are an average value for four cells. b Average of first five complete discharge processes from 4.2-2.8V; in brackets: first subsequent 4.2-2.5V discharge processes if applicable. cAverage of three cells only as fourth failed to charge or discharge entirely. dValues for one cell only. eMeasured at the thickest point, which is usually found near the positive end of the cell.

and discharging and conducting the charge and discharge processes at specific temperatures may well compensate for the remaining difference of 5%.

The factor of five difference between the rated and measured charge capacity of the UltraFire cells on the other hand cannot be explained by the applied cycling regime or ambient conditions. The incredible magnitude of the discrepancy, as well as the fact that the higher rated UltraFire cells performed even more poorly than the lower rated cells, casts some doubt on the validity of experimentation used to develop these capacity ratings.

4.3.3 Initial Capacity Discussion

Despite nominally all being 18650 cells, some were found to deviate from the format notably. Not only do these variations pose issues in terms of standardisation and replaceability of cells in applications, but they can also considerably distort analyses of battery development trends that use the format as a baseline for comparing energy densities.

Initial capacity testing found that the tested cells from well-known manufacturers (Panasonic and Sanyo) provided within 8% of their rated capacity. The two much cheaper
4.4 Cycle Ageing

In order to assess the impact of ageing, all cells were subjected to repetitive charge-discharge cycles following the initial testing. Of the four cells of each type, two underwent charge-discharge cycles between 2.8V and 4.2V, described from here on as full cycles. Like the initial characterisation cycles, the full cycles consisted of a constant-current, constant-voltage process with upper and lower limits as mentioned previously and a current limit of 1A. The cut-off current for the constant-voltage charge was chosen as 0.05A (or around 1/50C for the San2.6 cells which nominally have the lowest capacity). Following each charge and discharge step, the cells rested idle for 30 minutes. Partial cycles followed the same process, with the sole difference that the lower voltage limit was set to 3.2V and the upper voltage limit was set to 4.0V.

To provide a common basis for comparison, on every tenth cycle a special comparison cycle was run. These comparison cycles formed a basis of comparison between the cells undergoing full cycles and those undergoing partial cycles. While the comparison cycles adhered to the same voltage limits as the full cycles, the constant-voltage charging cut-off point was set as either the 0.05A as for the full cycles or one hour of charging, whichever came first. This cut-off criterion was considered to be a better simulation of real-life usage in which the charging time of the battery is finite and the full constant-voltage charge may not be completed if it takes too long. An example 10-cycle segment of one cell is illustrated in Fig. 4.5. By comparing the amount of energy stored during the constant-voltage process, it can be seen that for the cell illustrated, the charge in the comparison cycle was terminated due to the time limit rather than the current rate limit.
4.4.1 Full Cycle Ageing Results

Fig. 4.6 shows the capacity fade of the cells that underwent full cycles. Despite the 50-130 cycles undergone representing only a relatively small fraction of the commonly assumed Li-ion cycle life of several thousand cycles, a general ageing trend is clearly visible. While the Panasonic and Sanyo cells show a capacity decrease of only 5-10%, the UltraFire cells vary much more significantly. As mentioned previously, one cell failed to charge or discharge at all. Of the remaining three UltraFire cells, two cells showed only minor decreases in capacity, while the third showed dramatic loss of 80% of the initial capacity over 100 cycles.

4.4.2 Partial Cycle Ageing Results

Literature has shown that cells age especially strongly when cycled in the very high and very low SOC regions [85]. As a comparison to the full cycles, partial cycles were therefore implemented, which followed the exact same protocol with the exception of using lower and upper voltage limits of 3.2 and 4.0V, respectively. The main goal of this testing stage was to evaluate whether a small reduction in the depth-of-discharge offers signif-
icant benefits in cycle life for the cells considered. This addresses the decision between buying expensive higher capacity cells to cycle partially with potentially notably higher lifespans or buying lower capacity cells with potentially lower lifespans but which can be replaced at low cost. Based on this underlying focus, the goal was to limit the increased ageing which happens near the upper and lower bounds as much as possible while still maximising the useful capacity. The initial characterisation found the voltage-capacity slope to be considerably steeper at the end of discharge than at the end of charge for most cells. Therefore, an increase of the lower voltage limit represents less capacity loss than a the same magnitude of decrease in the upper voltage limit. As a result, for partial
cycles the lower limit was raised notably more than the upper limit was lowered.

Fig. 4.7 illustrates how partially cycled cells aged as compared with fully cycled cells. For the Sanyo and Panasonic cells there is a clear trend whereby partially cycled cells age less with each cycle than fully cycled cells, following expectations. However, due to partially cycled cells absorbing and supplying less charge and energy in each cycle than fully cycled cells, a comparison on the basis of cycles is somewhat less meaningful than a comparison on the basis of cumulative energy throughput as is shown in Fig. 4.8.

Comparing the cells by fitting linear curves to the energy throughput measurements
yields a non-conclusive result (see Table 4.3). While for both types of Panasonic cells and the UF4.9 cells the partial cycles lead to a lower average degradation per energy throughput than full cycles, the San2.6 and UF4.2 cells find that partial cycles lead to a higher degradation. This inconsistent result suggests that the sample size of two cells per type and discharge cycle is insufficient for conclusive studies of the impact of slight cycle variations on ageing.

4.4.3 Differential Capacity Analysis

Differential capacity analysis, sometimes also referred to as incremental capacity analysis, is a further in-depth method of analysing battery behaviour and degradation.

In the journal paper on battery testing [3], Anand Bhatt from the CSIRO led this analysis, so this will not be outlined in detail in this thesis.

4.5 Electrochemical Impedance Spectroscopy

Figure 4.9: Measurement variations during final EIS testing between frequencies of 0.1Hz and 100 kHz

4.5.1 Testing Methodology

To evaluate not only capacity fade but also power fade, EIS measurements were taken after both the initial and the final capacity testing. Over the frequency range of 0.1Hz to 10kHz, at each of six logarithmically distributed frequency points per order of magnitude, five measurements were taken and averaged. Additionally, during the final testing,
one Pan3.4 cell and one UF4.9 cell were randomly selected to be tested ten times each in a number of different holders, being disconnected between each trial. The purpose of this testing was to determine the extent to which battery holders impact the impedance measurements of cells.

The curves for the two cells that were tested ten times, are shown in Figure 4.9. In both cases it can clearly be seen that slight changes in connection with the holder lead to some variations in terms of the real impedance only, very little variation being notable in terms of the imaginary impedance. The differences were found to increase with a decrease in frequency. For the testing of Pan B cells, the maximum variation in real impedance was found to be around 5mΩ, or around 10% of the resistance at the crossing of the zero imaginary resistance point, whereas for the UF4.9 cells it was around 60mΩ, or around 30% of the imaginary zero-crossing point. Combining the variances from both cells, the standard deviation is found to be 12.7mΩ. This is relevant for determining the importance of our EIS measurement results.

To evaluate the power fade of the cell, initial and final EIS measurements were compared for a frequency of 876Hz. This frequency represented the closest measured point to the 1kHz frequency, which is widely used as a standardised characterisation point of batteries. At the 876Hz point, all cells were very close to the imaginary zero-crossing and
for both initial and final measurement had imaginary impedances of less than 6% of the real impedance.

![Graph showing EIS curves](image)

**Figure 4.11: Initial (top) and final (bottom) EIS curves.**

### 4.5.2 Results

The results as shown in Figure 4.10 show that the majority of cells increased in impedance by a number of percentage points. While the real impedance measurements for cells UB3, UA3 and PA1 decreased, the measured impedance of all twelve other cells increased. While this suggests some trends, the main value of the findings were not in the change of impedance but in the initial values themselves. While the Sanyo and Panasonic cells all show real internal resistances of around 50mΩ for the frequency considered, the UltraFire cells show impedances two to nine times higher. This highlights a further significant issue with the lower priced cells. Higher impedances not only reduce the energy storage efficiency of the cells but also increase the amount of heating that a given current generates. As elevated temperatures can lead to notable degradation and potential safety concerns for Li-ion cells, this is highly undesirable. All measured EIS curves are shown in Figure 4.11.
In the journal paper on battery testing [3], further analysis on cell EIS curves was conducted by Anand Bhatt from the CSIRO to determine further prospective causes for the cell performance differences. The results, mentioned here for reference only, indicated that the internal resistances, outlined above and likely linked to worse electrolyte and separator quality, represented the dominant difference in the UltraFire cells. Minor differences in SEI capacitance were found between cells manufactured by Panasonic and Sanyo.

![Figure 1: Opened UltraFire-labelled cell consisting of large shell with small internal cell (republished with permission from [1])](image)

![Figure 2: CT scans of typical and UltraFire-labelled cells (published with permission from [2])](image)

4.6 Destructive Analysis

Following publication of the comparative testing study of commercial battery cells described in Sections 4.2-4.4, a diligent reader brought to our attention further inconsistencies in cells sold under the UltraFire label. As shown in Fig. 4.12, contributors to online forums physically opened such cells up to find a large shell containing a much smaller cell within [100]. Our reader confirmed that some UltraFire cells opened by his research group had shown a similar internal structure. Their analysis found other UltraFire cells
contain only very short electrode foils, which as shown in Fig. 4.13 filled the cell only partially.

<table>
<thead>
<tr>
<th>18650 Cell</th>
<th>Side view</th>
<th>End view</th>
</tr>
</thead>
<tbody>
<tr>
<td>Typical</td>
<td><img src="image1.png" alt="Typical Side View" /></td>
<td><img src="image2.png" alt="Typical End View" /></td>
</tr>
<tr>
<td>UltraFire 3800mAh</td>
<td><img src="image3.png" alt="UltraFire Side View" /></td>
<td><img src="image4.png" alt="UltraFire End View" /></td>
</tr>
</tbody>
</table>

Figure 4.13: CT scans of typical and UltraFire-labelled cells (supplied by J. Dahn’s research group, published with permission in [4])

In response to these revelations, which added to the unfavourable findings regarding UltraFire-labelled cells published in our paper, our research team disassembled the cells we had previously tested. Tony Hollenkamp from the CSIRO conducted the physical opening of cells and the author of this thesis led the analysis and dissemination of results.

As can be seen in Figs. 4.14 and 4.15 below, neither sample of the tested UltraFire cells was found to contain a smaller cell unit inside. Cross-wide dissection of a further UltraFire cell sample shown in Fig. 4.16 did not highlight obvious unfilled spaces in the cell.

However, the cells were nonetheless found to have exceptionally small electrode foils for 18650 cells. As listed in Table 4.4 the UltraFire cells comprised only 73% and 74% of the area of the Sanyo and Panasonic cells, respectively. Opened samples of the tested Sanyo and Panasonic cells are shown in Fig. 4.17.

Small electrode foil area directly contributes to both low cell capacity and high cell impedance. It is therefore highly likely to be a key cause of the low testing performance identified in our research. Determining to which extent additional factors such as component quality also play a role is a prospective topic for further research work.
4.7 Differences between Identical Cells

As opposed to the earlier sections in this chapter investigating differences between cells of different types, this section specifically looks at the differences between cells of the same type.

Figure 4.18 shows the results of the initial capacity testing. All cells were delivered in a partially-charged state, which explains why the very first charge was a partial charge. During the fifth cycle, one of the UltraFire cells exhibited unexpected intermittent behaviour. Since the cell returns to suitable operation immediately after, the cause is presumed to be in an intermittent problem on the testing unit as opposed to the cell itself. From cycle seven onwards, the Panasonic cells underwent cycling to a lower voltage limit of 2.5V, which is responsible for the rise in capacity seen at this point. As a result, cycles two through to four were chosen as the basis for an analysis of cell-to-cell differences.
4.7 Differences between Identical Cells

The results of the analysis are listed in Table 4.5. Of particular interest here is the standard deviation between the four cells of each kind. For both types of Panasonic cell, the standard deviation for both charging and discharging is between 0.5-1%. For the Sanyo cells, the standard deviation was higher at 2%, whereas the UF4.2 cells, a standard deviation of around 3.5% is seen. For the UF4.9 cells, it was 13%, however it should be noted here that this is significantly influence by the single battery cell that failed entirely.

While at four cells per type, the sample size is far too small to provide statistical certainty, the findings do indicate two trends. Firstly, in agreement with the findings in related art outlined in section 4.1.2, it is found here that even at the very beginning of
life, there are distinct variations in the charge capacity of battery cells. And secondly, the cell-to-cell differences increased significantly with decreasing cell cost.

Due to the division of the four cells of each type into two streams, one undergoing full cycles and the other partial cycles, the sample size of cells with an identical manufacturer and usage history was reduced to two. This was deemed insufficient to draw conclusions from, so no post-ageing analysis of cell-to-cell differences was done.

### 4.8 Conclusions

This Chapter outlined the work done and results obtained during an experimental study investigating the performance of commercial 18650-format battery cells. Five types of cells were tested: two types of Panasonic cells, one type manufactured by Sanyo, and
two types sold under the UltraFire label.

In terms of physical parameters, the low-cost UltraFire cells were found to weigh 15-30% less than the Sanyo and Panasonic cells. It further found the Panasonic cells with the highest rated capacity to exceed the nominal 18650-format by more than 3% in terms of both length and diameter. This divergence from the format needs to be considered by both battery pack-designers as well as anyone comparing battery cell performance on the basis of their format.

During cycle ageing at currents of 1A, corresponding to 0.3 - 0.5C of the nominal cell
capacity, the Panasonic and Sanyo cells degraded at a relatively similar rate. These cells showed around 2-6% degradation over an energy throughput of 700Wh, equivalent to roughly 50-80 full cycles depending on the individual cell capacity. The lower-priced UltraFire cells performed less well, showing at best a 6% degradation over only 300Wh and at worst more than 10% degradation after less than 30Wh of throughput. On the basis of energy throughput, the testing did not conclusively show any differences in capacity degradation trends between cells aged using full cycles between 2.8 - 4.2V and cells aged using partial cycles between 3.2 - 4.0V.

Electrochemical impedance spectroscopy testing found the UltraFire cells to have internal resistances of two to nine times that of the Panasonic cells. This highlights a significantly lower energy efficiency and notably higher heat generation during use for these cells.

In destructive analysis, the UltraFire cells were shown to have an electrode foil around 25% smaller than the Sanyo and Panasonic cells. This represents a clear contribution towards both the lower weight, the low capacity, and the high cell impedance.

An analysis regarding cell-to-cell differences in capacity at the beginning of life found
all cells to show considerable cell-to-cell deviation and variability was found to increase with decreasing cell cost.

Overall, the key findings from this section for the work in this thesis are two-fold. Firstly, battery cells deviate significantly in quality. This highlights the importance of making a considered choice when selecting battery cells for battery system design. And secondly, even the same types of battery cells show significant cell-to-cell deviation in cell capacity. This provides incentive for proactive battery management, which can balance not only the state-of-charge, but further allows management of individual cells, allowing their full storage capacity to be used for their destined applications.

It should be noted that given inclusion of five different battery cell types, availability of battery testing channels allowed only four cells of each to be tested as part of this study. The associated limitation to the statistical significance of the findings here is an aspect that should, if feasible, be addressed in future research studies.
Introduction to Chapter 5

LITHIUM-ION cells are chemically limited to an output voltage of between two and four volts depending on the chemistry and state-of-charge. However, to minimise the transmission losses between the battery pack and the power electronics that supply current to the motor, a much higher battery system voltage is required. This higher voltage is achieved by connecting a number of cells in series. Most presently available electric vehicles connect between 80 and 110 cells in series, leading to a rated battery system voltage between 300 and 400V. Depending on the capacities of cells employed and the maximum power output and driving range required, two or more cells may also be connected in parallel blocks that are subsequently connected into the series arrangement discussed above.

While parallel connected cells automatically balance their output voltage, series connected cells do not. In an ideal system where cells are exactly alike in terms of capacity as well as state-of-charge at assembly, and experience exactly the same operating conditions, the sharing of currents between series connected cells means that the state-of-charge of all cells will remain uniform throughout their life. In practice, certain differences due to manufacturing variability and operating conditions are unavoidable. Series-connected cells (or blocks of parallel cells) therefore begin their life with some variations in the state-of-charge and if left unmanaged this difference tends to increase. Increased differences in state-of-charge can reduce the utilisable capacity, accelerate ageing and, if managed poorly, create unsafe operating conditions for individual cells (62).
5.1 Related Work

To minimise the differences in state-of-charge between series-connected cells, so-called balancing systems are employed. Balancing systems work by drawing energy from highly charged cells and/or supplying energy to less charged cells. The simplest method, which to date remains the dominant method in industry, is passive balancing. Cells are balanced by connecting a resistor in parallel with highly charged cells to dissipate surplus energy as heat. While passive balancing has a low complexity and component cost, it is doubly inefficient: it not only wastes energy as heat, but also requires additional cooling to remove this extra heat away from the battery system.

Much research in recent years has therefore been focussed on developing more efficient active balancing systems. These systems actively transfer energy from higher to lower charged cells using energy storage or conversion elements such as capacitors, inductors, transformers and DC-DC converters. Handling substantial differences in capacity, however, is typically not feasible due to limitations in balancing current. This is one shortfall of current battery systems.

Many battery applications require multiple output voltage levels. In electric vehicles, on-board devices including the lights and entertainment systems alongside a multitude of other electronics require a low-voltage supply in addition to the high battery voltage that powers the electric drivetrain. This low-voltage output is typically supplied from the battery system using a voltage converter. This supply needs to be available even when the main battery is disconnected for safety purposes, therefore a second battery with lower specific-energy is typically used. Figure 2.1 shows the layout of an electric vehicle using a conventional battery system. The need for a second battery and a DC-DC converter represents a second shortfall of conventional battery systems.

5.1.1 DC-DC auxiliary Supply.

A recent approach proposed by Garnier is to balance cells by intelligently supplying current to the low-voltage system via DC-DC converters on each cell or module. This approach allows utilisation of battery cells of different capacities, however only to a cer-
tain extent. This extent is defined by the proportion between primary and secondary system power draw, and as soon as one cell reaches its minimum or maximum state-of-charge no other cell can continue to be used. As such this only partially overcomes the first shortfall.

The system does have the potential to make the low-voltage battery redundant. However, instead of replacing the DC-DC converter, a number of such components are used. This increases the system cost and decreases the secondary supply efficiency. As a result, the second shortfall is also only partly addressed.

### 5.1.2 Switched Balancing

A different approach is cell redundancy-based balancing as proposed by Manenti et al [67]. For this method, which in this thesis will be referred to as switched balancing, two switches are inserted in series and parallel with each cell, respectively. By controlling these switches, each battery cell can independently be disconnected from the output and bypassed. The result is a battery pack where balancing is done in a proactive rather than retrospective fashion.

Switched balancing overcomes the first shortfall associated with active and passive balancing. Balancing is achieved by using the highest charged cells at a given instant to power an output load, or alternatively connecting the least charged cells to a power supply. This avoids any energy transfer between cells that impact both efficiency and can contribute to battery ageing. Also, cells with considerably different capacities can be

![Switched Balancing Diagram]

Figure 5.1: Example operating state of 3-cell switched system proposed by [67]. A single cell-and-switching block is indicated.
used within a single string. However, the method does not inherently address the second battery system shortfall of requiring a low-voltage battery as well as a DC-DC converter.

Integrating switches within a battery pack, as is done in switched balancing, provides a means of electrical isolation. Lack of isolation in standard battery packs is a core reason for requiring a low-voltage battery and DC-DC converter. This suggests an opportunity for the development of a battery system layout that solves all identified shortfalls of current battery systems in a single, integrated solution.

The resulting research goal is to develop a switch-based balancing method that is capable of fully utilising cells of vastly different capacities, as well as simultaneously providing power output at two different voltage levels - avoiding the need for both a low-voltage battery and a DC-DC converter. This chapter outlines the design, construction, and testing of such a system.

### 5.2 System Design

#### 5.2.1 Fundamental Approach

The approach proposed here builds upon the concept of switched balancing, but does so in a much more integrated fashion. Unlike any existing balancing systems to date, the proposed method is able to use each cell individually for either a primary side or a secondary side, which in an electric vehicle correspond to the electric drivetrain or the low-voltage supply, respectively, or to be disconnected altogether.

#### 5.2.2 System Layout

**Layout Constraints and Objectives**

Given the approach, the system needs to fulfil the following hard constraints:

1. Each cell needs to be capable of being switched into the primary side, secondary side, or be disconnected, independently of all other cells.
2. The positive terminal of each cell needs to be connectable to the negative terminal of any subsequent cell, and vice versa. This means that any combination of cells can be used for either the primary or secondary side, though the order of series-connected cells is not required to be flexible.

3. For all switching scenarios, there needs to be isolation between the primary and the secondary side.

Additionally, we have the following objectives from most to least important:

1. The circuit should have as few switches as possible to keep cost at minimum.

2. The circuit should aim to have a planar layout to avoid a need for multi-layer electronics, given their associated cost and complexity.

3. The circuit should have the primary current passing through as few switches as possible to avoid losses.

4. The circuit should have the secondary current passing through as few switches as possible to avoid losses.

**Iterative Development**

Figure 5.2 illustrates the iterative steps that lead to the system formation.

1. A switch (S1) is added between the cells to allow these to be isolated from one another.

2. A switch (S2) is added alongside each cell providing a controllable primary current bypass, and providing a path to bypass both cells.

3. Two further switches (S3 and S4) are added, allowing selective bypassing of just cell 2 or cell 1, respectively.

4. Steps 2-3 are repeated for the secondary side, providing a bypass path and allowing selective bypassing for the secondary circuit.
It can be seen from inspection that the resulting circuit matches the set of constraints outlined in Section 5.2.2. In terms of maximising objectives, inspection also shows that no switch can be removed without impairing the required functionality. This, however, does not necessarily guarantee optimality.

An outline of analytical work conducted to prove optimality of this configuration is provided in Appendix A.

Final Layout

Figure 5.3 shows the circuit layout of a 5-cell pack using the proposed integrated system. Each switching block contains a single battery cell or interchangeably a number of parallel-connected cells, as well as seven switches. Of the seven switches, four (S1-S4) are principally used to carry the primary current and three (S5-S7) to carry the secondary current. However, there is an exception for S1 as discussed subsequently. Note that depending on the application either side could act either as a load that discharges cells or as a supply of energy that charges cells.
5.2.3 Switching Methodology

Which switches are closed and which are open depends on two factors: the state (cell connected to the primary side, the secondary side or disconnected) of a switching block itself, and the state of the subsequent block in the positive direction (in Fig. 5.3, the block directly to the left).

Case 1: Given the primary load usually supplies/consumes the bulk of power, the most common case is for both the block and the subsequent block to be connected to the primary side. In this case the only switches conducting current are S1, which carries the main current, and S5, which carries the secondary current. This can be seen for the second and third cell from the right in Fig. 5.3.

Case 2: If a block’s cell is connected to the primary side and the subsequent cell to the secondary side, then only S3, S5 and S7 are closed (see e.g. the third and fourth cell from the right in Fig. 5.3).

Case 3: Conversely, if a block’s cell is connected to the secondary side and the subsequent cell to the primary side (i.e. the first and second cells from the right in Fig. 5.3), then only S2, S4 and S6 are closed.

Case 4: In the rare case that both cells are connected to the secondary side, either S2, S6
and S7 are closed, or closing S1 can replace S6 and S7 by carrying the secondary current.

Case 5: If a block’s cell is to be disconnected, S2 and S5 must be closed. Also either S4 or S7 or neither of the two would be closed, depending on whether the subsequent cell is connected to the primary side, secondary side or is also disconnected, respectively.

By choosing the number of series-connected cells attached to each side at any given time, the output voltage can be controlled to certain cell-voltage increments. In an EV battery system, for example, this can be used to directly supply both a high voltage for the power electronics that drive the motor, as well as a low voltage (12V) for headlights, the heating and air conditioning system, and other electrical and electronic devices. Thereby both the traditional 12V lead-acid battery and the DC-DC converter, which are required in today’s electric vehicles and add cost, volume and weight, become redundant. A second application could be a domestic or industrial multiple-kilovolt stationary battery storage system, which can power a high-voltage load on the primary side and simultaneously accept low voltage solar electricity on the secondary side.

### 5.3 Analytical Evaluation

#### 5.3.1 Cell Utilisation

In standard passive or active balancing systems that balance only during charging, a string of cells is limited by the cell with the smallest capacity and the capacity surplus of all other cells is not utilised. In advanced active systems that also balance during discharge, the utilisation is limited by the balancing currents allowed, which are usually from tens to hundreds of milliamperes. For electric vehicle systems with average discharge currents of tens of amperes, these balancing currents limit utilisation of cell capacity surplus to only 0.1-1% more than the smallest cell capacity. However, research has shown that even in mass-produced Li-ion cells, cell-to-cell capacity deviations of 1% at the beginning of life can grow to around 10% of the capacity at 1000 cycles and as much as 40% at 1500 cycles ([102]). As a result, the potential gain of using advanced active balancing for increasing utilisation of different capacity cells is somewhat limited.

Conversely, the integrated balancing system proposed here offers full utilisation of
cell capacities under certain conditions. The conditions are found by evaluating the discharge duration for the highest capacity cell when permanently connected to the primary side. This duration needs to be shorter than the durations of discharge for each of the remaining cells, taking into account how long cells can be connected to the lower power secondary side or disconnected entirely.

We are assuming all cells start fully charged. The goal is to reach a state where all cells are fully discharged without undercharging any individual cell. If all cells start fully charged and the same current rate is permanently applied to all cells then the smallest capacity cell will become empty first, then the second lowest, etc., and the highest capacity cell takes the longest time.

As we cannot discharge a cell faster than with the largest load current (assumed to occur on the primary side), we need to ensure that during discharge no cell is undercharged in the time it takes the largest capacity cell to discharge while carrying the primary current.

The duration of discharge for the highest capacity cell is therefore as follows:

\[ T_{\text{max}} = \frac{C_{\text{max}}}{I_1} \]  

(5.1)

where \( C_{\text{max}} \) is the charge capacities of the highest capacity cell; and \( I_1 \) is the average current on the primary side.

To be able to continue the discharge process until the largest capacity cell is fully discharged, all other cells need to be able to match this time by either discharging on the primary side, discharging on the secondary side or being disconnected. However, given both the primary and secondary sides require a certain number of cells to contribute at a given point in time, only a limited number of cells can be disconnected or connected to the secondary side respectively. Therefore for full utilisation:

\[ T_{\text{max}} \leq T_{\text{dch},1} + T_{\text{dch},2} + T_{\text{disc}} \]  

(5.2)

\[ T_{\text{max}} \leq \frac{C_{\text{cell},1}}{I_1} + \frac{C_{\text{cell},2}}{I_2} + T_{\text{disc}} \]  

(5.3)
where \( C_{cell} = C_{cell,1} + C_{cell,2} \).

Assuming cells can only be connected to the primary side or disconnected, for two cells with \( C_1 > C_2 \), full utilisation is possible if:

\[
\frac{C_1}{I} \leq \frac{C_2}{I} + T_{2,off}
\]

(5.4)

\[
\frac{C_1 - C_2}{I} \leq T_{2,off}
\]

(5.5)

This is quite intuitive as in order for both cells to be empty at the same time, the difference in capacity between the two cells has to be discharged by the current during the time that the smaller cell is disconnected.

Scaling this up to many cells:

\[
\sum_{\text{all cells excl. } C_{\text{max}}} (C_{\text{max}} - C_{cell}) \leq T_{\text{total,off}} \times I
\]

(5.6)

This is equivalent to:

\[
\frac{(n - 1) \times (C_{\text{max}} - C_{av})}{I} \leq T_{\text{total,off}}
\]

(5.7)

Next we define \( \alpha \) as a redundancy factor which describes how many cells can be completely disconnected at a certain point in time. Then we know that:

\[
T_{\text{total,off}} = \alpha \times \frac{C_{\text{max}}}{I}
\]

(5.8)

So:

\[
\frac{(n - 1) \times (C_{\text{max}} - C_{av})}{I} \leq \alpha \times \frac{C_{\text{max}}}{I}
\]

(5.9)

\[
\frac{C_{\text{max}} - C_{av}}{C_{\text{max}}} \leq \frac{\alpha}{n - 1}
\]

(5.10)

Now for being able to connect cells either to the primary or secondary side, or discon-
\[ \sum_{\text{all cells excl. } C_{\text{max}}} (C_{\text{max}} - C_{\text{cell}}) \leq T_{\text{total,off}} \times I_1 + T_{\text{total,2}} \times (I_1 - I_2) \] (5.11)

\[ (n - 1) \times (C_{\text{max}} - C_{\text{av}}) \leq T_{\text{total,off}} \times I_1 + T_{\text{total,2}} \times (I_1 - I_2) \] (5.12)

with:

\[ T_{\text{total,off}} = \alpha \times \frac{C_{\text{max}}}{I_1} \] (5.13)

and, defining \( \beta \) as a secondary redundancy factor which describes how many cells can be connected to the secondary side at a given point in time:

\[ T_{\text{total,2}} = \beta \times \frac{C_{\text{max}}}{I_1} \] (5.14)

\[ (n - 1) \times (C_{\text{max}} - C_{\text{av}}) \leq \alpha \times \frac{C_{\text{max}}}{I_1} \times I_1 + \beta \times \frac{C_{\text{max}}}{I_1} \times (I_1 - I_2) \] (5.15)

\[ (n - 1) \times (C_{\text{max}} - C_{\text{av}}) \leq \alpha \times C_{\text{max}} + \beta \times C_{\text{max}} \times \frac{I_1 - I_2}{I_1} \] (5.16)

\[ C_{\text{max}} - C_{\text{av}} \leq \frac{\alpha}{n - 1} \times C_{\text{max}} + \frac{\beta}{n - 1} \times C_{\text{max}} \times (1 - \frac{I_2}{I_1}) \] (5.17)

End result:

\[ \frac{C_{\text{max}} - C_{\text{av}}}{C_{\text{max}}} \leq \frac{\alpha}{n - 1} + \frac{\beta}{n - 1} \left(1 - \frac{I_2}{I_1}\right) \] (5.18)

where \( C_{\text{max}} \) and \( C_{\text{av}} \) are the charge capacities of the highest capacity cell and the average capacity of all other cells, respectively; \( \alpha \) is the number of cells that can be disconnected from both the primary and secondary side simultaneously; \( \beta \) is the number of cells that are required by the secondary side simultaneously; \( n \) is the number of series-connected cells; and \( I_1 \) and \( I_2 \) are the average currents on the primary and secondary side, respectively.

To illustrate this on a practical example, assume a standard electric vehicle battery system with 100 cells in series of which four are used to provide a secondary voltage of
12 to 16V. Assume further that the system has seen some usage and has an 8% difference between the maximum and average cell capacity, and that the secondary current is half the level of the primary current. Based on these assumptions, Equation 5.17 finds that a redundancy factor $\alpha$ of six blocks of cells is required to achieve full cell utilisation. Note that the cell redundancy factor has no impact on the energy storage capability and affects only the maximum instantaneous battery system power output which in fully electric vehicles is rarely if ever constrained. Therefore, in an electric vehicle battery system case as outlined above, the cell utilisation alone allows integrated balancing to unlock 7% or more additional range compared to standard active or passive balancing systems.

### 5.3.2 Technical Feasibility

The main feasibility concern is whether switches are able to meet the required specifications of high voltage, high current capacity and low on-resistance. These requirements depend strongly on the number of cells in the system and the instantaneous power output of the system.

To simplify our analysis, for now we will evaluate only the losses over S1 switches. This should cover the majority of losses since at any given time the primary side usually has the highest currents, most cells are connected to the primary side and in primary-connected blocks S1 switches are the only ones to carry the primary current and therefore incur the most notable losses.

### Output Current

The output current is the fundamental link between the power supplied by the battery system, the power output to the motor controller and the resistive loss in the switches. We can find this by evaluating the fundamental relationships between the primary output, battery and the switch resistance:

$$P_{out} = V_{out} \times I_{out}$$  \hspace{1cm} (5.19)
where $R$ is the cumulative resistance of S1 switches in the system.

Substitution of Equations 5.20 and 5.21 into Equation 5.19 gives:

$$P_{out} = (V_{battery} - I_{out} \times R) \times I_{out}$$

Solving this gives the output current as:

$$I_{out} = \frac{V_{battery} \pm \sqrt{V_{battery}^2 - 4RP_{out}}}{2R}$$

This suggests that a real solution of the system is only possible if:

$$R \leq \frac{V_{battery}^2}{4P_{out}}$$

Physically this means that there is an upper limit on the total resistance the switches can have if the given output power $P_{out}$ is to be achieved. For any resistance satisfying Equation 5.24 there are two solutions as given by Equation 5.23. In case 1 ($\pm = +$) the output current is high, leading to the majority of the energy output from the batteries being dissipated in the switches. In case 2 ($\pm = -$), the current is low and therefore the majority of the energy provided by the batteries is used to power the motor. Obviously the latter case is preferable for running the system, which is why the control system would ensure this operating condition.

We can therefore assume the following formula for the output current:

$$I_{out} = \frac{V_{battery} - \sqrt{V_{battery}^2 - 4RP_{out}}}{2R}$$

Analysis of this Equation 5.23 also finds that at the boundary case between the two
solutions exactly half of the power supplied by the batteries is dissipated as resistive losses in the switches and the other half runs the motor.

**Efficiency**

Having found the output current we can now define and calculate the system efficiency

\[ \eta = \frac{P_{\text{out}}}{P_{\text{battery}}} \]  

(5.26)

\[ \eta = \frac{P_{\text{out}}}{P_{\text{out}} + P_{\text{loss}}} \]  

(5.27)

\[ \eta = \frac{1}{1 + \frac{P_{\text{loss}}}{P_{\text{out}}}} \]  

(5.28)

As we are assuming that the only losses are those due to the switch resistances, this is equal to

\[ \eta = \frac{1}{1 + \frac{P_{\text{loss}}}{P_{\text{out}}}} \]  

(5.29)

Substituting our current from Equation 5.25 gives our final efficiency formula:

\[ \eta = \frac{1}{1 + \frac{P_{\text{loss}}}{P_{\text{out}}} \cdot \frac{R_{\text{sw}}}{R_{\text{out}}}} \]  

(5.30)

Note that the total on-resistance of the system is linked to the on-resistance of an individual switch \( R_{\text{sw}} \) as follows:

\[ R = \frac{R_{\text{sw}} n_s}{n_p} \]  

(5.31)

where \( n_s \) and \( n_p \) are the number of switching blocks connected in series and parallel, respectively. Also, the battery voltage \( V_{\text{battery}} \) is the product of the average individual cell voltage, which we assume to be 3.7V, and \( n_s \).

Figure 5.4 shows the relationship between the resistance of each individual S1 switch and the efficiency of integrated battery systems calculated from Equation 5.30. This as-
sumes a power output of 80kW, which is equivalent to the Nissan Leaf’s peak output. Interestingly, only the total number of blocks matters, which is the product of \( n_p \) and \( n_s \), rather than the exact configuration. It shows clearly that the more blocks are used, the larger each individual switch resistance can be to give the same efficiency. This means that a design, which uses several thousands of cells in its battery systems (such as is currently used by Tesla Motors) could use significantly lower spec switches than a design using less than 100 cells (e.g. the BMW i3).

Figure 5.5 show the calculated efficiency curves of a 200 block system (e.g. 100 series-connected sets of two parallel connected blocks, or 100S2P) for various output power values as a function of \( R_{sw} \). It is found that a reduction in the output power leads to a substantial increase in efficiency given the same switch resistance. This shows that the proposed integrated systems will be much more efficient when less power is consumed than at peak power events.
Availability of Suitable Switches

To evaluate whether the proposed system is technically feasible, we need to investigate the state-of-the-art of switching technologies. Three types of switches are considered: silicon-based semiconductors, wide band-gap semiconductors and electromechanical contactors.

Silicon-based semiconductor switches such as silicon MOSFETs and IGBTs remain the dominant switching technology. Connecting two such devices in series in opposing directions enables bidirectional switch functionality. Being both a mature technology and mass-produced, the cost of these switches is very low. However, silicon switches that are able to operate at the 400+V voltage levels required either have too high an on-resistance or too large a footprint to be feasible for the required application.

A more recent invention are wide band-gap semiconductor devices using materials such as silicon carbide (Si-C) and gallium nitride (GaN). These switches offer a much lower on-resistance per unit contact area for a given breakdown voltage. As shown in Figure 5.6, the theoretical minimum on-resistances of SiC and GaN materials are approximately 0.002% and 0.0003% of that of traditional silicon for the same contact area and breakdown voltage. From the 100 and 200V GaN devices already commercially available by the Efficient Power Corporation (EPC), 400V devices based on a 2-by-4mm footprint with an on-resistance of around 75mΩ seem technically feasible, which can be further decreased by enlarging the device footprint. Commercially available 400V+ devices with on-resistances in the low tens or high single digit milliohms might therefore be available within a number of years.

The third technology to be discussed here are electromechanical contactors, such as the starter solenoids in cars. These contactors are switches that isolate contacts not through polarising semiconductor layers like the technologies discussed previously, but by physically separating two contacts in a dielectric environment such as air or vacuum. While these switches can have a very low resistance in the order of single milliohms, they have the issue that when opening, their two contacts are initially separated by only a very thin layer of dielectric. If the layer is sufficiently thin and the voltage sufficiently high, the dielectric can break down and arcing occurs, which is damaging to the contractor
and can be difficult to extinguish. This limitation may be overcome via intelligent timing of the switching operation. In many applications such as electric vehicles, brief periods frequently occur during which the primary load neither draws power from, nor returns energy to, the battery system. If switching is controlled to occur exactly during these periods, arcing can likely be avoided.

![Figure 5.6: A comparison between traditional silicon (Si), SiC and GaN (modified from [103])](image)

### 5.3.3 Performance Comparison

To compare the efficiency between passive, active, switched and integrated management systems, we will make the following assumptions:

1. All cells have equal capacity. This is reasonably accurate for battery systems using new, high quality cells.

2. The maximum self-discharge of cells is $\gamma = 2\%$ of the current throughput and the average is $\delta = 1\%$.

3. Passive balancing dissipates the energy from all cells to the level of the cell with the highest self-discharge.
4. Based on [104] it is assumed that active balancing is $\epsilon = 70\%$ efficient in transferring the energy from higher to lower charged cells.

5. For integrated balancing, only the loss in the S1 switches is considered.

6. The DC-DC converter used for all but integrated balancing is $\zeta = 90\%$ efficient and has a throughput of $\theta = 20\%$ of the total power of the system.

7. Additional cooling consumes $\mu = 20\%$ of any generated heat, including those from active/passive balancing, switches and the DC-DC converter.

Note also that the efficiency is calculated using Equation [5.28] where $P_{loss}$ for the different systems is as calculated in the following sections, respectively.

**Passive Balancing**

In passive balancing, we have three sources of losses: the loss due to balancing, the loss due to the DC-DC converter and the additional cooling required to remove the heat from the first two processes.

\[
P_{loss,p} = (1 + \mu)(P_{balance} + P_{dc})
\]

\[
P_{loss,p} = (1 + \mu)(P_{out}(\gamma - \delta) + P_{out}\theta(1 - \zeta))
\]

**Active Balancing**

For systems using active balancing, the power lost is the same as for passive balancing apart from a decreased loss from balancing power due to the return of the majority of energy to lower charged cells.

\[
P_{loss,a} = (1 + \mu)(\epsilon P_{balance} + P_{dc})
\]

\[
P_{loss,a} = (1 + \mu)(\epsilon P_{out}(\gamma - \delta) + P_{out}\theta(1 - \zeta))
\]
5.3 Analytical Evaluation

Switched Balancing

In switched balancing, the balancing loss is now replaced by the loss in the switches. The current was previously calculated in Equation 5.25

\[ P_{\text{loss},s} = (1 + \mu)(P_{\text{sw}} + P_{\text{dc}}) \] (5.36)

\[ P_{\text{loss},s} = (1 + \mu)(I_{\text{out}}^2 R_{\text{total}} + P_{\text{out}}\theta(1 - \zeta)) \] (5.37)

Integrated Balancing

Finally, in systems using our proposed integrated balancing, the switching loss is the same as for the switched system, but there is no DC-DC converter loss as the system itself provides the voltage step-down.

\[ P_{\text{loss},i} = (1 + \mu)P_{\text{sw}} \] (5.38)

\[ P_{\text{loss},i} = (1 + \mu)I_{\text{out}}^2 R_{\text{total}} \] (5.39)

The results of the comparative efficiency analysis are shown in Figure 5.7. Under the assumptions made, the efficiency of systems using passive and active balancing are independent of the instantaneous power output with values of around 96.5% and 96.8% respectively. Conversely, the switched and integrated system efficiencies decrease with power output in a way that over the range of power outputs considered is close to linear.

Unsurprisingly, the slopes of the switched and integrated system efficiencies are highly dependent on both the on-resistance of the switches and the total number of cells. For a power output close to zero, the integrated system is close to 100% efficient, whereas the switched system is only around 97.8% efficient due to the power loss in the DC-DC converter, which is magnified by the cooling. Compared to the current industry standard of passive balancing, at 20kW output power, an integrated system with 800 cells and switches with low on-resistances of 1mΩ is able to increase efficiency by approximately
Figure 5.7: Comparison of calculated efficiencies of battery systems using passive, active, switched or integrated balancing.

3%. An integrated system using the same switches with 200 cells improves efficiency by around 2.5%, whereas an 800-cell system with notably higher switch on-resistances of 10mΩ still offers an efficiency gain of around 1%.

5.4 Prototype System Design and Build

In order to demonstrate the benefits of the proposed balancing system, a small-scale prototype of the system was constructed and evaluated.

5.4.1 Component Selection

Battery Cells

The cell testing work presented in Chapter 4 found Sanyo UR18650FM cells to match their technical specifications suitably well and compare favourably with other cells in terms of value-for-money. This type of cells, offering a nominal capacity of 2.6Ah, was therefore selected as the basis of the integrated battery management system prototype.

To create a prototype system representative of an electric vehicle, it was desirable to use a high number of cells in series. However, a high resulting voltage also leads to
increased safety risks, particularly for voltages above 30V. To mitigate these risks as well as possible, the system was designed to remain just below the 30V threshold at all times. Given an upper cell voltage limit of 4.2V, seven cells were selected to collectively provide a maximum system voltage of 29.4V.

**Switching Elements**

For switching devices, the initial intention was to use solid-state elements due to their high controllability, small physical footprint and fast switching response. However, the bidirectional functionality coupled with the desire for a very low on-resistance in the order of single-digit milliohms posed notable challenges. Following an evaluation of the options, electromechanical relays were eventually selected for the system prototype. These relays were available for purchase already integrated into a board with inputs isolated via optocouplers.

**Microcontroller**

An Arduino Due, illustrated on the left of Fig. 5.8, provided the processing unit for the system. This controller was chosen for its high number of both analog inputs and digital outputs required to measure the seven cell voltages and drive the 49 relays, respectively. Cell voltage measurements were taken directly at the positive cell terminal. As the chosen micro controller has a maximum analog voltage limit of 3.3V, voltage measurements were subjected to a voltage divider consisting of 1.2 kΩ and 10kΩ resistors with 1% tolerance, also shown in the centre of Fig. 5.8. This ratio was chosen to ensure the highest maximum system voltage fell within the voltage measurement threshold:

\[
v_{\text{meas, max}} = n_{\text{cell}} \times v_{\text{cell, max}} \times \frac{R_1}{R_1 + R_2} = 7 \times 4.2V \times \frac{1.2k\Omega}{1.2k\Omega + 10k\Omega} = 3.15V \quad (5.40)
\]

This meant that 12-bit analog-to-digital provided a cell voltage resolution of:

\[
v_{\text{res}} = \frac{7 \times 4.2V}{v_{\text{meas, max}}} \times \frac{3.3V}{4095} = 7.51mV \quad (5.41)
\]
Due to Arduino and laptop USB current limits, separate current supplies were used to provide 5V and 7V to the switches and Arduino, respectively. For the demonstration system these were powered through mains. In an operational automotive system this would be done from the secondary output via capacitors to overcome switching delay and ripple, as well as stabilising voltage converters. It should further be noted that in our set-up the Arduino did not use a dedicated reference voltage. Though the internal voltage showed some voltage ripple, even the very simple control algorithms implemented here were found to be robust enough not to notably be affected by this. For an operational pack where accurate SOC-measurement is critical, this ought to be incorporated though.

Further Safety Provisions

For additional safety, the positive terminal of each individual cell was connected to a mechanically-operated isolation switch, as well as a fuse box containing a 4A fuse. The switch ensured isolation of the corresponding cell during control system development and debugging. It was also used to prohibit any flow of leakage current during non-testing periods. The fuse provided bidirectional over-current protection.

To provide a final level of safety, cells were physically separated by a minimum distance of approximately 5cm. Each cell was contained on a bed of sand held in place by
a 3D-printed container (see Fig. 5.9). In the battery industry, sand is considered an outstanding test base for batteries due to its inflammable and highly temperature-resistant nature coupled with the ability to contain any electrolyte leakage.

**Power Loads and Supply**

The primary load representing the electric drivetrain in an electric vehicle was simulated via a Maynuo M9712C electronic load. This load was controlled and monitored via a RS-232 interface from a computer.

The secondary load representing the 12V system for lights and entertainment systems in an electric vehicle was simulated via a custom set of six LEDs with associated resistors. The resulting set up is shown in on the right of Fig. 5.8. The LEDs were selected as to provide a power consumption in the order of 0.5W when powered by two batteries. Following construction, a load characterisation was conducted to ensure suitable performance. As shown in Fig. 5.11, a power draw of 0.5W was achieved at approx. 7.4V. This fell comfortably within the voltage range for two series-connected cells of 5.6-8.4V.

To charge the battery system, a Delta Elektronika SM45-70D power supply was used.

The entire testing setup is shown in Fig. 5.12.
5.4.2 Assembly and Programming

Assembly

In order to minimise the system resistance and associated energy loss, cell terminal contacts were connected using an application-specific tab welder. Tab welding is a commercially established connection method that fuses contacts such as nickel tabs to cell terminals without heating the cell or sending currents through the inside of the cell itself. Tab-to-wire, wire-to-wire, wire-to-fuse and wire-to-mechanical-switch connections were all soldered prior to cells being connected. Finally, the wires were connected to relays
5.4 Prototype System Design and Build

![Characterisation of secondary load graph](image)

**Figure 5.11:** Characterisation of secondary load

![Overview of testing setup](image)

**Figure 5.12:** Overview of testing setup: 1) Power supply; 2) Laptop used for data collection; 3) Electronic load; and 4) Integrated balancing system prototype.

using board-provided screw-down clamps.

**Programming**

Standard battery systems contain a number of series-connected battery cells. If one cell is used, all cells are used. And if one cell is to be disconnected, then all cells cease to be in operation.

Conversely, this integrated battery system layout and components allows cell-by-cell
control of the battery system. For the purpose of the testing presented subsequently, the system was configured in such a way as to intelligently divide the cells into two sets. The first set contained five cells, which were connected to the primary load or supply. A second set of two cells were used to power the secondary load.

The intelligence of the system came from the continuous selection of cells into the two sets. For all experiments described here, the selection process was configured to take place approximately every three minutes. Each selection process consisted of multiple stages. First cell voltages were measured one at a time. For cells connected to the primary side, the measurement was taken without any changes in cell connection. Cells connected to the secondary side were, one-at-a-time, connected to the primary side. After a delay of 0.5s to allow voltages some time to adjust, the voltage measurement taken, before the cell was re-connected to the secondary side. This process was necessary because of a considerable voltage-drop in the resistance in the wiring on the secondary side, which distorted voltage measurements when a cell was connected to the secondary side. The resting period of a half-second was found to be sufficiently long to account for the most of the change in voltage over the internal resistance.

Once all cell voltages had been measured, the control algorithm determined the two cells to be connected to secondary. For the purpose of the experiments outlined here, a straightforward algorithm was used. Whenever the primary side was discharging, the two lowest voltage cells was selected to power the secondary load. Whenever the primary side was charging, the two highest voltage cells were selected to power the secondary load.

This approach has a very simple justification. During discharging, it is known that cells connected to primary load discharged at a higher rate than those connected to the secondary load. To achieve balancing, it is therefore intuitive to connect the two lowest-voltage cells to the primary load, slowing their further discharge. During charging, the cells connected to the primary side charge, while those connected to the secondary side continue to discharge. This is the equivalent of having radio or lights on in a charging electric vehicle. Balancing is therefore intuitively achieved by connecting the highest voltage cells to the secondary side and charging lower voltage cells.
5.5 Experimental Evaluation

It should be mentioned that this methodology relies on cells having similar charge storage capacities and similar relationships between the state-of-charge and open-circuit voltage. The Sanyo cells used in the prototype system had each seen less than ten charge and discharge cycles, so could be assumed to fulfil these assumptions.

It should also be noted that during any and all switching a 20ms delay was initiated between operating of any two relays. This was done for safety purposes as to avoid any risk of cell short circuits or parallel connections. In total, the system’s testing and selection process was conducted in approximately three seconds.

5.5 Experimental Evaluation

To evaluate the performance of the integrated battery balancing system prototype, two stages of testing were conducted.

5.5.1 Voltage Balancing Experiment

In the first stage, the ability to balance unbalanced cells was evaluated. This is a standard testing approach used to demonstrate functionality of balancing systems (e.g. [105,106]).

In traditional active or passive balancing systems, balancing is typically done towards the end of the charging process. There are three reasons for this. Firstly, when balancing begins, the rate of charging is typically reduced drastically. From a consumer satisfaction perspective where the battery may need to be used before a full charging process concludes, it is therefore advantageous to balance once the battery is has already charged to a high SOC. Secondly, at the end of charge, the SOC-voltage curve is relatively steep. This allows a voltage measurement to provide an improved resolution of the state-of-charge. Finally, this further allows energy losses from passive or active balancing to immediately be replenished via further charging.

Conversely, the proposed system balances as a side product of operation. Balancing therefore occurs during any stage of activity, that is, during both charging or discharging of the battery system. In the integrated system, balancing does not require a reduction of power flow in or out of the battery. Furthermore, as the system has neither active
conversion nor passive balancing energy losses, there is no need to limit operation to the end of charging only. In the experiment outlined in this work, repetitive charge and discharge processes were used.

Methodology

In preparation for the experiment, the cells were initially brought to distinctly different SOC levels. Specifically, the seven cells were charged and/or discharged individually until their voltages $V_1, \ldots, V_7$ measured after 20 seconds at open-circuit, were within a small tolerance of 4.1, \ldots, 3.5V, respectively. As a final stage of preparation and prior to the experiment commencing, all cells were left to rest at open-circuit for ten minutes in order to allow voltages to reach steady-state conditions.

For the experiment itself, first a load of 1A, then a supply of 1A was provided to the primary side of the system, respectively. This discharge-charge cycle was repeated a total of three times. The respective discharging and charging processes concluded whenever one of two cut-off conditions occurred. The first was a charging or discharging period of 30 minutes. The second was the measured voltage of a cell deviating from the predefined operating region of 3.0-4.2V. Following each cut-off and therefore at each change of loading polarity, all cells were left to rest for a period of 10 minutes.

Throughout this experiment, whenever charging or discharging occurred, the system operated according to the integrated battery system programming as described in Section 5.4.2.

Results

The results of this experiment are illustrated in Figs. 5.13 and 5.14. It can be seen in Fig. 5.13 that upon conclusion of the initial resting phase, the balancing system correctly identifies the two cells with the lowest voltages, cells 6 and 7. It then uses these for the secondary load for the first discharge. This remains the case until cell 5, which is connected to the primary load, has discharged sufficiently much that its voltage becomes lower than that of cell 6. This occurs during the final selection process of the first dis-
At this point, cells 5 and 7 are connected to the secondary side, and cell 6 joins the remaining cells on the primary side.

Correspondingly, during charging, the highest voltage cells (cells 1 and 2) are identified and disconnected. It can be seen in Fig. 5.13 that during charging the secondary-connected cells began changing immediately as opposed to during discharging where the two lowest cells remained connected into the secondary side for some time. There is a direct explanation for this.

During discharging, the absolute difference in current rate seen by the primary and secondary cells is:

\[
\Delta i = |i_{\text{prim,dch}}| - |i_{\text{sec,dch}}| \tag{5.42}
\]

where \(i_{\text{prim,dch}}\) and \(i_{\text{sec,dch}}\) are the primary and secondary discharge currents, respectively.

Conversely, during charging, the rate difference becomes:

\[
\Delta i = |i_{\text{prim,ch}}| + |i_{\text{sec,dch}}| \tag{5.43}
\]

where \(i_{\text{prim,ch}}\) and \(i_{\text{sec,dch}}\) are the primary charge and secondary discharge currents, respectively.

With primary charging and discharging currents being of the same magnitude, it is clear that the difference in currents is larger during charging than it is during discharging. As this rate difference is the driving force for cells being balanced, charging is bound to see a faster rate of voltage convergence and therefore to begin switching in other cells sooner.

To evaluate the success of the system operation in balancing the battery cells, Fig. 5.14 shows the voltages during the resting period before the very first discharge, as well as during the rest after each complete discharge-charge cycle. It can clearly be seen that from the initial deliberately unbalanced level, with each cycle the cells converge notably more. The voltage differences are best compared towards at end of each resting phase once the cell voltages have had time to recover from transient voltage effects caused by charging and discharging. For the last minute of the resting periods before the cycling,
and after successive cycles, the standard deviation of average voltages was found to be 0.212, 0.088, 0.039, and 0.026V, respectively. Over a cumulative operating period of less than five hours, the cell unbalance has therefore decreased by approximately one order of magnitude.

The results from this experiment demonstrate that even with straightforward programming algorithms, this system rapidly balances the battery cells. It is expected that by reducing the period of time between selection stages, as well as by using SOC models rather than simple voltages, the rate of balancing could be increased further.

![Figure 5.13: Cell balancing experiment; from top: cell states, cell voltages, system charging current.](image)

### 5.5.2 Effective Capacity Experiment

The prior experiment outlined in Section 5.5.1 confirmed the ability of the proposed system to reduce voltage unbalance between cells. In contrast, the experiment outlined in this section evaluates the system’s ability to operate effectively despite significant cell-to-cell variations in capacities. This experiment evaluates the ability of the proposed system
to increase effective system capacity when using cells with different capacities. Typical battery systems that balance only at the end of charging have no ability to increase this capacity. As a result the capacity is limited to that of the since lowest-capacity cell. As such, this experiment is not typically conducted for traditional battery system layouts with active or passive balancing.

**Methodology**

A variety of cells with different capacities was were available for conducting this experiment. To replicate different capacity cells, we therefore implemented a selective discharging regime to remove specific amounts of energy from certain cells. This method allowed reducing the remaining energy in cells to show identical capacity distributions to those in a published experimental study of ageing of identical battery cells.

The grey traces in Fig. 5.15 show the capacity development of 48 identical cells cycled under identical conditions [102]. For our purposes, we chose to use the measurements at 1400 cycles. These measurements was chosen due to this being the last point in life for which the capacity of the individual cells was well-identifiable in the plot. We then selected seven of these cells, including the highest capacity cell, the lowest capacity cell,
and five measurements chosen to be equidistant between the first two in terms of cell indices ordered by capacity.

Our battery cells had a rated capacity of 2.6Ah. Conversely, those used in the study were rated at 1.85Ah. This was accounted for in the desired start capacity of cells \( n = 1 \ldots 7 \) as follows:

\[
C_{\text{start},n} = C_{\text{study},n} \times \frac{2.6}{1.85} \tag{5.44}
\]

The difference in capacity between the highest charge cell \( n = 1 \) and the remaining cells was then calculated for cells \( n = 1 \ldots 7 \) as follows:

\[
\Delta C_{\text{start},n} = C_{\text{start},1} - C_{\text{start},n} \tag{5.45}
\]

This calculated cell capacity difference was subsequently implemented on the cells in preparation for experiments. Initially cells were individually brought to 4.1V until constant-voltage current rate had fallen to 10mA or less. Cell 1 was left to remain at this level. The remaining cells were connected to the primary load, which was set to 1A. After specific time intervals for each cell corresponding to the difference in capacity between

Figure 5.15: Battery spread for selected subset of digitised measurement points. Modified from [102].
cell 1 and the other cells, the cells were disconnected. Once all cells were disconnected, they were left to rest for 10 minutes before the subsequent experiments began.

In the first of two experiments, the integrated system operation was tested. For this, the primary load was set to discharge a set of five cells at a constant-power rate of 30W. Simultaneously, two cells powered the secondary load. Every two minutes, the cell selection occurred as outlined Section 5.4.2. The experiment was left to run until the first cell crossed a low-voltage threshold of 3.0V.

Upon completion of the first experiment, the voltage experienced by the secondary load was evaluated. A voltage-current function was fitted to the prior secondary load characterisation in the measurement range relevant for two battery cells indicated in Fig. 5.16. Using this in combination with the voltage profile during the prior test, the secondary power was calculated. The average power over the full experiment was found to have a value of 0.471W.

![Graph](image)

**Figure 5.16**: Characterisation measurements for secondary load with fitting function.

This result was used to conduct a second experiment that was aimed to provide a baseline. First the preparation was repeated and battery cells were redistributed accord-
ing to the calculations and methodology used previously. Following this, the baseline experiment commenced. In the baseline experiment, all cells were connected to the primary side and none to the secondary side. A primary load of 30.471W was then set, accounting for the cumulative power consumption of primary and secondary load in the previous experiment. This mirrors a typical electric vehicle system in which the secondary load is supplied by the primary side via a step-down converter. Converter losses, a further downside of the baseline system, were not considered here. This second experiment again concluded when the first cell reached the low voltage threshold set at 3.0V.

Results

The results of the effective capacity experiments for integrated system operation and baseline operation are shown in Figs. 5.17 and 5.18, respectively. On both graphs the time axes have been set so that the discharge begins at $t = 0$.

In the baseline experiment, shown in Fig. 5.17, all cells remain connected to the primary load throughout and discharge at a uniform current rate. As a result, the cells with less stored energy corresponding to lower capacity cells, reach an empty state considerably earlier than other cells. As expected, the cell that started off with the lowest capacity, cell seven, is the first to cross the minimum voltage threshold. This occurs after 74 minutes and 28 seconds.

The results for the integrated battery system operation are shown in Fig. 5.18. It can be seen that the balancing system actively connects the two lowest voltage battery cells to the secondary side at every 2 minute intervals as per the programming. As in the previous case, the cell with the lowest starting stored energy, cell 7, is the first to cross the threshold. However, disconnection only occurs after 80 minutes and 22 seconds.

Fig. 5.19 compares the results of the two experiments head-to-head in terms of both operating time and energy. In terms of operating duration, the integrated system operation is found to enable an increase of 7.9% over the standard system operation.

In terms of energy, the graph for $t < 70$ min confirms that the slightly raised primary power level for the standard system operation very suitably compensated for the sec-
5.5 Experimental Evaluation

Figure 5.17: Traditional battery system operation at 30.471W primary load.

The standard system operation yielded a total useful energy capacity of 37.75Wh, whereas the integrated system operation yielded 40.45Wh. This corresponds to a 7.1% increase in energy unlocked through the integrated system operation. The slight difference between the increase in energy and runtime can be attributed to the secondary load, which at the low voltage levels seen towards the end of discharge is below the average power consumption.

One aspect worth noting here is that the demonstration system was tailored disproportionately towards storage connected to the secondary side. In the integrated system operation, two out of seven cells, were used to power the secondary load. Conversely, in an electric vehicle system with a rating at 300-400V and containing around 100 series-connected cells, around three to four cells would be used to provide a voltage in the range of 12 to 15V. The impact of this disproportionality is that in the prototype during integrated operation the primary load was powered by only five cells. A rate of 30W provided by five cells rated at 3.7V corresponds to a current of approximately 1.6A. In a truly representative system, where 96% of the cells are available to power the primary load, the current per cell would only have been 1.2A. The reduction in current would
have led to a decrease in voltage drop over the internal resistance, allowing the system to operate for a further increased duration.

Despite the disproportionally high integrated cell current and the straightforward control algorithms, the integrated system operation outperforms the standard system operation. This suggests that in a more representative system with more advanced control based on SOC-estimation rather than voltage measurements only, the proposed system design holds the potential to provide considerable improvements.
5.6 Conclusions

This chapter has outlined the development of a novel battery system layout specifically tailored towards use in electric vehicles including construction and experimental testing of a small-scale prototype.

Key findings of the work presented here are as follows:

- Passive and active battery management approaches used in conventional battery systems are unable to fully utilise series-connected battery cells with considerable cell-to-cell variations in capacity.

- Conventional electric vehicle systems require a low-voltage battery and DC-DC converter to power low-voltage electronics.

- Existing switch-based battery systems can overcome the utilisation issue by using cells selectively, but did not address the requirement of a low-voltage battery and DC-DC converter.

- In this work, layouts were developed that solve both the cell utilisation and component requirement issues in a single, integrated solution. By utilising the electrical
isolation provided by switches, both a high- and a low-voltage output is provided from the same battery system without requiring voltage converters.

- Advanced layouts developed require as little as 6.5 switches per series-connected cell (see App. A), of which only a single switch is connected in series with the primary current flow per battery cell connected to the primary output.

- Implementing this approach in an electric vehicle battery pack having a rated output voltage of 300-400V with high efficiency requires switches to have an on-resistance of or below single digit milliohms. It is expected that GaN transistors with such characteristics will soon become commercially available.

- A small-scale prototype was designed and built. It consists of a network of electromechanical relay switches controlled by an Arduino Due microcontroller.

- Experimental evaluation of a prototype showed a strong ability of the system to rebalance previously unbalanced battery cells.

- Further testing demonstrated the developed system to unlock more than 7% additional runtime and energy storage compared to standard battery system operation. This is despite straightforward control methodologies and a disproportionality in currents that was unfavourable for the integrated system design.

The analytical and experimental findings suggest that the developed integrated battery system layout holds promising potential. Assuming suitable electronics become available and cost-effective, the strong benefits offered by this developed battery system encourage future implementation in electric vehicles or other applications with similar design requirements.
Chapter 6
Conclusion

6.1 Thesis Summary

The work in this thesis set out to address three specific problems.

To develop models for battery cell self-discharge and ageing

Chapter 3 outlined the work conducted to model battery cell self-discharge and ageing. The self-discharge model that was developed takes into account cell temperature and state-of-charge. The developed battery ageing model takes into account charging and discharging currents, temperature, average state-of-charge and depth-of-discharge.

To experimentally investigate cell-to-cell differences in Li-ion batteries

The experimental work done to investigate cell-to-cell differences in Li-ion batteries is outlined in Chapter 4. During the work, four cells from each of five different types of batteries by three manufacturers underwent a seven-stage testing procedure including a cycle-ageing stage. Even identical cells from established manufacturers were found to have some capacity variations at the beginning of life. Low-cost manufacturers showed higher variations yet. The cell-to-cell variations between different types of battery cells of the same format were significant. While cells from established manufacturers performed largely to expectation, low-cost cells showed extremely poor performance.
To design and evaluate a non-dissipative balancing system that utilises external loads

Chapter 5 described the development, analytical evaluation, prototyping and experimental testing of a novel battery system layout using switches to control battery cells. This layout provides both high-voltage and low-voltage outputs, which are intelligently used to balance battery cells internally. The evaluation found the system to be very effective at balancing cells. It further found this system to unlock notable additional runtime and energy storage when using different capacity battery cells as compared to a standard baseline system.

For a full listing of the contributions of this thesis, please refer to Section 1.2.

6.2 Potential Future Work

Battery modelling

As identified in Section 3.3.6, there is notable value in extending the developed battery ageing model. In particular, future work should focus on the extension of the model for different Li-ion chemistries as well as to account for calendar ageing.

Cell testing

In terms of cell testing, the self-discharge battery modelling work identified a lack of experimental data capturing the self-discharge of Li-ion battery cells. The results from the experimental testing conducted highlight the need for compulsory battery cell standards in terms of cell dimensions as well as testing procedures used to develop capacity ratings.

Integrated battery system

There is significant scope for extending the work on integrated battery systems. For the system developed here, there remains scope to develop more intelligent algorithms for
controlling the switches. There is also value in investigating the potential of implement-
ing it in an application such as solar storage where the secondary side can connect to a
source.

In a broader sense, the work conducted here highlights the potential of battery sys-
tems that take a more integrated view. This encourages development of alternative bat-
tery system layouts that address the identified shortfalls of current systems.
Appendix A

Circuit Layout

Sections 5.2 and 5.2.2 outlined the manual approach taken to develop the circuit. As a comparison and in extension, a brute-force approach was developed in an attempt to solve this problem. This section first outlines the methodology and subsequently works through an example to illustrate the functionality.

Optimisation Scope and Nodes  The very first step is to define the problem to be solved. This is done by defining the number of nodes $n$. Each node corresponds to a point to which a switch or link could be attached.

Constraints  To start off, the constraints need to be defined in form of a connection matrix. The constraints consist of a number of scenarios of certain cells being in a certain state e.g. connected to primary, connected to secondary, or disconnected.

For each of these scenarios, it is then possible by inspection to define the links between all possible sets of two nodes. If there are $n$ nodes, the number of sets of two nodes that could be connected is:

$$N_{\text{sets}} = \frac{n \times (n - 1)}{2} \quad (A.1)$$

The connection matrix contains one row for each scenario and a number of columns equivalent to the number of sets of nodes. For each scenario, it defines whether a specific set of nodes has to be disconnected ($0$), connected ($1$), or allowed to be either $2$. It can be filled out by inspection.
Layouts and States  In the next step, all possible system layouts are defined. As each set of two nodes is independent from all others and can be connected either by a fixed connection, a switch, or not be connected, the number of possible battery layouts can be calculated:

\[ N_{\text{layouts}} = 3^{\frac{n \times (n-1)}{2}} \]  \hspace{1cm} (A.2)

Each of these layouts has \(2^{n_{\text{sw}}}\) possible switching states, where \(n_{\text{sw}}\) is the number of switches it contains. Switch-less layouts have only one possible state.

After forming each state, a process ensures that if two connections \(A - B\) and \(A - C\) have links, then connection \(B - C\) is also turned into a link.

Validity Check, Cost Calculation and Sorting  For a given layout to be a viable option, each constraint scenario must be fulfilled by at least one switching state. If for a given layout, no switching state is found to fulfil a specific constraint, the layout is not viable and as a result is discarded.

Each layout that meets each constraint via at least one state is valid. For these layouts, cumulative cost of switches and links is then calculated. In electronics, using a controllable switch is more expensive than simply connecting two points electrically. The approach taken here was to give each switch a cost of 1 and each link a cost of 0.1. A lack of connection between two points incurs no cost. This cost calculation is done for all viable layouts.

Finally, all layouts are sorted by lowest cost. This means that the solutions with the lowest number of switches and links are identified.

Example  To illustrate this process, consider an example problem where each cell is to have the ability to either conduct the main current or be bypassed. In this case, there is no secondary side. This is a similar problem as tackled in [67].

Assuming each switching block between two cells Cell 1 (C1) and Cell 2 (C2) is to be uniform, effects on far sides of the cells are not taken into account, and there is one free node that can be used if desired, this becomes a \(n = 5\) node problem as illustrated in Fig. A.1.
There are four different potential scenarios a suitable layout needs to cater for:

1. Both C1 and C2 are connected into the circuit.
2. C1 is connected into the circuit, C2 is disconnected.
3. C1 is disconnected, C2 is connected into the circuit.
4. Both C1 and C2 are disconnected.

As per Equation \[A.1\] there are six sets of two nodes: 1-2, 1-3, 1-4, 2-3, 2-4, and 3-4. The connection matrix is found by forming one line for each scenario defined above, for which each set of nodes either needs to be isolated (0), connected (1), or either is allowable (2). The resulting connection matrix is the following:

\[
C = \begin{bmatrix}
1 & 0 & 0 & 2 & 0 & 0 & 2 & 2 & 2 & 2 \\
0 & 0 & 1 & 2 & 0 & 2 & 0 & 2 & 2 & 2 \\
0 & 0 & 0 & 2 & 1 & 2 & 2 & 0 & 2 & 2 \\
2 & 0 & 0 & 2 & 0 & 0 & 2 & 1 & 2 & 2 \\
\end{bmatrix} \tag{A.3}
\]

Next, all possible connection layouts are formed. From Equation \[A.2\] it is clear that there are 59,049 potential layouts. Validity checking reduces this set significantly to 476 valid layouts.

Using cost factors as described above with a value of one for a switch and one tenth for a permanent connection, only the two layouts shown in Fig. \[A.2\] achieve a minimum cost of four. All other layouts have a cost of 4.1 or higher, with the worst being a layout having a cost of ten, which has a switch connecting every set of two nodes.

![5-node example problem](image-url)
Scaling issues As illustrated in the example above, the developed brute-force methodology works well for problems with a small number of nodes. However, from Equation \[ A.2 \] it is clear that the number of layouts grows exponentially with the number of nodes. To make matters worse, a larger number of layouts increases the number of sets between nodes as per Equation \[ A.1 \]. This in turn allows a larger number of switches to be contained in a given layout, which increases the number of states this layout can have.

This clearly leads computation requirements to increase rapidly with the number of nodes. The integrated balancing system is inherently at least a six-node problem due to both primary and secondary bypass options, which grows to seven if a floating node is considered. However, the optimisation only becomes interesting if effects between two subsequent switching blocks are considered. Integrating a floating node leads to a final problem that is made up of nine nodes.

On a laptop computer with a 2.4GHz Intel Core 2 Duo processor, the computation of the five node problem with 59,049 layouts required just over one hundred seconds. Equation \[ A.2 \] finds that increasing the number by just one to a six-node problem will create approximately 14.3 million potential layouts, respectively. By seven nodes, the number of potential layouts exceeds ten billion. Ignoring the additional effects of increased number of sets, these computation problems are expected to take approximately 6.7h and 200 days, respectively. And these are still non-interesting problems and still two nodes short of the desired problem.

After a number of approaches at further vectorisation and intelligently limiting the
number of layouts from the outset all led to only minor computational reductions, further work on this was deemed outside the scope of this thesis. Instead a decision was made to opt for a more iterative strategy to create improved layouts.

**Further Development**

Sacrificing planarity leads to some further developments. As shown in the top image in Fig. A.3 this allows forming a system where regardless of connecting or bypassing, only one switch is connected in series within both the primary and secondary side, respectively. This is advantageous in terms of efficiency.

Closer inspection of this system highlights a star-type connection in which one node is not connected to any cell but to terminals of S2 for both connections as well as S3 of C1-2 and S4 of C2-3. An identical node is found on the secondary side. This star-type of connection leads current to pass through a switch at either side of this node.

This provides scope to attempt the graph theory equivalent of an electrical star-delta transformation. Evaluating the switching scenarios that need to be fulfilled and removing the node in favour of creating direct switch paths leads to the layout shown in Fig. A.4. This circuit reduces the number of switches in series with both the primary and secondary current. However, the transformation also led to the duplication of the path containing S7, one of which can be removed, leading to the reduction of one switch. Essentially, using this approach, instead of working with blocks that connect one cell to another, it becomes an integrated block for connections between three cells.

Such an integrative approach can be extended further yet as shown e.g. in Fig. A.5 for four cells. However, in doing so, it is found that the cell savings are not uniform.
As a result, the relationship between the number of cells shown $C$ and switches $S$ was investigated further. From each of the four corners, $C - 1$ switching connections are formed:

$$S_1 = 4 \times (C - 1)$$  \hspace{1cm} (A.4)

The first cell has $C - 1$ connections to the following cells. Then the second cell has $C - 2$ connections to other cells, excluding the connection to the first cell already accounted for. By continuing this way, the total number of connections can be calculated as:

$$S_2 = (C - 1) + (C - 2) + ... + 1$$  \hspace{1cm} (A.5)

This can be analytically solved to be:

$$S_2 = \frac{(C - 1) \times C}{2}$$  \hspace{1cm} (A.6)
Finally, there are also two switching connections between opposite corners

\[ S_3 = 2 \] (A.7)

For a number of cells \( C \), the total number of switches \( S \) therefore becomes:

\[ S = S_1 + S_2 + S_3 = (4 + \frac{C}{2}) \times (C - 1) + 2 \] (A.8)

To consider the block to be repeatable, of the two cells at the extreme ends, only one can be considered. The numbers of switches per cell can therefore be found to be:

\[ \frac{\text{Switches}}{\text{Cell}} = \frac{(4 + \frac{C}{2}) \times (C - 1) + 2}{C - 1} \] (A.9)

For feasible battery systems with two or more cells and where \( C \) is an integer, this relationship has a minimum of 6.5 at \( C = 3 \). At \( C = 5 \), this function already grows to 7, i.e. equivalent to the initial planar layout, and for any value above exceeds this.
# Appendix B

## Abbreviations

Table B.1: Abbreviations

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Meaning</th>
</tr>
</thead>
<tbody>
<tr>
<td>BDC</td>
<td>Brushed DC (motors)</td>
</tr>
<tr>
<td>BLI</td>
<td>Brushless induction (motors)</td>
</tr>
<tr>
<td>BLPM</td>
<td>Brushless permanent magnet (motors)</td>
</tr>
<tr>
<td>BLSR</td>
<td>Brushless switched reluctance (motors)</td>
</tr>
<tr>
<td>DOD</td>
<td>Depth-of-discharge</td>
</tr>
<tr>
<td>EV</td>
<td>Electric vehicle</td>
</tr>
<tr>
<td>HEV</td>
<td>Hybrid-electric vehicle</td>
</tr>
<tr>
<td>ICE</td>
<td>Internal combustion engine</td>
</tr>
<tr>
<td>ICEV</td>
<td>Internal combustion engine vehicle</td>
</tr>
<tr>
<td>LCA</td>
<td>Life-cycle assessment</td>
</tr>
<tr>
<td>LCO</td>
<td>Lithium cobalt oxide (chemistry)</td>
</tr>
<tr>
<td>LFP</td>
<td>Lithium iron phosphate (chemistry)</td>
</tr>
<tr>
<td>Li-ion</td>
<td>Lithium-ion (battery)</td>
</tr>
<tr>
<td>LMO</td>
<td>Lithium manganese oxide (chemistry)</td>
</tr>
<tr>
<td>LNO</td>
<td>Lithium nickel oxide (chemistry)</td>
</tr>
<tr>
<td>NCA</td>
<td>Lithium nickel cobalt aluminium oxide (chemistry)</td>
</tr>
<tr>
<td>NiMH</td>
<td>Nickel-metal hydride (battery)</td>
</tr>
<tr>
<td>MNC</td>
<td>Lithium manganese nickel cobalt oxide (chemistry)</td>
</tr>
<tr>
<td>OCV</td>
<td>Open-circuit voltage</td>
</tr>
<tr>
<td>PHEV</td>
<td>Plug-in hybrid-electric vehicle</td>
</tr>
<tr>
<td>PWM</td>
<td>Pulse-width modulation</td>
</tr>
<tr>
<td>SOC</td>
<td>State-of-charge</td>
</tr>
<tr>
<td>VRLA</td>
<td>Valve-regulated lead-acid (battery)</td>
</tr>
</tbody>
</table>


[75] D. Andre, M. Meiler, K. Steiner, C. Wimmer, T. Soczka-Guth, and D. Sauer, “Characterization of high-power lithium-ion batteries by electrochemical impedance spec-


[96] B. Stiaszny, J. C. Ziegler, E. E. Krau, J. P. Schmidt, and E. Ivers-Tiffe, “Electrochemical characterization and post-mortem analysis of aged LiMn$_2$O$_4$Li(Ni$_{0.5}$Mn$_{0.3}$Co$_{0.2}$)O$_2$/graphite lithium ion batteries. Part I: Cycle aging,” *Journal of Power Sources*, vol. 251, pp. 439–450, 2014.


