Active Balancing and Online Electrochemical Impedance Spectroscopy for Electric Vehicle Battery Management

by

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A thesis submitted in conformity with the requirements for the degree of Master of Applied Science
The Edward S. Rogers Sr. Department of Electrical and Computer Engineering
University of Toronto

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Abstract

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The Electric Vehicle (EV) battery system performance-to-cost ratio has been identified as a roadblock in the mass commercial adoption of EVs. This ratio can be increased by improving the models and management algorithms used in the Battery Management System (BMS). In this work, the potential for impedance-based battery models to enable such BMS improvements is explored. A power management architecture featuring active balancing and high-current online Electrochemical Impedance Spectroscopy (EIS) for real-time model identification of high-capacity, low-impedance automotive cells is proposed and experimentally demonstrated. The active balancing system eliminates the vehicle’s auxiliary power supply and incurs less cost than existing designs. The high-current EIS is enabled by a hybrid linear and switched-mode power architecture. The final vision of this work is the implementation of an EV BMS with real-time model identification and advanced model-based balancing, and the analysis and results here represent a starting point toward achieving that vision.
Acknowledgements

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<th>Abbreviation</th>
<th>Description</th>
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<tbody>
<tr>
<td>EV</td>
<td>Electric Vehicle</td>
</tr>
<tr>
<td>BEV</td>
<td>Battery Electric Vehicle</td>
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<tr>
<td>PHEV</td>
<td>Plug-in Hybrid Electric Vehicle</td>
</tr>
<tr>
<td>SOC</td>
<td>State-of-Charge</td>
</tr>
<tr>
<td>BMS</td>
<td>Battery Management System</td>
</tr>
<tr>
<td>EMF</td>
<td>Electro-Motive Force</td>
</tr>
<tr>
<td>NMC</td>
<td>Nickel-Manganese-Cobalt</td>
</tr>
<tr>
<td>ECM</td>
<td>Equivalent Circuit Model</td>
</tr>
<tr>
<td>SOH</td>
<td>State-of-Health</td>
</tr>
<tr>
<td>EIS</td>
<td>Electrochemical Impedance Spectroscopy</td>
</tr>
<tr>
<td>FTP (US)</td>
<td>(US) Federal Test Procedure</td>
</tr>
<tr>
<td>EPA (US)</td>
<td>(US) Environmental Protection Agency</td>
</tr>
<tr>
<td>CAN</td>
<td>Controller Area Network</td>
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<tr>
<td>SCS</td>
<td>Single Cell Supervisor IC</td>
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Chapter 1

Introduction

The transportation sector accounts for 23% of the current global energy-related greenhouse gas emissions that contribute to climate change, due primarily to the use of fossil fuels as the main energy source for vehicles [1]. Among all categories, light-duty passenger vehicles and heavy-duty cargo trucks accounted for more than half of global transportation energy consumption in 2015 [2]. It is clear that in order to reduce emissions and minimise the effect of climate change, alternative energy solutions for the transport of people and goods need to be implemented on a global scale.

The electric car is among the most promising of alternative solutions for reduced-emissions transportation. The US Department of Energy (DOE) reports that among passenger cars currently available for purchase in the US, the most efficient purely-electric Battery Electric Vehicle (BEV) achieves nearly four times better mileage per unit of energy compared to the most efficient gasoline car [3]. Although the benefits in emissions are clear, use of electric vehicles is not growing quickly enough to make significant large-scale impact. In the US, sales numbers of BEV and Plug-in Hybrid Electric Vehicles (PHEV) have seen steady increase since 2011, as shown in Fig. 1.1. However, the 2016 combined sales of 160 thousand EVs are still small compared to overall vehicle sales, which are reported to be more than six million [4].

1.1 Energy Storage in Electric Vehicles

Lithium-ion batteries are commonly accepted as one of the most promising primary energy storage option for commercial PHEVs and BEVs, but the acceptance comes with an expectation of continued improvement. Benchmark metrics from DOE-sponsored research for a generic Lithium-ion PHEV battery system with 14 kWh capacity are shown in Fig. 1.2. The DOE considers a price-per-kWh of less than 150 USD sufficient
for mass commercial adoption of EVs, and has set a target of 125 USD by 2020. It can be seen from Fig. 1.2 that battery pack cost will need to decrease by half from the 2016 value of 268 USD/kWh to meet this target. In the same time-frame, the volumetric energy density of the pack is only projected to increase by one quarter, and the growth has been decreasing steadily since 2010.

In [10], it is reported that for lithium batteries, a trade-off exists between the capacity window used during the lifetime and the total available capacity of the battery. This indicates that over a vehicle’s total life, metrics of interest such as the DOE’s volumetric...
energy density and price-per-kWh are not only dependent on the initial design of the cell and system, but on the management algorithms as well. Thus the 2020 projections can be met in multiple ways, categorised primarily as: 1) raw cell performance improvements and cost reduction, and 2) improved models and management algorithms allowing operation closer to physical limits. The focus of this thesis lies within the second category.

1.1.1 BEV Power Architecture

A high-level schematic of a typical electric vehicle power architecture is shown in Fig. 1.3. The two primary power distribution networks in the vehicle are:

- The high-voltage bus, which supports the vehicle drivetrain, and
- The auxiliary bus, which supports auxiliary system electronics including thermal, chassis, body, and controls.

The energy source for both power networks in a BEV is the primary battery system. This battery must support the combined loads of driving the vehicle and operation of the auxiliary system. The primary battery system is a critical component to optimise because the energy storage and power flow capabilities of the battery directly determine the range and acceleration behaviour of the car. The auxiliary system power is provided through the auxiliary power supply, which is typically an isolated dc-dc converter. The auxiliary battery present on the auxiliary bus is typically used for voltage stabilisation at high load transients. The auxiliary battery can also support the auxiliary system load for a short duration, in case of emergency. In this thesis, unless otherwise indicated, the term *battery system* refers to the primary battery system.

1.2 Lithium-Ion Battery Systems

From an electrical point of view, an ideal battery is equivalent to an ideal voltage source, allowing arbitrary current draw without any change in voltage. In reality, batteries are complex electrochemical systems, and have highly non-linear electrical behaviour that is dependent on factors including temperature, State-of-Charge (SOC), and usage history. Due to their common use in EVs, Lithium-ion batteries are the sole focus of this thesis. Before proceeding with detailed technical discussion on battery systems, it is important to highlight some key terminology.
1.2.1 Key Terminology

The following terms are used to describe sub-units of battery cells in the pack:

- A **cell** is the smallest battery unit in the pack.
- A **sub-module** is a group of parallel-connected cells.
- A **module** is a group of series-connected sub-modules.
- A **pack** is the group of all modules connected in series.

The following terms are time-varying battery system performance metrics:

- The **Pack Current**, $I_{pack}$, in Amperes, is the instantaneous current in the battery pack. All module and sub-module currents are equal to $I_{pack}$, but the cell currents are smaller, depending on the distribution of current within each sub-module.

- The **Terminal Voltage**, $V_{term}$, in Volts, is the voltage at the physical positive and negative terminals of the battery. In this thesis, unless otherwise stated, $V_{term}$ refers to a sub-module terminal voltage. Based on the chemical composition, the cell manufacturer determines an operating range for $V_{term}$, which is typically 3V to 4.2V.

- The **Open-Circuit Voltage**, $V_{oc}$, in Volts, is the voltage at the physical positive and negative terminals of the battery, when zero current is passing through the
battery and the electrochemical dynamics have subsided beyond a pre-determined threshold. A practical method for determining $V_{oc}$ is to allow the battery to rest at zero current until the rate-of-change of $V_{term}$ falls below a pre-determined threshold, then use the $V_{term}$ value as $V_{oc}$.

- The **Capacity**, $Q$, in Ampere-hours, is the amount of charge a battery can hold. In order to capture all affecting factors, $Q$ is typically characterised at a pre-determined charge current, discharge current, and ambient temperature. Specific test details can be found in various battery testing standards, including ISO 12405.

- The **Maximum Current**, $I_{max}$, in Amperes, is the highest current that can be drawn from the battery pack. This parameter is typically limited by one of $V_{term}$ or cell temperature. In practice, determining $I_{max}$ is difficult because the sub-module impedance, temperature, $V_{oc}$, and $V_{term}$ all need to be considered.

- The **State-of-Charge**, $SOC$, in per-cent, is the amount of charge a battery contains relative to its $Q$. In practice, the $SOC$ is typically determined using a combination of $V_{oc}$ measurements and the integral of $I_{pack}$.

- The **Impedance**, $Z$, in Ohms, is the electrical impedance of a battery. The impedance is heavily related to the cell chemistry, and describes different major chemical reactions, depending on the frequency range. Impedance is best measured through a method called Electrochemical Impedance Spectroscopy (EIS), which involves perturbation of the battery with a sinusoidal current and measurement of the resulting voltage response. The method is described further in Section 1.3.4.

### 1.2.2 Architecture and Design

The architecture of a typical battery system is shown in Fig. 1.4. In the design phase, a set of requirements for the pack voltage, capacity, and impedance is determined based on targets for the vehicle range, power capability, thermal management capability, and longevity. These requirements are then used to determine an optimal series-parallel cell configuration. Battery cells can be connected in various ways to meet the required series-parallel configuration. In this thesis, the battery cells are assumed to be configured in parallel-connected groups assembled in one series-connected string, as shown in the *Pack* block in Fig. 1.4. The other possible configuration, assuming the same number of cells, consists of parallel-connected groups of fewer cells assembled in multiple series-connected strings. From the battery system perspective, the multiple-strings-alternative
is both more expensive and complex, requiring more connection hardware and electrical measurement channels.

Figure 1.4: High-level diagram of a typical EV battery system. Definitions are provided in Sections 1.2.1 and 1.3.1.

1.3 Battery Management Systems

Due to the complex non-linear behaviour of lithium-ion batteries under varying temperature, \( SOC \), and degradation conditions, it is necessary to monitor and manage the use of the battery cells using a Battery Management System (BMS). The BMS is the primary controller of the battery system. A high-level description of the typical functional blocks and signals is shown in Fig. 1.4, and a breakdown of BMS-relevant battery system metrics is shown in Fig. 1.5. In general, the BMS performs the following tasks:

1. Monitoring of the cells through real-time measurements,

2. Estimation of the battery operational state and safe operating area through battery models and state estimation algorithms,

3. Enforcement of operation within the safe operating area through communication with other vehicle systems, and

4. Optimisation of the battery performance through balancing of cell performance metrics including charge, capacity, voltage, and impedance.

The vehicle’s use of the battery system is directly limited by the information provided by the BMS. All time-varying performance metrics of the highly non-linear battery must be accurately estimated under a wide range of environmental conditions. Since
the pack performance is generally limited by the weakest cell, imbalances in cell performance metrics such as capacity, state-of-charge, and impedance must be identified and corrected. An ideal BMS with accurate state estimation and effective balancing allows the vehicle to use the battery pack to its physical limits. Inaccurate state estimation and ineffective balancing necessitate conservative operating limits, leading to limited vehicle performance. For example, since the state-of-charge of the cell cannot be directly measured, it must be inferred from a model. One basic method of determining state-of-charge is through Coulomb counting, where the battery current is integrated to determine the net charge. However, integrating an erroneous current due to measurement error leads to an erroneous value of charge, leading to an erroneous inferred state-of-charge. In this case, the battery system designer must account for the potential error by narrowing the operational state-of-charge range, or risk unknowingly reaching the actual zero or full charge limit during operation. Before proceeding with detailed technical discussion on
BMS, it is important to highlight some key terminology.

1.3.1 Key Terminology

The **Model and State Estimation** sub-system computes the system models and estimates the system state, including all model-dependent time-varying performance metrics. The system thermal model is also computed in this sub-system, but is not covered in this thesis. Design of this sub-system is discussed in more detail in Section 1.3.3. The following are relevant design metrics of the Model and State Estimation sub-system:

- **Model Accuracy** is a measure, in per-cent, of how accurate the system models and state estimation algorithms are in predicting their respective performance metrics. This is a key design metric due to its importance in determining the confidence level the BMS has in its knowledge of the actual battery state.

- **Model and Estimation Bandwidth**, \( f_{est} \), in Hertz, of the update rate of the model and state estimation. This metric is determined by the harmonic content of \( I_{pack} \) and has impact on the selection of the system models, estimation algorithm, and computation hardware.

- **Measurement Accuracy** is a measure, in per-cent, of how accurate the system measurements are. This metric contributes directly to the model accuracy and has similar impact on system performance.

- **Model Identification Time**, \( T_{ID} \), in a unit of time, is the amount of time required to determine the salient model parameters. For example, it is necessary to complete a full charge and discharge cycle in order to characterise the battery capacity, and the overall duration is multiplied if characterisation is to be done at various charge and discharge currents. In many cases, \( T_{ID} \) is too long for the model to be continuously updated in real-time. This imposes the need for model parameters to be determined for a wide range of operating conditions prior to use in the vehicle. However, depending on the test requirements and availability of time and resources, determination of model parameters can still be prohibitively long. Thus practical battery models need to have low \( T_{ID} \) in addition to meeting accuracy requirements.

The **Cell Balancing** sub-system carries out the electrical balancing action in response to the imbalance in performance metrics identified by the Model and State Estimation
sub-system. The sub-module selection signal $\text{sel}$ is used to indicate the balancing configuration. The $\text{SOC}$ is an example of a commonly-examined metric to balance, because it directly limits pack performance during operation. For example, the lowest $\text{SOC}$ sub-module in a pack limits the discharge and prevents the extra remaining energy left in the other sub-modules from being used. Causes of imbalance and design of the Cell Balancing sub-system is discussed in more detail in Section 1.3.2. The following are relevant design metrics of the Cell Balancing sub-system:

- **The Balancing Efficiency**, $\eta_{\text{bal}}$, in per-cent, is the power efficiency of performing electrical balancing on a battery unit. This metric has direct impact on the overall system capacity because balancing actions always use pack energy as input. In the $\text{SOC}$ balancing example from above, if charge from all other sub-modules is used to balance the low-$\text{SOC}$-sub-module, then the total charge used only for balancing purpose is proportional to $\eta_{\text{bal}}$. Generally, increasing the balancing efficiency adds cost and volume to the battery system.

- **The Balancing Rate**, expressed as a unit’s rate-of-change, is the rate at which performance metrics approach the target balanced value. As a minimum, this design metric must meet the dynamic requirement of the system for the performance metric being balanced. For example, if the $\text{SOC}$ imbalance is increasing at some rate, then the balancing system must decrease $\text{SOC}$ imbalance at the same rate to counter the effect. The rate requirement may increase due to cases where it is desirable for an initial imbalance condition to be alleviated within a time limit, for example when the vehicle is first assembled. If the balancing rate requirement cannot be met, then the sub-modules will be imbalanced, and system performance will suffer.

### 1.3.2 Sub-Module Balancing

Sources for mismatch between sub-module time-varying parameters can result from issues in manufacturing, temperature gradients across the pack, and parasitic currents in battery management electronics [11]. Electrical sub-module balancing is performed by applying current to individual sub-modules, and two common balancing variables are:

1. Terminal voltage, $V_{\text{term}}$, can be balanced by applying current until the measured $V_{\text{term}}$ values for all sub-modules are equal. This has the effect of increasing the magnitude of $I_{\text{max}}$, thus increasing charge or discharge power.
2. State-of-Charge, $SOC$, can be balanced by applying current over time until the $SOC$ values for all sub-modules are equal. This has the effect of increasing the usable $Q$ of the battery pack. An example scenario is shown in Fig. 1.6. As shown, the lowest $SOC$ sub-module would limit pack discharge when it loses all charge, preventing the remaining charge in the other cells from being utilised.

Recently, interest has increased in performing advanced model-based balancing, with balancing goals including thermal [12] and capacity degradation [13]. However, the basic balancing action is still application of current to the sub-modules.

![Diagram showing example SOC imbalance scenario.](image)

Figure 1.6: Example SOC imbalance scenario.

Carrying out electrical balancing is a power electronics challenge. A large number of balancing architectures and algorithms have been reported in the literature, and extensive reviews of these are provided in [14, 15]. The two major classes of balancing architectures are 1) active, and 2) passive. Active balancing involves using power converters to transfer energy between sub-modules, while passive balancing involves dissipating energy as heat. Active balancing achieves the best efficiency and speed among all methods, but incurs the most cost and volume. However, in EV applications where the sub-module capacity is high (more than 100Ah), active balancing is the only thermally-feasible way to introduce the high equalising current (more than 10A) necessary for advanced model-based balancing. In some active balancing architectures, each sub-module is connected to a common bus through an isolated converter, which controls the energy transfer [16–18]. In [19, 20], this is extended to EV applications by using the vehicle’s 12V auxiliary bus as the common bus. The control objective is to simultaneously balance the sub-modules and regulate the bus voltage, and the system does not consider the auxiliary battery. The major strength of this architecture is cost reduction through the elimination of the
external auxiliary power supply. Two weaknesses are:

1. The cost of having one converter per sub-module is high, and

2. Disregarding the auxiliary battery in the system control means its energy storage cannot be used to buffer the auxiliary bus voltage while the controller prioritises the balancing speed or low-loss operation.

1.3.3 Battery Models and State Estimation Algorithms

Battery models represent the battery’s physical behaviour, and state estimation algorithms are processes used to infer useful information from the models. It is necessary to perform model and state estimation at the sub-module level because the temperature and voltage operation limits are applied at the sub-modules. In general, during vehicle operation, all model-dependent system-level metrics in Fig. 1.5 except the impedance require inference. That is, it is necessary to:

1. Take measurements,

2. Generate new information using one or more models, and

3. Infer the metric of interest using the measured and generated information.

One example of such a process is estimation of $SOC$. It was mentioned in Section. 1.2.1 that the $SOC$ is typically estimated using a combination of $V_{oc}$ and the time-integral of $I_{pack}$. In this case, two models are used for $SOC$, and the results are combined to infer a more accurate estimate of the real $SOC$. The models are:

1. Coulomb counting, where the net charge is determined by integrating the battery current, and

2. The Electro-Motive Force (EMF) curve of battery, as shown in Fig. 1.7. The curve is based on the electrochemical characteristics, and is not significantly dependent on the temperature or historic usage of the battery [21]. The EMF curve data is typically measured outside the vehicle, as a set of $V_{oc}$-$SOC$ points, and the curve is implemented as a look-up table or using curve-fitting techniques [22].

In practice, the Coulomb-counting $SOC$ model is simple and easily computed, however the $SOC$ can drift from the true value over time due to current measurement error. The EMF curve is more accurate than Coulomb counting, but it cannot be used while driving due to the requirement for the battery to be at rest when taking $V_{oc}$ measurements.
One state estimation algorithm that infers $SOC$ using both models involves relying on both Coulomb counting and estimates of $V_{oc}$ provided by a model that takes current, temperature, and $V_{term}$. A review of recent $SOC$ estimation methods and challenges is given in [23].

![State-of-Charge (%)

0 20 40 60 80 100

$V_{oc}$ (V)

3 3.5 4

Figure 1.7: Sample EMF curve of a Lithium Nickel-Manganese-Cobalt (NMC) oxide cell.

A large body of work exists that reports battery models and state estimation algorithms, and new research is still ongoing. A comprehensive review of the existing work is given in [24]. The major trade-off in selection of models and estimation algorithms is between the accuracy, $TID$, and $f_{est}$. More accurate models such as those with electro-chemical basis require heavy computation and result in low $f_{est}$. If the computation load is reduced, then the accuracy suffers due to lower-order modeling. Another approach is to directly collect performance metric data using empirical tests, but this method suffers from high $TID$ due to the number of independent variables that must be considered in the tests.

1.3.4 Impedance-Based Models

One promising category of battery models relies on impedance as indicator of other time-varying metrics. Impedance is typically measured across a frequency range relevant for the sub-module size and chemistry to produce a set of Nyquist curves, as shown in Fig. 1.8. Curve fitting is then used to identify the electrical circuit parameters of an Equivalent Circuit Model (ECM), as shown in Fig. 1.9. A closed-loop estimator such as a state observer or Kalman filter is typically used to combine state estimates of the $V_{oc}$ and $SOC$ with real-time measurements of $V_{term}$ and $I_{pack}$ to improve the accuracy of estimated values. As applied to the $SOC$ example from above, this method can contribute
accurate real-time estimates of $V_{oc}$, which improves the overall accuracy of estimation. The impedance also allows prediction of $I_{max}$ based on a given allowable range of $V_{term}$ and the $V_{oc}$ estimate.

Figure 1.8: Sample Nyquist plots of a Lithium NMC cell across a range of temperatures.

Figure 1.9: Second-order equivalent circuit model of a battery.

In addition to estimating the voltage dynamics through the ECM, impedance-based battery models have been demonstrated that accurately predict other performance met-
rics of interest. In [25, 26] it is shown that the internal temperature of a cell can be estimated by identifying the perturbation frequency at which its impedance reaches a certain value. Impedance has also been directly related to the cell SOC and SOH [27, 28], as well as aging [29]. A graph comparing electrochemical, empirical, and impedance-based model types along the metrics listed in Fig. 1.5 is shown in Table 1.1. It can be seen that the impedance-based models achieve a practical balance between accuracy and computation requirement.

Table 1.1: Qualitative comparison between electrochemical, empirical, and impedance-based battery models

<table>
<thead>
<tr>
<th>Design Metric</th>
<th>Electrochemical</th>
<th>Empirical</th>
<th>Impedance-based</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model Accuracy</td>
<td>Better</td>
<td>Neutral</td>
<td>Neutral</td>
</tr>
<tr>
<td>Model Identification Time</td>
<td>Worse</td>
<td>Worse</td>
<td>Better</td>
</tr>
<tr>
<td>Model and Estimation Bandwidth</td>
<td>Worse</td>
<td>Better</td>
<td>Neutral</td>
</tr>
<tr>
<td>Measurement Accuracy</td>
<td>Neutral</td>
<td>Better</td>
<td>Better</td>
</tr>
</tbody>
</table>

1.3.5 Electrochemical Impedance Spectroscopy

The EIS technique has long been used to measure impedance in order to characterise the behaviour of electrochemical cells including ultracapacitors and Lithium-ion batteries [30]. A sinusoidal perturbation current is applied to the battery and the impedance is calculated based on the current and voltage phasors. In the BMS application, curve-fitting can be used to estimate the ECM parameter values, and a model can be produced for a wide range of independent operating conditions such as SOC, temperature, and usage history. Due to the non-linear response of the battery impedance to current, a trade-off between model accuracy and measurement Signal-to-Noise Ratio (SNR) must be made when selecting the perturbation current amplitude and test duration [31]. The amplitude should be small enough to maintain the necessary linearity, and large enough to provide the necessary SNR.

The practicality of impedance-based models make them a good candidate for exploration of real-time characterisation. However, in automotive applications where the high-capacity sub-modules can have impedance below 0.25 mΩ, reaching practical voltage response (greater than 10mV) can require high perturbation currents (greater than 40A). Impedance-based models for Lithium-ion cells typically require EIS data from DC up to 10 kHz [30], and a single-frequency measurement requires a low (less than 10) number of perturbation cycles to be applied, thus the $T_{ID}$ is low. The DC impedance can be characterised by the application of a short pulse. Interest has recently grown
in performing online EIS measurements in order to explore the potential of improved real-time battery state estimates [32–36]. Since modeling and parameter estimation occur at the sub-module level, it is necessary for any online EIS system to measure the impedance of each sub-module. Current perturbation for online EIS has been proposed at both pack and cell levels. Pack-level perturbation is a low-cost solution because it can be carried out by the pack-connected converters that already exist in the vehicle, for example, the charger or traction inverter. However, pack-level parasitic impedances such as those resulting from the layout and wiring of the cells may interfere with the perturbation application to all sub-modules. Furthermore, the challenge of synchronising all cell-level measurements to a pack-level perturbation is significant, especially in the presence of parasitic impedances. In order to maximise the benefits of online EIS, it is necessary to maximise the accuracy of measurements. Thus, it is necessary to both perturb and measure at the cell-level.

1.4 Bison Electric Pickup Truck

The Havelaar Bison, as shown in Fig. 1.10(a), is an electric pick-up truck that provides the design context for this thesis. Key preliminary specifications of the prototype vehicle are listed in Table 1.2. The Bison has two electric motors with a combined maximum 200 kW power draw. The Bison primary battery system consists of 18 custom liquid-cooled battery modules, as shown in Fig. 1.10(b), and each module contains 24 44 Ah Lithium Nickel-Manganese-Cobalt-Oxide (NMC) cells in a 6S4P series-parallel configuration.

<table>
<thead>
<tr>
<th>Name</th>
<th>Value</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mass</td>
<td>1855</td>
<td>kg</td>
</tr>
<tr>
<td>Drag Coefficient, $C_d$</td>
<td>0.44</td>
<td></td>
</tr>
<tr>
<td>Frontal Area</td>
<td>2.62</td>
<td>m²</td>
</tr>
<tr>
<td>Rolling Coefficient $C_{rr1}$</td>
<td>0.012</td>
<td></td>
</tr>
<tr>
<td>Maximum Motor Power</td>
<td>200</td>
<td>kW</td>
</tr>
<tr>
<td>Maximum Inverter DC Voltage</td>
<td>450</td>
<td>V</td>
</tr>
<tr>
<td>Auxiliary Power Bus Nominal Voltage</td>
<td>12</td>
<td>V</td>
</tr>
<tr>
<td>Auxiliary Power Bus Average Load</td>
<td>800</td>
<td>W</td>
</tr>
</tbody>
</table>

Key specifications for the prototype battery system are shown in Table 1.3. The specifications are meant to provide insight into the necessary scale of the BMS for the system. To maintain modularity, it is best to assign one BMS module per battery module, thus 18 BMS modules are required. Each sub-module consists of four cells in parallel,
Figure 1.10: (a) Bison electric pick-up truck prototype. (b) Custom liquid-cooled battery module.

and the pack consists of all 108 sub-modules in series.

Key BMS hardware specifications derived from the battery specifications in Table 1.3 are shown in Table 1.4. Each time-varying performance metric, as defined in Fig. 1.5, must be tracked by the BMS at the sub-module level, thus the minimum number of channels required for the measurements and balancing are as shown in the table. The computation hardware must support the model selection and estimation bandwidth, $f_{est}$. These two design decisions are determined primarily from accuracy requirements and cost constraints.
Table 1.3: Bison battery system key specifications

<table>
<thead>
<tr>
<th>Name</th>
<th>Value</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cells in Series</td>
<td>108</td>
<td></td>
</tr>
<tr>
<td>Cells in Parallel</td>
<td>4</td>
<td></td>
</tr>
<tr>
<td>Number of Modules</td>
<td>18</td>
<td></td>
</tr>
<tr>
<td>Capacity</td>
<td>176</td>
<td>Ah</td>
</tr>
<tr>
<td>Operating Temperature</td>
<td>15 to 35</td>
<td>°C</td>
</tr>
<tr>
<td>Nominal Cell $V_{term}$</td>
<td>3.65</td>
<td>V</td>
</tr>
<tr>
<td>Allowable Cell $V_{term}$</td>
<td>3 to 4.2</td>
<td>V</td>
</tr>
<tr>
<td>Nominal Cell Impedance</td>
<td>1</td>
<td>mΩ</td>
</tr>
</tbody>
</table>

Table 1.4: Bison BMS key hardware specifications

<table>
<thead>
<tr>
<th>Name</th>
<th>Value</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sub-module $V_{term}$ measurement</td>
<td>108</td>
<td>Channels</td>
</tr>
<tr>
<td>Sub-module temperature measurement</td>
<td>108</td>
<td>Channels</td>
</tr>
<tr>
<td>$I_{pack}$ measurement</td>
<td>1</td>
<td>Channel</td>
</tr>
<tr>
<td>Real-time impedance measurement</td>
<td>108</td>
<td>Channels</td>
</tr>
<tr>
<td>Sub-module balancing</td>
<td>108</td>
<td>Channels</td>
</tr>
<tr>
<td>Nominal sub-module impedance</td>
<td>0.25</td>
<td>mΩ</td>
</tr>
</tbody>
</table>

1.4.1 Battery Discharge Profiles

In order to evaluate the performance of a battery system, it is necessary to use realistic current profiles, obtained ideally from operation of the vehicle itself. However, as the Bison is in the prototype stage, the preliminary vehicle performance specifications listed in Table 1.2 are used in a simple vehicle power loss model, as described in [37]. In the power calculation, the component rotational inertia, road incline angle, and wind are disregarded. The US standard Federal Test Procedure (FTP) speed profile [38], as shown in Fig. 1.11(a), is selected as the speed profile. The FTP profile simulates urban driving, which is the most dynamic in nature. The corresponding current profile is shown in Fig. 1.11(b).

The US EPA uses speed profiles such as FTP to test for vehicle range. In the range test, the general procedure is to operate the vehicle according to the speed profile, repeating from beginning if necessary, until the vehicle is no longer able to follow the specified speed [39]. At this point, the total distance travelled is recorded and used as the range. An analogous test procedure for EV battery systems involves operating the battery until it can no longer meet the current profile, which typically occurs due to reaching either the terminal voltage or thermal limit. In this thesis, battery model validation tests and simulations are carried out using scaled versions of the current profile shown in Fig. 1.11(b).
Figure 1.11: US EPA FTP profiles: (a) Speed, and (b) Estimated current from simple vehicle loss model.
Scaling of the magnitude and number of repetitions is performed according to the appropriate current and the necessary amount of charge or discharge for the cell combination under test.

1.5 Thesis Motivation and Objectives

This thesis is motivated by the potential for impedance-based battery models to improve the performance of electric vehicle battery systems. It is envisioned that future BMS designs making use of impedance-based battery models will also employ algorithms capable of optimising battery use. The goal of this thesis is to design and implement an EV BMS in order to better understand the technical challenges associated with impedance-based battery management. In particular, the objectives are to:

- Design and implement a cost-effective active balancing architecture that enables future deployment of advanced model-based balancing algorithms, and

- Design and implement a high-current online EIS architecture that enables the use of impedance-based battery models in EV battery systems through real-time impedance measurements of high-capacity, low-impedance battery cells.

The work is carried out in a realistic EV setting, provided by the Bison electric pickup truck. The primary research contributions are:

- An active balancing architecture that uses a switch matrix to enable time-shared use of isolated dc-dc converters, with a rule-based control method that achieves balancing and auxiliary bus regulation, thus eliminating the high-voltage-to-12V auxiliary dc-dc converter, and

- A hybrid linear and switched-mode power architecture for online EIS that is embedded in the active balancing system and designed for thermally-limited operation, thus achieving high perturbation current at minimal incremental system cost.

The remainder of the thesis is organised as follows:

- The battery model and state estimation architecture of the EV BMS are described in chapter 2, including experimental results of the state estimation under a realistic drive-cycle.

- The proposed active balancing hardware and control algorithm are described in chapter 3, along with prototype experimental results. The hardware and control algorithm will be presented at the 2018 International Power Electronics Conference.
• The proposed hybrid power architecture is described in chapter 4, along with prototype experimental results. The online EIS architecture will be presented at the 2018 IEEE Applied Power Electronics Conference.
References


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Chapter 2

Battery Model and BMS State Estimation Architecture

This chapter presents the battery model and state estimation architecture of the BMS. Two second-order ECMs, non-negligible voltage-to-current response over two different frequency ranges, are used to predict the battery terminal voltage. As mentioned in Section 1.3.4, accurate predictions of the sub-module $V_{term}$ can contribute to improved accuracy in the estimation of battery states including $SOC$ and $I_{max}$. It is discussed in [1, 2] that the battery pack current can contain significantly large harmonic content up to 1 kHz, indicating that accurate response over a similar frequency range is required for a fully-accurate model. However, implementing model computation and state estimation at the sub-module level using a model with voltage-to-current response up to 1 kHz is a significant data communication and computation challenge. Therefore the trade-off between model computation frequency and estimation accuracy must be analysed to inform BMS model and state estimation design decisions. The following sections present a preliminary analysis of the $V_{term}$ estimation frequency-to-accuracy trade-off, including experimental results with a BMS operating with estimation frequency $f_{est} = 1$Hz.

2.1 Equivalent Circuit Model Characterisation

Identification of the model is divided into two portions: 1) the $V_{oc}$-$SOC$ curve, and 2) the ECM parameters. The $V_{oc}$-$SOC$ curve is obtained by discharging the cell from the maximum terminal voltage at constant current and regular intervals until the nominal capacity is met. A $V_{term}$ curve obtained from one $V_{oc}$-$SOC$ characterisation test is shown in Fig. 2.1. The discharge interval is 4.4 Ah, which represents 10% $SOC$ if the nominal capacity is 44 Ah. The $V_{oc}$ at each interval is found by taking the voltage at the end of
the rest period following each discharge period. The end result is a $V_{oc}$-SOC curve with 11 points. The results from three single-cell $V_{oc}$-SOC curve characterisation tests with varying cell temperature is shown in Fig. 2.2. The average of all curves is used in the final model.

![Graph of $V_{term}$ vs. Time](image1)

![Graph of Cell Current vs. Time](image2)

Figure 2.1: Data from a $V_{oc}$-SOC curve characterisation test for a single 44 Ah cell: a) $V_{term}$, and b) Current.

The model frequency response is largely defined by the ECM parameters, as shown in Fig. 2.3, except when the current is high enough to cause fast changes in $V_{oc}$. The total $\Delta V_{oc}$ over the full SOC range is 1.2 V, and the Bison’s maximum motor power of 200 kW
corresponds to a current of 2.88 C at the nominal pack voltage of 394.2 V, which results in full discharge in 20.8 minutes. In comparison, it is necessary for a practical \( I_{\text{max}} \) prediction calculation to support \( V_{\text{term}} \)-limited current draw from the pack over single-digit seconds. Thus, in practice, it is the ECM parameters that must provide the necessary insight into the higher-frequency \( V_{\text{term}} \) dynamics. In contrast to this requirement, to maintain discrete model computation stability, the BMS computation frequency, \( f_{\text{est}} \), must at least match the upper frequency where the voltages of the ECM capacitors have significant response to current. Given a limited \( f_{\text{est}} \) constrained by data communication and processing speeds, the ECM capacitor voltage frequency responses may need to be artificially limited to lower frequencies for practical implementation. Since this is equivalent to lowering the cut-off frequency of a low-pass filter, the frequency response characteristic of the ECM is referred-to as the ECM bandwidth. The goal of the ECM identification performed in this thesis is to analyse the bandwidth-to-accuracy trade-off in the prediction of \( V_{\text{term}} \). One constraint is the presence of the capacitive elements of the ECM, which is imposed to enable potential future study of the battery’s electrochemical behaviour. Such a study requires electrochemical insight into the battery, and is not covered in this thesis.

The ECM parameter characterisation is performed at the cell level using two methods, both of which are described in [3]:

Figure 2.2: \( V_{\text{oc}} \)-SOC curves from three characterisation tests.
1. The EIS method, for \( f_{\text{est}} = 1\text{kHz} \), which involves curve-fitting of the ECM Nyquist plot to Nyquist plots built from bench-top EIS measurements.

2. The pulse method, for \( f_{\text{est}} = 1\text{Hz} \) which involves curve-fitting of the ECM \( V_{\text{term}} \) response to the \( V_{\text{term}} \) response from a series of discharge pulses.

The ECM parameter names, operating points, and relevant test specifications used for characterisation with the EIS and pulse methods are listed in Table 2.1. The difference in methods for the two models is arbitrary, and a better comparison requires characterisation for ECM parameters for both bandwidths to be performed using the same method. Surface plots of the ECM and pulse method fitted ECM parameters, with linear interpolation between the measured operating points, are shown in Figs. 2.4, 2.5, 2.6, 2.7, and 2.8. It can be seen that there is significant difference between the ECM parameters obtained from the EIS and pulse methods, which is expected based on the long sample period of the pulse test and high maximum frequency of the EIS test.

Identifying and inferring causation from the trends seen in the model parameters is a challenging task that is not be covered in this thesis. However, it is promising that \( R_0 \), the ECM component that contributes most to the magnitude of impedance, increases as the temperature decreases. This is in agreement with previous studies, such as in [4, 5].
Table 2.1: ECM parameter characterisation test conditions and relevant parameters

<table>
<thead>
<tr>
<th>Name</th>
<th>Value</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>ECM Parameters</td>
<td>$R_0, R_1, C_1, R_2, C_2$</td>
<td>Ω, F</td>
</tr>
<tr>
<td>Temperature</td>
<td>15, 25, 35</td>
<td>°C</td>
</tr>
<tr>
<td>SOC</td>
<td>0, 50, 100</td>
<td>%</td>
</tr>
<tr>
<td>EIS Method Parameters</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Frequency Range</td>
<td>1 to 2000</td>
<td>Hz</td>
</tr>
<tr>
<td>Perturbation Current Amplitude</td>
<td>10</td>
<td>A</td>
</tr>
<tr>
<td>Voltage and Current Sample Rate</td>
<td>20</td>
<td>kHz, min.</td>
</tr>
<tr>
<td>Pulse Method Parameters</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Discharge Pulse Amplitude</td>
<td>14.66</td>
<td>A</td>
</tr>
<tr>
<td>Discharge Pulse Interval</td>
<td>4.4</td>
<td>Ah</td>
</tr>
<tr>
<td>Rest Period</td>
<td>40</td>
<td>Minutes</td>
</tr>
<tr>
<td>Voltage and Current Sample Rate</td>
<td>0.33</td>
<td>Hz</td>
</tr>
</tbody>
</table>

Figure 2.4: Second-order ECM $R_0$ surface plots: a) EIS method and b) Pulse method.
Figure 2.5: Second-order ECM $R_1$ surface plots: a) EIS method and b) Pulse method.

Figure 2.6: Second-order ECM $C_1$ surface plots: a) EIS method and b) Pulse method.

Figure 2.7: Second-order ECM $R_2$ surface plots: a) EIS method and b) Pulse method.
Figure 2.8: Second-order ECM $C_2$ surface plots: a) EIS method and b) Pulse method.
2.1.1 Model Validation

Model validation is conducted by comparing the measured and simulated $V_{term}$ of a single cell. The current profile is one cycle of the FTP test, as shown in Fig. 2.10. The profile is scaled-down from what is shown in Fig. 1.11(b), in order to accommodate the lower cell capacity compared to the sub-module. A *Chroma 17020* battery cycler is used to apply the FTP drive cycle and measure the real $V_{term}$. Simulations of the models developed using the EIS and pulse methods are conducted in *Simulink*. The simulation diagram is shown in Fig. 2.9. A thermal model is not implemented, therefore the validation test assumes the temperature is stable at 25°C. The ECM parameters only change with $SOC$.

![Battery model validation simulation block diagram.](image)

The measured temperature, and measured and simulated cell $V_{term}$ under the FTP drive cycle are shown in Figs. 2.11 and 2.12, respectively. A low-frequency ($\ll 1Hz$) error can be seen between the simulated and measured voltages in Fig. 2.12(a). The similarity between the low-frequency error of both model predictions to the measured voltage suggests that the low-frequency error source is not in the ECM parameters. While slight temperature increase in the cell is observed, it is unlikely that temperature is the contributor to the low-frequency error. The remaining model variable that can
Figure 2.10: Scaled-down FTP drive cycle current used for model validation: a) Full cycle, and b) Zoomed view of the first 140 seconds.
contribute to the low-frequency error is the \( V_{oc} - SOC \) curve, which may be inaccurate or lack sufficient resolution.

![Graph of cell surface temperature during the FTP drive cycle test.](image)

**Figure 2.11:** Cell surface temperature during the FTP drive cycle test.

In addition to the low-frequency error, there is also an error matching the current profile frequency that can be seen in the zoomed view of the voltage comparison shown in Fig. 2.12(b). The voltage prediction from the EIS-based ECM contains a more accurate dynamic response than the pulse-based, which is likely due to the limited bandwidth of the latter. The low-bandwidth ECM generally predicts smaller voltage swings than the high-bandwidth ECM when compared to the measured value. Thus, to prevent the sub-modules from reaching the \( V_{term} \) limits, the BMS must impose more conservative operating limits on \( SOC \) or \( I_{max} \) when using the low-bandwidth ECM compared to the high-bandwidth ECM.
Figure 2.12: Comparison of actual and estimated dynamic voltage response of a 44 Ah Lithium NMC cell over a discharge from 38.5% to 28.5% SOC, at 25°C, with current derived from a vehicle model operating according to the US EPA Federal Test Procedure (FTP) standard speed profile: a) Full test, and b) Zoomed view of the first 140 seconds.
2.2 Information Flow

A diagram of the system architecture is shown in Fig. 2.13. The BMS modules measure the sub-module terminal voltages, $V_{\text{term}}$, and temperatures, $T$, and the BMS supervisor measures the pack current, $I_{\text{pack}}$. Communication of data between the BMS modules and the BMS supervisor takes place over a Controller Area Network (CAN) bus. For best model computation accuracy, it is important to measure $V_{\text{term}}$ and $I_{\text{pack}}$ at the same time. This is enabled by a global measurement start command issued by the BMS supervisor over the BMS CAN bus. Upon receiving this command, the BMS modules take a series of measurements and send the information to the supervisor. The ECM, state estimation, and sub-module balancing algorithm are all computed in the BMS supervisor. In order to compute the balancing algorithm, the supervisor also measures the auxiliary bus voltage. The balancing algorithm and sub-module balancing blocks are covered in more detail in Chapter 3. The BMS supervisor communicates battery operating limits to the rest of the vehicle over the vehicle CAN bus, and issues the sub-module balancing command signal, $sel$, to the BMS modules. An aging model has not been chosen for implementation at the present time, therefore the capacity, $Q$, is assumed to be constant for each sub-module. The thermal management system is not covered in this thesis.

Figure 2.13: Bison BMS measurement and computation architecture.
2.3 Battery State Estimation Using State Observer

A state observer, similar to what is proposed in [6], is implemented for estimation of the ECM states at the sub-module level. The motivation behind using a closed-loop state estimator is the need to correct for measurement and model errors. In [7], the idea is extended to include adaptation of the model parameters, which can provide information about the long-term evolution of the battery behaviour. Other state estimators suitable for application in conjunction with an ECM include variations of the Kalman filter [8–10] and particle filter [11, 12]. Compared to the other estimators, the state observer requires less computation: computing the state estimate using a Kalman filter involves a matrix inversion, and the particle filter requires multiple iterations of model computation per estimation step [13]. The state observer requires only one model computation per estimation step, and does not require matrix inversion. In theory, the Kalman and particle filters generally result in more accurate state estimation than the state observer for non-linear systems where measurements have statistically-relevant variation in error. However, the increased computation requirement translates to decreased estimation bandwidth for the BMS. In the present design, bandwidth is favoured over raw accuracy.

Performing real-time updates of the ECM parameters based on pre-measured impedance data and real-time-measured \( \text{SOC} \) and \( T \) represents a linearisation of the battery ECM. Given the linearised ECM with parameters as listed in Table 2.1, the discrete state-space representation of the ECM internal states is expressed as follows:

\[
\begin{bmatrix}
\text{SOC}[k] \\
V_1[k] \\
V_2[k]
\end{bmatrix} =
\begin{bmatrix}
1 & 0 & 0 \\
0 & 1 - \frac{T_{\text{est}}}{R_1C_1} & 0 \\
0 & 0 & 1 - \frac{T_{\text{est}}}{R_2C_2}
\end{bmatrix}
\begin{bmatrix}
\text{SOC}[k-1] \\
V_1[k-1] \\
V_2[k-1]
\end{bmatrix}
+ T_{\text{est}}I_{\text{pack}}[k-1]
\begin{bmatrix}
\frac{1}{3600Q_{\text{submod}}} \\
\frac{1}{C_1} \\
\frac{1}{C_2}
\end{bmatrix},
\]

where \( T_{\text{est}} = \frac{1}{f_{\text{est}}} \) is the estimation period, and \( Q_{\text{submod}} \) is the sub-module Ampere-hour capacity. The ECM output, \( V_{\text{term}} \), is expressed as follows:

\[
V_{\text{term}}[k] = V_{\text{oC}}(\text{SOC}[k]) + R_0I_{\text{pack}}[k-1] + V_1[k] + V_2[k],
\]

(2.2)

Where the open-circuit voltage term, \( V_{\text{oC}} \), is obtained from the EMF curve using the sub-module \( \text{SOC}[k] \) as input. The state-space representation is used for formulation of the state observer estimation equations. In practice, the \( V_{\text{term}} \) and \( I_{\text{pack}} \) are measured by the BMS in real-time and used as inputs to the state observer. The observed ECM
internal states are expressed as follows:

\[
\begin{bmatrix}
S\dot{O}C[k] \\
\hat{V}_1[k] \\
\hat{V}_2[k]
\end{bmatrix} = \begin{bmatrix}
1 & 0 & 0 \\
0 & 1 - \frac{T_{est}}{R_1C_1} & 0 \\
0 & 0 & 1 - \frac{T_{est}}{R_2C_2}
\end{bmatrix}
\begin{bmatrix}
S\dot{O}C[k-1] \\
\hat{V}_1[k-1] \\
\hat{V}_2[k-1]
\end{bmatrix} + T_{est}I_{pack}[k-1]
\begin{bmatrix}
\frac{1}{3600}\frac{Q_{submod}}{C_1} \\
\frac{1}{C_2}
\end{bmatrix}
\]

\[+ L(V_{term}[k-1] - V_{term}[k-1]), \]

(2.3)

where \(V_{term}[k-1] - V_{term}[k-1]\) is the error between the measured and estimated submodule terminal voltages, and \(L\) is the observer correction gain vector. The observed ECM output, \(\hat{V}_{term}\), is expressed as follows:

\[
\hat{V}_{term}[k] = V_{oc}(\hat{S}O\dot{C}[k]) + R_0I_{pack}[k-1] + \hat{V}_1[k] + \hat{V}_2[k].
\]

(2.4)

Given the ECM parameters and estimated \(V_{oc}\), estimates are computed for the maximum and minimum sub-module currents, \(I_{submod,max}\) and \(I_{submod,min}\). These are expressed as

\[
I_{submod,max}[k] = \frac{1}{R_0} (V_{term,max} - V_{oc}(\hat{S}O\dot{C}[k]) - \hat{V}_1[k] - \hat{V}_2[k])
\]

(2.5)

and

\[
I_{submod,min}[k] = \frac{1}{R_0} (V_{term,min} - V_{oc}(\hat{S}O\dot{C}[k]) - \hat{V}_1[k] - \hat{V}_2[k]),
\]

(2.6)

where \(V_{term,max}\) and \(V_{term,min}\) are the maximum and minimum allowable sub-module terminal voltages, respectively. The maximum and minimum pack currents, \(I_{max}\) and \(I_{min}\), are expressed as

\[
I_{max}[k] = \max_{i=1}^{n} I_{submod,max,i}[k]
\]

(2.7)

and

\[
I_{min}[k] = \min_{i=1}^{n} I_{submod,min,i}[k],
\]

(2.8)

where \(n\) is the number of sub-modules in the pack. It is possible at each estimation step to predict the future pack current limits by advancing the time increment \(k\), in the calculations. However, a loss of accuracy is expected due to loss of linearity. Analysis of a valid prediction horizon for pack current limit using this method is recommended for
future exploration.

2.3.1 Error Gain Tuning

As part of the state observer design, the error gain $L$ can be tuned to improve the estimation accuracy. The goal of the observer design is to correct for measurement and model errors, therefore tuning of $L$ is performed with anticipated sources of error in mind. In this thesis, state observers are implemented to estimate the battery $V_{term}$ of both the EIS and pulse method-derived models. A qualitative indication of the difference in error between the two models is shown in Section 2.1.1. Tuning of the observers is performed using a single cell simulation similar to what is shown in Fig. 2.9, and the data flow is shown in Fig. 2.14. The measured $I_{pack}[k]$ is sampled from the measured scaled FTP drive cycle shown in Fig. 2.10, and the measured $V_{term}[k]$ is sampled from the measured $V_{term}$ shown in Fig. 2.12. The ECM parameters are updated every estimation cycle according to the estimated $SOC$, and the constant Temperature of $25^\circ C$. The estimation update frequency, $T_{est}$, is 1 s for the pulse-derived ECM and 1 ms for the EIS-derived ECM. During the tuning process, simulations are repeated until a close qualitative match is found between the model estimate and measured values. Optimal tuning of the state observer parameters using feedback from known model and measurement errors is recommended for future exploration. The same FTP current profile and measured $V_{term}$ as in the model validation of Section 2.1.1 is used in the simulation, thus the measured $V_{term}$ is as shown in Fig. 2.12.

![State Observer Data Flow](image)

Figure 2.14: BMS state observer data flow, implemented in Simulink to perform tuning of the error gain $L$.

As discussed in Section 2.1.1, the EIS-derived model estimates the higher-frequency components of $V_{term}$ well, but suffers from a low-frequency error that likely originates from an erroneous $V_{oc}$-$SOC$ curve. This suggests that it is sufficient for the state observer to correct only the $SOC$ state of the ECM in order to provide an accurate estimated $V_{term}$. It is also discussed in Section 2.1.1 that the pulse-derived model estimates the higher-frequency components of $V_{term}$ poorly, in addition to the low-frequency error that likely originates from the erroneous $V_{oc}$-$SOC$ curve. The higher-frequency error of the
pulse-derived model suggests that the observer must correct \( V_1 \) and \( V_2 \), the ECM capacitor voltages, in addition to the \( SOC \).

Simulation outputs of the observers are shown in Figs. 2.15, 2.16, 2.17, and 2.18. The EIS and pulse-derived models have different bandwidths, therefore the simulation uses different state estimation periods for each model: the EIS-based model estimation period, \( T_{est,EIS} = 1\text{ms} \), and the pulse-based model estimation period, \( T_{est,pulse} = 1\text{s} \). In the simulation, estimation error gain is applied in two ways: 1) \( SOC \) only, indicated by \textit{partial}, and 2) all states, indicated by \textit{full}. The partial and full gains are applied to both ECMs in order to analyse the evolution of the battery states under various estimation configurations. It can be seen from Fig. 2.15 that the estimation of \( V_{term} \) has improved accuracy over the model validation result from Fig. 2.12. However, the pulse-based ECM with partial error gain does not track the \( V_{term} \) as well as the other configurations. This supports the notion that \( V_1 \) and \( V_2 \) in the low-frequency model must be corrected in order to predict the \( V_{term} \) accurately. It can be seen from Figs. 2.16, 2.17, and 2.18 that the system states are similar for the EIS model, regardless of full or partial error gain, but significant difference exists for the pulse model. Overall, the tuning result confirms that the pulse-based model is more erroneous than the EIS-based model in tracking \( V_{term} \). Good estimation accuracy can be achieved using both models, but the necessary deviations in the pulse model to achieve accurate \( V_{term} \) suggest that significant model correction is required to match reality, which can be problematic if the battery states are to be related to chemical phenomena in the future.
Figure 2.15: State observer tuning simulation $V_{term}$ under varying models and estimation error gain, $L$: a) over full FTP drive profile, and b) the first 140s.
Figure 2.16: State observer tuning simulation $SOC$ under varying models and estimation error gain, $L$: a) over full FTP drive profile, and b) the first 140s.
Figure 2.17: State observer tuning simulation $V_1$ under varying models and estimation error gain, $L$: a) over full FTP drive profile, and b) the first 140s.
Figure 2.18: State observer tuning simulation $V_2$ under varying models and estimation error gain, $L$: a) over full FTP drive profile, and b) the first 140s.
2.3.2 Real-Time ECM Updates

The availability of pre-characterised ECM parameters can cover a pre-determined set of vehicle operating conditions. However, collecting empirical data spanning the full set of possible operating scenarios over the full vehicle life is a time and resource-intensive model identification task. It is therefore beneficial to design a BMS where real-time ECM characterisation can be performed, such that high-fidelity models can be generated as necessary over the course of the vehicle life. One example of scheduling characterisation events using such a system follows the adaptive observer concept from [7], where updates to ECM parameters are performed according to the error between estimated and measured $V_{term}$. If the error exceeds a pre-determined threshold at a moment in time, then an update to the ECM parameters is required for the corresponding temperature and SOC operating point. The BMS controller could then attempt to schedule a set of measurements at the next appropriate moment where the same operating point exists, in order to obtain the updated ECM parameters. A prototype system for performing real-time impedance measurements through EIS, thus enabling real-time ECM parameter updates, is proposed in Chapter 4. A more detailed discussion of the scheduling algorithm is not covered in this thesis.

2.4 Experimental Results

The BMS measurement and computation is implemented with a scaled-down, two-module battery system, BMS hardware, and operating specifications listed in Table 2.2. Temperature measurements and the pack current limit estimation are not currently implemented in the BMS. The safe operating current, voltage, and temperature limits are enforced by a Chroma 17020 battery cycler system with temperature sensing capability. The estimation frequency is set to 1 Hz to accommodate the large amount of data that must be transferred over the CAN bus in a full-scale system with 108 sub-modules. This limits the BMS to using the lower-bandwidth ECM derived using the pulse characterisation method. Optimisation of the communication and computation system to accommodate estimation frequency up to 1 kHz is recommended for future implementation. An image of the hardware setup is shown in Fig. 2.19.

Experimental results from operation of the BMS for two different sub-modules (A and B) are shown in Figs. 2.20 and 2.21. The data is collected from a test with the same operating conditions as described for the simulations in Section 2.3.1. Due to the hardware limitation on $f_{est}$, the pulse-based model is used with full observer error gain.
Table 2.2: BMS measurement and computation experimental hardware and specifications

<table>
<thead>
<tr>
<th>Name</th>
<th>Value</th>
<th>Unit</th>
</tr>
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<tr>
<td>Number of BMS Modules</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>Module Cell Configuration</td>
<td>6S2P</td>
<td></td>
</tr>
<tr>
<td>BMS Module MCU</td>
<td>SPC560P40L3</td>
<td></td>
</tr>
<tr>
<td>BMS Module ADC</td>
<td>LT6804</td>
<td></td>
</tr>
<tr>
<td>BMS Supervisor MCU</td>
<td>NI sbRIO-9607</td>
<td></td>
</tr>
<tr>
<td>BMS Supervisor ADC</td>
<td>NI sbRIO GPIC</td>
<td></td>
</tr>
<tr>
<td>Estimation Bandwidth $f_{est}$</td>
<td>1</td>
<td>Hz</td>
</tr>
<tr>
<td>$V_{term}$ Measurement</td>
<td>12</td>
<td>Channels</td>
</tr>
<tr>
<td>$T$ Measurement</td>
<td>0</td>
<td>Channels</td>
</tr>
<tr>
<td>$I_{pack}$ Measurement</td>
<td>1</td>
<td>Channel</td>
</tr>
<tr>
<td>BMS CAN Bus Bit-rate</td>
<td>500</td>
<td>kbps</td>
</tr>
<tr>
<td>$V_{term}$, $T$ Measurement Data Size</td>
<td>16</td>
<td>bits per sample</td>
</tr>
</tbody>
</table>

Figure 2.19: BMS hardware setup.
It can be seen that the two sub-modules have different voltage response. This is likely due to differences in connection resistance between the sub-modules, which arise due to mechanical fastening inconsistencies. In the battery module, the BMS voltage measurement wire is not located directly at the sub-module terminals, therefore differences in fastening can lead to differences in the effective sub-module series resistances, $R_0$. It can be seen that the experimental observer estimate matches the measured values well for both sub-modules, demonstrating successful implementation of the battery model and $V_{term}$ estimation in the BMS hardware.
Figure 2.20: BMS state observer output and measured $V_{term}$ for sub-module $A$: a) over full FTP drive profile, and b) the first 140s.
Figure 2.21: BMS state observer output and measured $V_{term}$ for sub-module $B$: a) over full FTP drive profile, and b) the first 140s.
2.5 Chapter Summary

A state-observer-based $V_{term}$ estimation system is demonstrated to achieve accurate estimates under a limited operating temperature, state-of-charge, and dynamic current range. Preliminary analysis of the trade-off between estimation bandwidth and accuracy is examined through two different battery models, which are identified in order to be used at estimation frequencies of 1 Hz and 1 kHz, and the low-bandwidth model is found to be less accurate. The state observer error gain design indicates that only a partial error gain is required to achieve accurate $V_{term}$ prediction with the high-bandwidth model, while a full error gain is required for the low-bandwidth model. This suggests that relating estimated system states to real chemical phenomena may be more difficult with the low-bandwidth model. The observer tuning result also provides motivation for increasing the system estimation frequency, $f_{est}$, to achieve better real-time understanding of battery behaviour at the cost of increased computation requirements. A survey of existing literature on relationships between ECM states and chemical phenomena is necessary to better inform selection of model bandwidth and $f_{est}$. 
References


Chapter 3

BMS Power Architecture

This chapter describes the proposed BMS power architecture, which provides both active balancing and auxiliary bus regulation functionality. From an economic point-of-view, active balancing is difficult to justify including in battery systems, due primarily to the increased cost and complexity compared to passive balancing. However, as mentioned in Section 1.3.2, active balancing is the only way to achieve the balancing current levels required of advanced model-based balancing techniques. Under such techniques, balancing parameters such as temperature and capacity fade can require high power, depending on the sub-module capacity, but can yield system-level performance benefits such as pack longevity and increased capacity. Thus it is desirable to decrease the cost and complexity of active balancing systems. The main benefit of the proposed architecture is its potential for cost reduction. While a quantitative analysis is not provided here, it is sufficient to mention that the system eliminates the external auxiliary power supply, such as in [1, 2], and also makes efficient use of the converter power capability by dividing usage among sub-modules, such as in [3].

3.1 Principle of Operation

The proposed architecture, as shown in Fig. 3.1, works as follows: at any given time, one isolated converter transfers energy from either a module or one of its constituent sub-modules to the vehicle’s auxiliary bus, which includes the auxiliary battery. The fundamental difference from previous work is that the connection of the converter to the entire module allows for high auxiliary bus power to be supplied by increasing the converter input voltage rather than current. This results in a lower converter count and input current rating compared to systems with one converter per cell, thus cost and volume are reduced. The active balancing system enables the design of a balancing
algorithm that can optimally trade-off bus regulation fidelity for sub-module balancing speed, using the auxiliary battery as a voltage buffer. In this thesis, a simple rule-based controller is proposed that highlights the system control challenges, thus contributing to the future development of an optimal controller.

![Diagram of Bison BMS power architecture](image)

**Figure 3.1:** Bison BMS power architecture.

In module mode, the converter input \( V_{in} \) is connected across the entire module. In sub-module mode, \( V_{in} \) is instead connected across any of the sub-modules within the module. The switch matrix configuration is controlled by the \( sw\_sel \) signal. To actuate the switch matrix, the BMS module periodically updates \( sw\_sel \), based on the supervisor’s periodic balancing command. To maximise efficiency, the converter is operated at only the peak-efficiency or thermally-limiting current at each input voltage. Burst-mode operation is used to control the average combined current of all converters, and one burst-mode operation cycle is shown in Fig. 3.2.

The burst-mode period is \( T_{cycle} \). In order to vary the total average output current of all converters, \( I_{out\_avg} \), both the converter on-time, \( t_{on} \), and the total output current of all converters, \( I_{out} \), can be varied. The switch matrix configuration \( sw\_sel \) must be
used to vary $I_{out}$. The configuration phase $T_{config}$ is when $sw_{sel}$ is first updated and the converter is then activated. Since $T_{config}$ is short compared to $T_{cycle}$, it can be neglected for calculation of $I_{out,avg}$. The next cycle’s $t_{on}$ and $sw_{sel}$ are determined during $T_{calc}$, based on the control algorithm, and this period can overlap with $t_{on}$. In this thesis, the $t_{on}$ of all converters is the same, however it is recognised that operation with varying $t_{on}$ for different converters improves the control flexibility, and this is recommended for future exploration. It is also recognised that EMI and synchronisation challenges may arise in the simultaneous burst-mode operation of the 18 dc-dc converters, and these challenges are also recommended for future exploration.

### 3.2 Rule-Based Control Algorithm

One simple method for simultaneously performing active balancing and auxiliary bus regulation is to model the combination of all converters as a current source, and apply a closed-loop controller which calculates a current command for auxiliary bus regulation. The controller uses a set of rules to determine an appropriate $sw_{sel}$ and $t_{on}$ to satisfy the current command. A model for the rule-based control system is shown in Fig. 3.3.

![Figure 3.3: Bison BMS: Rule-based power system control schematic.](image)

The current source, $I_{out,avg}$, represents the same current as in Fig. 3.2, and is defined
as follows:

$$I_{out,avg} = \frac{t_{on}}{T_{cycle}} \left( \eta_{mod} n_{mod} I_{mod} \frac{V_{mod}}{V_{bus}} + \eta_{submod} n_{submod} I_{submod} \frac{V_{submod}}{V_{bus}} \right),$$

(3.1)

where $n_{mod}$ and $n_{submod}$ are the number of converters operating in module and sub-module input mode, $I_{mod}$ and $I_{submod}$ are the converter module and sub-module input mode currents, and $\eta_{mod}$ and $\eta_{submod}$ are the module and sub-module input mode efficiencies of the dc-dc converters at the module and sub-module input mode currents. The 12V lead-acid battery is modelled according to the method described in [4]. The auxiliary bus load is modelled as a current source operating with time-varying current $I_{aux}$. The auxiliary bus voltage, $V_{bus}$, is regulated to the reference voltage, $V_{ref}$, by varying $I_{out,avg}$ through a current command, $I_{cmd}$, calculated using a PI compensator. The current command is converted into $sw_{sel}$ using the SW Sel. Control block. The signal $par$ is an arbitrary balancing parameter, for example $SOC$ or the $V_{term}$, which is determined by the BMS based on the system-level goal. The SW Sel. Control block operates according to the following rules:

1. Set $t_{on}$ to $T_{cycle}$.

2. Use eq. (3.1) to find $n_{submod}$, $n_{mod}$ combination that meets or just exceeds current command and maximises $n_{submod}$, to maximise sub-module balancing.

3. Use eq. (3.1) to find $t_{on}$ that meets $I_{cmd}$ with $n_{submod}$ and $n_{mod}$ from step 2).

4. Choose the $n_{mod}$ highest-minimum-$par$-modules in the pack to operate in module input mode.

5. Choose the highest-$par$-sub-module in each remaining module to operate in sub-module input mode.

6. Issue $sw_{sel}$ and begin converter operation.

7. Wait for new current command, return to step 1.

### 3.2.1 Simulation Results

Simulation of the rule-based control algorithm is performed using the same scaled-down battery system as described in Chapter 2 for the state observer tuning and experimental validation. A list of key system specifications used in the simulation is provided in Table 3.1. The auxiliary load profile contains a 1.7 hour drive phase, where the current is
higher and variable, and a 4.3 hour idle phase, where the current is lower and relatively static. The same profile is used for all simulations, and current is scaled down by a factor of 18 from 800 W average while driving, and 200 W average while idle, to account for the reduced module count and sub-module capacity. This ensures that the same balancing current is applied to each cell in the scaled-down modules as what would appear in the full-size system. Operation of essential auxiliary bus loads including electronics involved in management of thermal, chassis, body, and interior systems are analysed to develop the load profile. The pack power can impact SOC imbalance, state observer estimation, and potentially other parameters, but it is not necessary for demonstration of the control algorithm, therefore it is omitted from the simulation. The balancing parameter $par$ is the sub-module SOC and the initial chosen sub-module imbalance varies over a range of 5%.

<table>
<thead>
<tr>
<th>Name</th>
<th>Value</th>
<th>Unit</th>
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<tr>
<td>Number of Modules</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>Cell Configuration per Module</td>
<td>6S2P</td>
<td></td>
</tr>
<tr>
<td>Auxiliary Battery Chemistry</td>
<td>Lead-acid</td>
<td></td>
</tr>
<tr>
<td>Auxiliary Battery Capacity</td>
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<td></td>
</tr>
<tr>
<td>Average Auxiliary Load</td>
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<td></td>
</tr>
<tr>
<td>Auxiliary Bus Voltage Reference</td>
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<td></td>
</tr>
<tr>
<td>Converter Module Mode Current</td>
<td>3 A</td>
<td></td>
</tr>
<tr>
<td>Converter Sub-module Mode Current</td>
<td>3 A</td>
<td></td>
</tr>
<tr>
<td>Burst-mode cycle time, $T_{cycle}$</td>
<td>10 s</td>
<td></td>
</tr>
<tr>
<td>Balancing Parameter $par$</td>
<td>SOC</td>
<td></td>
</tr>
<tr>
<td>Initial Maximum $SOC$ Difference</td>
<td>5 %</td>
<td></td>
</tr>
</tbody>
</table>

The simulation output is shown in Fig. 3.4. The sub-module SOCs from each module converge to the same point, however there is still a difference in the average SOC of the modules. Since $I_{aux}$ is relatively low beyond 6000 s, the rule-based algorithm operates with $n_{submod} = 2$ and $n_{mod} = 0$. To maintain SOC balance, the sub-modules in each module are discharged in sequence, and the algorithm must wait for $I_{aux}$ to increase again before further reducing the imbalance. This particular weakness of the rule-based algorithm suggests the need for a different algorithm with more control freedom over the distribution of $par$ and fluctuation of $V_{aux}$, in order to achieve more effective use of the auxiliary battery energy storage.
Figure 3.4: Simulation results of the rule-based control with 5% maximum initial sub-
module imbalance: (a) simulation data, and (b) the switch matrix configuration and
\( t_{on}/T_{cycle} \) for the first 2000 s of operation: positions 1-6 refer to sub-module input, and 7
refers to module input, \( n_{\text{submod}} \) and \( n_{\text{mod}} \) are labelled for relevant periods.

### 3.3 Active Balancing Converter

Enabling module or sub-module connections to the active balancing converter presents
a power electronics design challenge: the converter must be 1) isolated and 2) capable of
operating in step-up and step-down modes. A list of key converter operating requirements
is provided in Table 3.2. In order to reduce the system cost, the converter only operates
in uni-directional power transfer mode. The auxiliary load draws 800 W average power
during vehicle operation, thus the converters must provide an average of 44.4 W each.
Due to the need to operate in sub-module mode to accommodate balancing requirements, the module mode power is required to be above 44.4 W, and the magnitude is dependent on the necessary portion of operating time spent in sub-module mode. A formal study of the balancing needs of the battery system, given practical imbalance scenarios, is out of the scope of this thesis. The input current in module mode is selected as 3 A for the design, which corresponds to 54 W into the converter at the minimum module voltage. This provides sufficient over-head power to meet the minimum output requirement and account for system losses. A target efficiency of 85 % is set to provide slightly higher output power than the minimum, for some flexibility in operation of the algorithm. Full optimisation of the converter power ratings requires the balancing requirement analysis to be complete, which is recommended for future exploration.

<table>
<thead>
<tr>
<th>Name</th>
<th>Value</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Input Voltage, $V_{in}$</td>
<td>3-4.2 cell mode, 18-25.2 module mode</td>
<td>V</td>
</tr>
<tr>
<td>Output Voltage, $V_{aux}$</td>
<td>10-14</td>
<td>V</td>
</tr>
<tr>
<td>Total Number of Converters</td>
<td>18</td>
<td></td>
</tr>
<tr>
<td>Auxiliary Load Average Power</td>
<td>800</td>
<td>W</td>
</tr>
<tr>
<td>Minimum Module Mode Output Power</td>
<td>44.4</td>
<td>W</td>
</tr>
<tr>
<td>Module Mode Input Current</td>
<td>3</td>
<td>A</td>
</tr>
<tr>
<td>Minimum Module Mode Efficiency</td>
<td>85</td>
<td>%</td>
</tr>
</tbody>
</table>

### 3.3.1 Topology Selection

Isolated topologies that use the full-bridge and half-bridge are not considered for implementation due to cost arising from the number of switches and necessary gate-drivers. Resonant topologies are not considered due to their limited range of voltage conversion ratio. Topologies with only step-up or step-down conversion ratio require high transformer turns ratio to meet the minimum voltage conversion requirements. This results in high peak voltages and currents in the converter that unnecessarily constrain component selection, and reduce the efficiency. Thus the most suitable converter topologies are those with isolation and both step-up and step-down conversion ratio, including flyback and isolated Čuk. Between these two, the flyback has discontinuous input current, whereas the isolated Čuk has continuous. Electrochemical studies show that the presence of high frequency current ripple can increase the aging rate of Lithium batteries [5]. Therefore it is beneficial for the current being drawn from the sub-modules to be as close to DC as possible, and the isolated Čuk topology is chosen for implementation of the active balancing converter.
### 3.3.2 Converter Analysis

The isolated Ćuk converter is shown in Fig. 3.5. The converter is operated in the continuous conduction mode to take full advantage of the low input current ripple. To achieve direct control over the balancing current, the average converter input inductor current, $I_{L1}$, is regulated using a Proportional-Integral (PI) compensator implemented digitally in the BMS MCU. A simple RC snubber is used to suppress the high-voltage ringing that results from the hard switching action. To achieve low volume, a switching frequency of 250 kHz is chosen. The RC snubber component values are tuned experimentally.

![Converter Diagram](image)

Figure 3.5: Isolated Ćuk converter power stage and control.

The averaging method is used to obtain the relevant steady-state and small-signal inductor current and capacitor voltage equations [6]. The converter is assumed to be lossless and the transformer ideal. The steady-state converter voltages and currents are expressed as:

$$V_{C1} = V_{in}, \quad (3.2)$$

$$V_{C2} = V_{aux}, \quad (3.3)$$
\[
\frac{V_{aux}}{V_{in}} = \frac{D}{n(1-D)}, \tag{3.4}
\]

\[
I_{L1} = I_{in}, \tag{3.5}
\]

\[
I_{L2} = \frac{n(1-D)}{D}I_{L1}. \tag{3.6}
\]

The small-signal inductor currents are expressed as:

\[
L_1 \frac{di_{L1}(t)}{dt} = v_{in}(t) - (1-D)v\hat{C}_1(t) + n(1-D)v\hat{C}_2(t) + (V_{C1} - nV_{C2})\hat{d}(t). \tag{3.7}
\]

\[
L_2 \frac{di_{L2}(t)}{dt} = -v_{aux}(t) + \frac{D}{n}v\hat{C}_1(t) - Dv\hat{C}_2(t) + (\frac{V_{C1}}{n} - V_{C2})\hat{d}(t). \tag{3.8}
\]

The input and output voltages are stabilised in part by the sub-module and auxiliary batteries, and the duty ratio is ramped up and down at start-up and shut-down, respectively. It is expected that transient currents on the primary and auxiliary battery systems will cause voltage steps whose magnitudes are dependent on the battery impedances. The effect of these voltage steps on the stability of individual and the combined converters is recommended for future exploration. The control-to-\(i_{L1}\) transfer function is expressed as:

\[
\frac{\hat{i}_{L1}(s)}{d(s)} = \frac{V_{C1} - nV_{C2}}{L_1s}. \tag{3.9}
\]

The control design is performed in the continuous-time domain and the discrete-time PI compensator is obtained from application of the bi-linear transform to the continuous-time PI controller. The discrete-time controller is expressed as follows:

\[
duty[k] = \text{duty}[k-1] + (K_P + \frac{K_I}{2f_{sa}})I_{error}[k] + (\frac{K_I}{2f_{sa}} - K_P)I_{error}[k-1], \tag{3.10}
\]

where \(K_P\) and \(K_I\) are the continuous-time proportional and integral constants, respectively, and \(f_{sa}\) is the controller sample frequency.
3.4 Experimental Results

3.4.1 Isolated Ćuk Implementation

The isolated Ćuk converter component values are shown in Table 3.3. The objective in implementation is to use automotive-qualified, commercially-available components where possible. Due to the high dependence of the converter steady-state and dynamic operation on the transformer turns ratio, the first step in converter implementation is to source an off-the-shelf transformer with appropriate magnetic specifications, minimal conduction loss, and turns ratio between 1-2 to maintain practical duty cycles and currents in the converter. All capacitors in the design are ceramic.

<table>
<thead>
<tr>
<th>Name</th>
<th>Value</th>
<th>Unit</th>
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</thead>
<tbody>
<tr>
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<td>µF</td>
</tr>
<tr>
<td>$C_1$</td>
<td>10</td>
<td>µF</td>
</tr>
<tr>
<td>$C_2$</td>
<td>10</td>
<td>µF</td>
</tr>
<tr>
<td>$C_{out}$</td>
<td>30</td>
<td>µF</td>
</tr>
<tr>
<td>$L_1$</td>
<td>15</td>
<td>µH</td>
</tr>
<tr>
<td>$L_2$</td>
<td>15</td>
<td>µH</td>
</tr>
<tr>
<td>$R_{snub}$</td>
<td>15</td>
<td>kΩ</td>
</tr>
<tr>
<td>$C_{snub}$</td>
<td>1</td>
<td>µF</td>
</tr>
<tr>
<td>Turns ratio $n$</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Transformer</td>
<td>HA3648-BL</td>
<td></td>
</tr>
<tr>
<td>Inductor $L_1$ and $L_2$</td>
<td>XAL1010-153ME</td>
<td></td>
</tr>
<tr>
<td>Switching MOSFET $Q$</td>
<td>STD48N10F7AG</td>
<td></td>
</tr>
<tr>
<td>Switching Diode $D$</td>
<td>V35PWM12</td>
<td></td>
</tr>
<tr>
<td>Snubber Diode $D_{snub}$</td>
<td>FSV20100V</td>
<td></td>
</tr>
<tr>
<td>$f_s$</td>
<td>250</td>
<td>kHz</td>
</tr>
<tr>
<td>Control frequency</td>
<td>10</td>
<td>kHz</td>
</tr>
</tbody>
</table>

The PI compensator is tuned to achieve stable operation at all input and output voltages, but is not currently optimised for load transients. The continuous-time PI compensator gains are $K_I = 1$ and $K_P = 0$. The converter primary and secondary-side switch node waveforms are shown in Fig. 3.6.

Start-up and shut-down transient waveforms for sub-module mode are shown in Fig. 3.7. Both the positive and negative input terminals of the converter are shown. The switch matrix is configured to connect the sixth sub-module, therefore the common-mode voltage of the two terminals is high, but the differential voltage is that of the sub-module. During the start-up sequence, the PI compensator slowly ramps the input
current to the reference value of 3.7 A over 100 ms. During the shut-down sequence, the
duty cycle is ramped down to zero from its operating value over 1 ms.

The converter input voltage and current from one burst cycle is shown in Fig. 3.8,
with $T_{cycle} = 10s$ and $T_{on} = 5s$. It can be seen that $T_{config}$ occupies more than 1 s, which
is 10 % of the $T_{cycle}$ shown. The configuration time can be significantly reduced with
further tuning of the PI compensator and optimisation of the MCU task management.
A transition of the switch matrix configuration from module mode to the fourth sub-
module is shown by the change in $V_{in}$ during $T_{config}$. In-rush current to the converter
input capacitors can be seen at the switch matrix transition instant. Sporadic errors in
current regulation are present due to current measurement noise, which can be resolved
with improved filtering.

The converter efficiency at the two nominal operating voltages is shown in Fig. 3.9.
The efficiency is obtained with a laboratory power supply at the input and electronic
Figure 3.7: Isolated Ćuk converter experimental waveforms: a) $V_{in}$ and $I_{in}$ at start-up, and b) $V_{in}$ and $I_{in}$ at shut-down.
load at the output, to simulate the sub-module, module, and auxiliary batteries. It can be seen that the converter exceeds the minimum module mode efficiency requirement of 85% at the minimum input power of 44.4W.

Figure 3.9: Isolated Ćuk converter efficiency at the two nominal operating voltages.
3.4.2 Active Balancing and Auxiliary Bus Regulation

The BMS power architecture experimental setup uses the same setup as described in Chapter 2, and same balancing system specifications as listed in Table 3.1. The auxiliary bus dynamic load is simulated using a Chroma 17020 battery cycler, and the BMS operates with the rule-based balancing control algorithm. The lead-acid battery is a conventional 60 Ah automotive battery. An image of one BMS module is shown in Fig. 3.10. The circuit board occupies below 1% of the battery module volume with which it is associated.

![Experimental prototype BMS module PCB.](image)

Figure 3.10: Experimental prototype BMS module PCB.

The measurements from the BMS are shown in Fig. 3.4.2. Both the SOC evolution over time and bus regulation match well with the rule-based balancing control algorithm simulation, demonstrating successful operation of the hardware.
Figure 3.11: Experimental operation with two modules under scaled-down auxiliary bus load profile.
3.5 Chapter Summary

Active balancing is necessary for next-generation model-based balancing algorithms, but is costly to include in the BMS. The proposed BMS power architecture eliminates the auxiliary power supply, reduces converter input current ratings, and makes effective use of the existing auxiliary battery. The system and rule-based control is demonstrated experimentally to simultaneously perform: 1) active cell balancing of twelve sub-modules across two modules with 5% initial SOC imbalance, and 2) regulate the auxiliary bus under a reduced-scale auxiliary load profile. The dc-dc converter is implemented as an isolated Čuk topology with operation up to 75 W at the rated input current of 3 A and maximum module voltage of 25.2 V. The rule-based algorithm provides limited independent control over the sub-module SOC balance and auxiliary bus voltage $V_{aux}$, and does not fully decouple the two control variables, thus trade-offs between balancing speed and auxiliary bus regulation cannot be made arbitrarily in real-time. The successful demonstration of the hardware operation is a promising step toward implementation of a system with a new control algorithm designed to fully decouple the balancing parameter $par$ and $V_{aux}$. Such an algorithm would maximise use of the auxiliary battery energy storage, which represents a more effective use of the existing vehicle components, thus further contributing to the cost-effectiveness of the proposed architecture.
References


Chapter 4

Hybrid Power Architecture for Online EIS

This chapter presents the proposed hybrid linear and switched-mode power architecture for online EIS. Online EIS has the potential to significantly improve the fidelity of BMS state estimation by providing real-time updates to impedance-based models such as the second-order ECM. The motivation for introducing the hybrid power architecture is based primarily on the low impedance of the high-capacity sub-modules typically used in automotive applications. In general, a higher perturbation current amplitude is required for cells with low impedance, if the same SNR is to be obtained. The goal of the proposed design is to achieve 40 A peak perturbation current while adding minimum incremental cost and volume to the BMS, and the approach is to maximise the use of existing power processing components.

4.1 Online EIS in Bison

The signal and power processing requirements for EIS are coupled to each other and primarily influenced by the magnitude of impedance being measured. In this thesis, a prototype BMS IC, called the Single Cell Supervisor IC (SCS), is used for signal processing, thus the instrumentation capability is fixed. EIS measurements are supported at a fixed peak current of 200 mA, up to a frequency of 8 kHz. The SCS is currently being developed for commercial battery system applications and the key IC blocks are:

- Low-noise filters and a ΔΣ ADC for voltage measurement,
- A DAC that can draw programmable current up to 200mA for EIS current injection and optional dissipative cell balancing,
• A dual-wire serial digital communication interface, and

• A digital control block to perform digital signal processing and impedance extraction.

The built-in EIS capability of the SCS is suitable for higher-impedance cells (>30mΩ), but in the automotive application, where high-capacity cells are connected in parallel to form sub-modules, the impedance is much lower (<1mΩ). When taking voltage and current measurements for EIS, an arbitrary signal-to-noise ratio (SNR) can be achieved either by averaging the signal over more perturbation cycles, or increasing the perturbation current level. In the selection of online EIS measurement duration and power level, it is important to consider both the linearity of the battery and the time constraints imposed by the BMS. For example, it may be necessary for the online EIS system to wait for the vehicle to pause power draw from the battery before taking a measurement. In anticipation of the development of an algorithm that schedules real-time EIS measurements by identifying scenarios such as traffic stops or short coasting periods, it is assumed that an online EIS system for the Bison BMS is required to measure impedance with minimal time. Therefore, an auxiliary power stage is required to augment the power processing capability of the SCS for online EIS measurements. In this thesis, a peak signal value of 10 mV is considered acceptable for online EIS using the SCS as instrumentation, considering the EMI-heavy automotive environment. Impedance measurements are assumed to be performed only through discharge of the battery, thus eliminating the need for bi-directional current control. With four cells in parallel, each having a 1 mΩ nominal ESR, a 40 A peak perturbation current (0.22 C) is required to achieve a 10 mV peak signal at the SCS’s ADC, which is 0.3% of the nominal cell voltage. This peak current corresponds to a peak load of 168 W in the EIS circuit at the maximum cell voltage of 4.2 V, which is a significant amount of power to process, considering that EIS measurement frequency falls below 1 Hz. Thus an optimal power stage design for online EIS must operate the primary power processing components close to their thermal limits.

### 4.1.1 Design Alternatives

Metrics for evaluating designs for the high-current online EIS power stage are:

• Volume, to be minimised,

• Cost, to be minimised, and

• Level of integration with existing components, to be maximised.
The Bison BMS shown in Fig. 3.1 contains two power processing components available for use in online EIS: the switch matrix MOSFETs in linear mode, and the dc-dc converter. Relevant specifications of each component are listed in Table 4.1. It can be seen that the switch matrix MOSFET is unable to independently process the power required for online EIS. While the converter has adequate switching frequency and control resolution to generate a sinusoidal current, the maximum operating current is too low.

Table 4.1: Specifications of BMS components considered for use in online EIS

<table>
<thead>
<tr>
<th>Name</th>
<th>Value</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Switch Matrix MOSFET</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( R_{th,jc} )</td>
<td>4.3</td>
<td>K/W</td>
</tr>
<tr>
<td>Package</td>
<td>SO-8L</td>
<td></td>
</tr>
<tr>
<td>Isolated Ćuk Converter</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Maximum Constant Input Current</td>
<td>6</td>
<td>A</td>
</tr>
<tr>
<td>Switching Frequency</td>
<td>300</td>
<td>kHz</td>
</tr>
<tr>
<td>DPWM Resolution</td>
<td>6</td>
<td>bits</td>
</tr>
</tbody>
</table>

Based on the available power processing components in the BMS, two design alternatives are considered to achieve the necessary EIS perturbation current:

1. External shunt MOSFET with low \( R_{th,jc} \) in linear mode. This alternative is not desirable because the necessary increased MOSFET thermal ratings contributes significantly to cost.

2. Use the isolated dc-dc converter to send the perturbation current into the 12V battery. This imposes a costly increase (more than double) on the current rating of magnetic elements, and may cause EMI issues at high perturbation frequencies.

4.2 Hybrid Linear and Switched-Mode Power Architecture

The new hybrid architecture for high-current online EIS makes efficient use of the Bison BMS power processing components by combining both a switched-mode converter and a linear regulator, as shown in Fig. 4.1. The system is not currently integrated into the switch matrix of the BMS, however the shunt MOSFET \( Q_{shunt} \) has similar specifications to the switch matrix MOSFET described in Table 4.1. The dc-dc converter is the same as that used in the active balancing system. A small ultracapacitor, \( C_{uc} \), is used to
reduce the drain-source voltage of $Q_{\text{shunt}}$, thus greatly reducing the thermal losses. The isolated dc-dc converter from the BMS also contributes to EIS operation by decreasing the $C_{\text{uc}}$ voltage ripple, further reducing thermal losses. The ultracapacitor maximum voltage rating is 2.7 V, which is lower than the cell voltage of 3-4.2 V. Therefore, the MOSFET $Q_{\text{uc}}$ is used as a switch for voltage blocking while EIS is not operating. The system incurs a minimal incremental cost since the dc-dc converter is already utilised for auxiliary supply, while the 50F ultracapacitor represents 0.03%, 0.001% and 0.2% of the module’s volume, energy capacity and cost, respectively. The ultracapacitor is operated over a narrow voltage range in order to reduce total cycle stress, thus improving the lifetime.

![Diagram](image)

Figure 4.1: Prototype implementation of the hybrid power architecture, not currently integrated with switch matrix.

Table 4.2 summarises a comparison of the shunt MOSFET, dc-dc, and proposed hybrid architecture alternatives when operating at 40 A peak perturbation current at a minimum of 1 Hz perturbation frequency. It is possible to design the system such that each online EIS circuit in the pack is used in sequence by all sub-modules in a module through the switch matrix, thus the incremental volume and cost are incurred at the module level. It can be seen that the shunt MOSFET option occupies the least volume, but must operate at high power dissipation concentrated into one costly device. Scaling the dc-dc current rating higher would result in the least power dissipation, but adds the most volume. The hybrid system provides the best balance between the compar-
ison metrics, achieving the necessary reduction in power dissipation to enable the use of MOSFETs already present in the switch matrix, without any increase in the dc-dc volume.

<table>
<thead>
<tr>
<th>Design Alternative</th>
<th>RMS Power Loss (W)</th>
<th>Volume (cm(^3))</th>
<th>Cost (USD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shunt MOSFET</td>
<td>103</td>
<td>11</td>
<td>20</td>
</tr>
<tr>
<td>dc-dc</td>
<td>23</td>
<td>24</td>
<td>4</td>
</tr>
<tr>
<td>Hybrid</td>
<td>45</td>
<td>13</td>
<td>4</td>
</tr>
</tbody>
</table>

**4.2.1 Principle of Operation**

Key ideal waveforms of the hybrid architecture performing sequential EIS measurements are shown in Fig. 4.2. The order of events is as follows:

1. At system startup (not shown), \(C_{uc}\) needs to be precharged to \(V_{uc,start}\), hence \(Q_{uc}\) is turned on and \(Q_{shunt}\) is controlled to regulate the ultracapacitor current according to a constant reference, \(V_{ref,pre}\).

2. Over repeated measurements, prior to extracting the sinusoidal perturbation, the system enters the preconditioning phase, \(T_{pre}\), where \(V_{uc}\) is discharged by the dc-dc converter down to the measurement start voltage \(V_{uc,start}\). At the end of this period, \(Q_{uc}\) is turned off.

3. During the measurement phase, \(T_{measure}\), \(Q_{uc}\) is turned on again, and \(Q_{shunt}\) is controlled to regulate the battery current according to \(V_{ref,EIS}\), which is generated by the SCS, and has a fixed amplitude of \(I_{EIS,peak}\) and a period equal to \(T_{EIS}\).

Multiple \(T_{EIS}\) cycles are included in \(T_{measure}\) to improve the measurement accuracy. In the experimental prototype, the triggering of successive impedance measurements and data aggregation is performed using a PC that acts as the Coordinator in place of the pack-level BMS, while the local micro-controller (MCU) controls the Čuk converter within the module.

An optimal design of the hybrid architecture minimises cost and volume by appropriately distributing the energy discharged from the battery during EIS to three locations: 1) the auxiliary bus through the dc-dc converter, 2) \(C_{uc}\), to be discharged during \(T_{pre}\) by the dc-dc, and 3) losses in \(Q_{shunt}\). Given a set of EIS parameters, \(I_{EIS,peak}\), \(T_{EIS}\), and
Figure 4.2: Ideal operating waveforms of the hybrid power architecture.

\( T_{\text{measure}} \), the necessary capacitance, \( C_{\text{uc}} \), is expressed by

\[
C_{\text{uc}} = \int_0^{T_{\text{measure}}} I_{\text{uc}}(t) \, dt, \quad \frac{V_{\text{uc,max}} - V_{\text{uc,start}}}{V_{\text{cell}}},
\]

(4.1)

where the time-varying ultracapacitor current \( I_{\text{uc}} \) is expressed by

\[
I_{\text{uc}}(t) = I_{\text{cell}}(t) - I_{\text{conv}},
\]

(4.2)

where \( I_{\text{cell}} \) is the sinusoidal battery cell current with amplitude \( I_{EIS,\text{peak}} \) and period \( T_{EIS} \), and \( I_{\text{conv}} \) is the constant dc-dc converter current during \( T_{\text{measure}} \). The time-varying power dissipated in \( Q_{\text{shunt}} \) is defined as \( P_{\text{shunt}} \) and is expressed by

\[
P_{\text{shunt}}(t) = I_{\text{cell}}(t)(V_{\text{cell}}(t) - V_{\text{uc}}(t)).
\]

(4.3)
The component design parameters are:

1. $I_{\text{conv}}$, the dc-dc current,

2. $C_{uc}$, the ultracapacitor capacitance, and

3. the die heat capacity and junction-to-case resistance of $Q_{\text{shunt}}$.

For a given set of EIS parameters, trade-offs exist between each of the component design parameters. For example, $C_{uc}$ can be increased to accommodate lower $I_{\text{conv}}$. Thus, given 1) the EIS parameters, 2) dc-dc current rating, and 3) switch matrix MOSFET thermal ratings in the Bison BMS, it is possible to minimise the incremental cost and volume of introducing online EIS by calculating the minimum necessary ultracapacitor size required in the hybrid power stage. In this work, due to the high EIS current, the ultracapacitor size is limited by the ESR and maximum operating voltage, rather than capacitance.

For a given SNR requirement, the $T_{\text{measure}}$ and $I_{\text{EIS,peak}}$ must be selected according to the power stage thermal limit and the cell linearity. The same SNR can be reached by either 1) using high perturbation current and averaging measurements over fewer cycles, or 2) using low perturbation current and averaging measurements over more cycles. If the measurement removes sufficient charge from the cell to significantly change its operating point over the frequency range of interest, then the model accuracy will be reduced. High perturbation current can also induce undesirable cell self-heating. To highlight one possible operating scenario, $P_{\text{shunt}}$ and the $Q_{\text{shunt}}$ junction and case temperatures from a thermal-electrical simulation are shown in Fig. 4.3, for which the parameters are shown in Table 4.3. The listed EIS parameters are the initial test parameters for the prototype system, and are used for the oscilloscope waveforms shown in Section 4.2.2. The experimental Nyquist plots in Section 4.2.2 are measured using $I_{\text{EIS,peak}} = 40$ A and $T_{\text{measure}} = 1$ s at all $T_{\text{EIS}}$ points. The other system parameters in the simulation are chosen to reflect the system described in section 3.4, and match the experimental setup. An optimal design and calibration of the system considering all relevant parameters is not presented in this thesis.

It can be seen in Fig. 4.3 that as the measurement occurs from 0 to 10s, the amplitude of $P_{\text{shunt}}$ decreases due to the increase in $V_{uc}$. The peak junction temperature of 113 °C indicates the system operates near the thermal limit, which is an indicator of optimal component use.
Figure 4.3: Thermal-electrical simulation of the hybrid power architecture: $Q_{shunt}$ power loss and junction and case temperatures.

Table 4.3: Hybrid architecture system parameters used in thermal-electrical simulation

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>EIS peak perturbation current, $I_{EIS,peak}$</td>
<td>30</td>
<td>A</td>
</tr>
<tr>
<td>EIS perturbation period, $T_{EIS}$</td>
<td>0.02</td>
<td>s</td>
</tr>
<tr>
<td>EIS measurement duration, $T_{measure}$</td>
<td>9</td>
<td>s</td>
</tr>
<tr>
<td>dc-dc constant current, $I_{conv}$</td>
<td>6</td>
<td>A</td>
</tr>
<tr>
<td>Ultracapacitor capacitance $C_{uc}$</td>
<td>50</td>
<td>F</td>
</tr>
<tr>
<td>Ultracapacitor ESR</td>
<td>21</td>
<td>mΩ</td>
</tr>
<tr>
<td>Shunt MOSFET $R_{th,jc}$</td>
<td>3</td>
<td>K/W</td>
</tr>
<tr>
<td>Shunt MOSFET package</td>
<td>TO-263</td>
<td></td>
</tr>
</tbody>
</table>

### 4.2.2 Experimental Results

The experimental setup, as shown Fig. 4.4, consists of four 44 Ah NMC cells in parallel, the EIS module board, EV battery prototype BMS module board (currently without the switch matrix), SCS communication interface, and an electronic load (not shown) to emulate the 12V auxiliary battery. EIS perturbation of a single cell is shown in Fig. 4.5(a) at a single frequency, and in Fig. 4.5(b) at multiple frequencies. The EIS current and timings are tuned to showcase system operation. The waveforms match well with Fig. 4.2, except for some noticeable current distortion due to the limited accuracy of the current-loop, as well some switching noise from the converter. The ultracapacitor is operated at 2.4 V peak to stay safely below the 2.7 V rating and prolong its lifetime.

To highlight the thermal challenge imposed by EIS measurement at such high perturbation currents, the case temperature of the shunt MOSFET from two calibration experiments is shown in Figs. 4.6(a) and 4.6(b). During repeated measurement cycles,
the steady-state temperature rise from ambient is 45°C, and the maximum rise rate is 3°C/s. It can be seen that the temperature rise directly impacts the maximum measurement speed. The case temperature curve shows consistency in shape with the simulation from Fig. 4.3. The discrepancy in temperature could be due to inaccuracy in both the measurement and thermal model. In a system with only the shunt MOSFET and without the ultracapacitor, the maximum heat dissipation would be approximately double under the same conditions, which provides a strong motivation for the hybrid approach.

Nyquist curves of EIS measurements taken with the hybrid power stage are shown in Fig. 4.7. All measurements are taken with the same power stage operating with \( I_{\text{cell}} = 40 \, \text{A}, \, T_{\text{measure}} = 1 \, \text{s}, \) and frequency varying from 2 to 2000 Hz. Fig. 4.7(a) shows two Nyquist curves of a single cell. The curves correspond to measurements made with either 1) an oscilloscope, or 2) the SCS. The oscilloscope measurement setup consists of a Preamble Instruments 1855 differential amplifier with LeCroy DXC 100A differential probe for voltage measurement, and Tektronix TCP303 current probe with TCPA300 amplifier for current. While the oscilloscope instrumentation setup is meant for precision measurements, it should not be considered an ideal reference. The discrepancy between the two curves in Fig. 4.7(a) indicates that further tuning and verification of the accuracy and precision of all instrumentation used is necessary. The impedance of four cells in parallel, measured at two SOC points with the hybrid power stage and SCS, is shown in Fig. 4.7(b). The measured real impedance at low frequency is higher at 10% SOC compared to 90%, which is consistent with what is described in [1].
Figure 4.5: Hybrid topology experimental results: (a) single impedance measurement cycle, (b) three subsequent impedance measurement cycles.
Figure 4.6: Hybrid topology experimental results: (a) MOSFET case temperature over single 50 Hz impedance measurement cycle, and (b) MOSFET case temperature over 6 impedance measurement cycles with 25 s delay between each.
Figure 4.7: Hybrid topology experimental results: (a) Nyquist plots of a single 44 Ah cell using hybrid topology perturbation and measurement with oscilloscope and SCS, (b) Nyquist plots of four parallel 44 Ah cells at two SOC points using hybrid topology perturbation and measurement with SCS.
4.3 Chapter Summary

The low-impedance cells used in larger EVs impose a high SNR requirement for EIS. The proposed hybrid architecture presents one method to meet this requirement, by significantly increasing the perturbation current amplitude. By introducing a small ultracapacitor in each battery module, and leveraging the isolated dc-dc converter that is used for auxiliary supply, the thermal loss on the shunt device is reduced. This enables the addition of high-perturbation-current online EIS to the BMS presented here at minimal incremental impact to system size and cost. The hybrid architecture has been successfully used to measure the impedance of a 44 Ah, 1 mΩ nominal ESR Lithium NMC cell, as well as four such cells connected in parallel.
References

Chapter 5

Conclusion

5.1 Thesis Summary and Conclusions

An EV BMS that uses an impedance-based ECM to estimate sub-module $SOC$ and $V_{term}$ is designed and a two-module prototype is implemented in this thesis. Active balancing is incorporated in the BMS power architecture, real-time estimation of $V_{term}$ is achieved with an ECM, and the system is demonstrated through the experimental prototype. In general, the prototype system represents only a first step in the path toward a BMS that takes full advantage of impedance-based battery models, therefore this thesis should be regarded as a starting point, rather than a final step.

The application of one impedance-based battery model is highlighted through the characterisation of a 44 Ah lithium NMC pouch battery cell and identification of ECMs for 1 Hz and 1 kHz BMS state estimation frequencies. State observers are designed through simulation for estimation of the states of both models, and the low-frequency model and 1 Hz state observer are implemented in an experimental measurement and computation hardware setup. It is a promising result that the estimation of sub-module $V_{term}$ is accurate in the qualitative sense, but relationships between the estimated model states and electrochemical phenomena need to be explored before quantitative validation can be performed in earnest.

The primary research contributions of this thesis are:

- The BMS power architecture with rule-based control for active balancing and auxiliary bus regulation, which is demonstrated experimentally in a scaled-down, two-module prototype. The rule-based algorithm provides limited control freedom due to the coupling of the balancing speed to the auxiliary bus load, and achieves near-balance of the sub-module $SOC$s after 20,000 s of operation. The active balancing
converter has high efficiency, but suffers from slow dynamic response, which has a small effect on the burst-mode control accuracy.

- The hybrid linear and switched-mode online EIS architecture, which is demonstrated in an experimental setup separate from the BMS module, but with a clear path toward integration. The system is used to measure the impedance of a 176 Ah sub-module with 0.25 mΩ nominal impedance over a 2 kHz frequency range. The shunt MOSFET in the prototype is shown to be operating close to its thermal limit over six single-frequency measurement cycles while operating at 30 A peak perturbation current. The sub-module impedance measurements seem to lack accuracy, likely due to poor tuning of the hardware resulting in poor SNR.

5.2 Future Work

One valuable concluding insight that can be drawn from the work presented in this thesis is that it is necessary to explore battery modeling using a multidisciplinary approach such that electrical implementation constraints can be appropriately balanced with electrochemical theory. At a high-level, future work on battery management systems that use impedance-based models requires taking BMS implementation constraints into account. It is therefore necessary to further explore the deployment of impedance-based battery models in a BMS such as the one demonstrated in this thesis, with practical limitations on: 1) impedance measurement accuracy and speed, 2) active balancing power, 3) data transfer rate, and 4) computation capability. Selection of practically-feasible and performance-enhancing models for implementation in a BMS can then be performed, with consideration of the cost impact presented by scaling component ratings according the following hardware-related requirements:

- BMS state estimation frequency, \( f_{\text{est}} \), which has a large impact on the data communication and computation hardware. Given the exact bandwidth requirement of the models to be deployed, a distributed computing architecture can be explored where high-bandwidth computations are performed at the point-of-measurement, in order to avoid communication speed limitations.

- Active balancing power level for model-based balancing to achieve balance of temperature or capacity fade. This requirement is likely to vary with cell size, pack thermal and mechanical design, and age of the system, therefore an efficient methodology for determining system performance evolution over time and use needs to be developed.
• Time constraints for the online impedance measurements, so an appropriate perturbation current level can be selected, given a necessary SNR. In the ideal case, the measurements occupy only one perturbation cycle per frequency. Thus a minimum-duration, full-spectrum measurement can be performed using the hybrid power stage if the ultracapacitor is discharged after the spectrum instead of each frequency. This may require measurement instrumentation beyond what is available in the context of Bison.

Additional BMS features to be implemented in the future are:

• Maximum pack current prediction, including exploration of an appropriate prediction time horizon.

• A control algorithm for active balancing that decouples the balancing speed from the auxiliary bus regulation, thus enabling optimal use of the auxiliary battery energy storage. The control algorithm should enable variation of the burst-mode $t_{on}$ for different converters in the balancing system.

• A scheduling algorithm for online EIS measurements that takes into account 1) the relevant impedance frequency ranges, 2) the necessary estimation frequencies, and 3) typical geography or user-demographic-dependent battery current flow patterns, to optimally schedule online EIS measurements.