

CRANFIELD UNIVERSITY

YOU (BOB) GONG

AN INTEGRATED BATTERY UNIT REGULATION
STRATEGY

SCHOOL OF AEROSPACE, TRANSPORT AND
MANUFACTURING
PhD in Transport Systems

PhD
Academic Year: 2019–2023

Supervisor: Dr Daniel Auger
Associate Supervisor: Dr Abbas Fotouhi
March 2023

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requirements for the degree of PhD.

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Abstract

In the research community, hybrid battery systems (HBSs) employing dual battery chemistries have been proposed as a solution to address the suboptimal overall performance exhibited by most state-of-the-art single-chemistry battery systems used in electric vehicle (EV) applications. Currently, the predominant approach for regulating power distribution among different battery chemistries in HBSs is to configure DC/DC converters. However, the cost and weight associated with this configuration pose a significant barrier to its practical application. To overcome these limitations, this project presents a novel HBS design that utilizes a discrete-switched structure combined with intelligent low-frequency switching algorithms to replace DC/DC converters. The discrete-switched structure offers a simpler system architecture and lower power electronics costs while still maintaining the power allocation functionality of DC/DC converters. The switching algorithms developed, encompassing heuristic and model-predictive control algorithms, enable the switching of cells within battery strings based on battery status and power demands, facilitating effective power management. Through simulations and experiments, the HBS equipped with intelligent algorithms effectively regulates power distribution among different batteries and ensures a broadly balanced state of charge. Moreover, the novel HBS configuration employing nickel cobalt manganese oxide (NCM) and lithium-sulfur (Li-S) batteries has been thoroughly investigated, encompassing the hardware structure and control algorithms. This design enables both a long-range capability and high-power performance in EV applications. It should be noted that this work assumed the usage of homogeneous cells and effective cell cooling. Future research endeavors will focus on exploring cell-to-cell

variations and the development of corresponding thermal management systems.

Keywords

Batteries, Modeling, Control algorithm, Topology, Costs, Switches, Resource management.

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List of Abbreviations

Li-ion	lithium-ion
EV	electric vehicle
PHEV	plug-in hybrid electric vehicle
VRLA	valve-regulated lead-acid
Na-NiCl	sodium-nickel chloride
LFP	lithium-ion phosphate
HBS	hybrid battery system
LTO	lithium titanate oxide
NCM	nickel cobalt manganese oxide
NCA	lithium-nickel-cobalt-aluminum
LMO	lithium-manganese spinel
LCO	lithium cobalt oxide
BMS	battery management system

Li-S	lithium-sulfur
PHEV	plug-in hybrid electric vehicle
ECM	equivalent circuit model
BMS	battery management system
OCV	open circuit voltage
SOC	state of charge
FET	field-effect transistors
AEKF	adaptive extended kalman filter
FFRLS	forgetting factor recursive least square

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Chapter 1

Introduction

1.1 Background

Automotive industries have significant impacts on the worldwide economy and social development. Unfortunately, they also bring some side effects, e.g., massive consumption of fossil fuels, the ensuing environmental pollution, and excessive exploitation of fossil fuels. Over a decade, governments and organizations, especially the European Union, China, and the United States, have been actively pursuing legislation and policies related to reducing emissions and improving fuel economy in automotive industries [1]–[4]. Electric vehicles (EVs) are generally realized as a promising technology replacing internal combustion energy vehicles to reduce climate impacts [5]. Legislation pushing for lower emissions, technological progress, and awareness of petroleum as a finite resource have increased consumer purchasing enthusiasm for EVs.

In recent years, EV markets have been expanding and penetrating quickly. Figure 1.1 illustrates the world's markets of EVs and plug-in hybrid electric vehicles (PHEVs) in China, the United States, Europe, and others. It can be seen that the EV sales volume

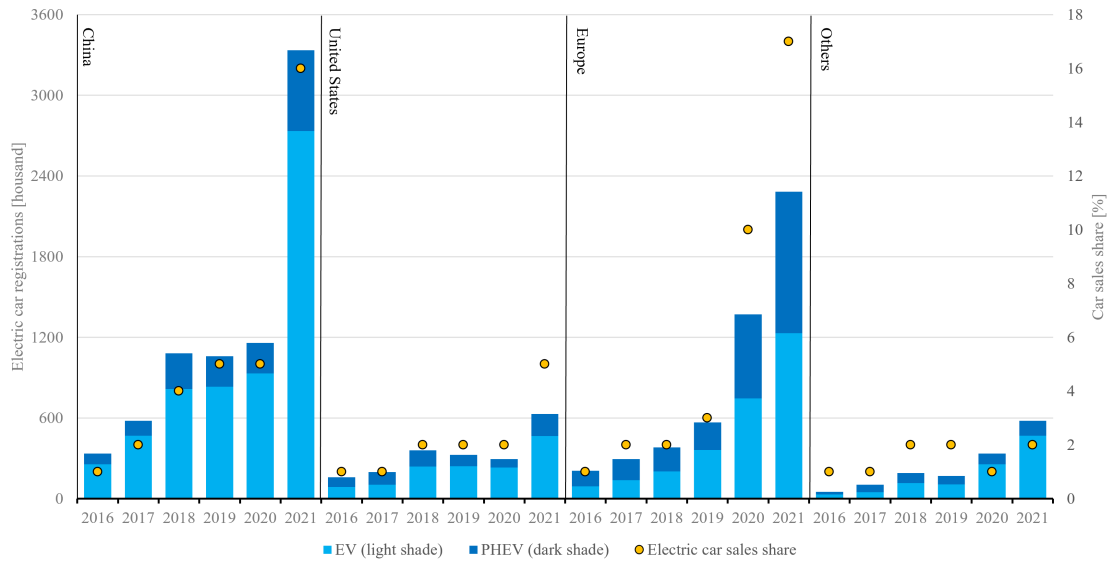


Figure 1.1: Electric car registrations and sales share in various regions, 2016-2021 [6]

and penetration rate in three major automobile markets worldwide present rapid growth. Especially their worldwide market share in 2021 was four times that in 2019 [6]. Extending the time scale, the breakthrough changes can be revealed: 120 thousand EVs were sold worldwide in 2012, but in 2021 they may have been sold in a week.

Unlike conventional internal combustion engine vehicles, the driving power for EVs is mainly drawn from batteries. Therefore, battery systems play a critical role across various EV applications. However, compared to batteries in consumer electronics and devices, batteries in vehicles (i.e., traction batteries) put forward higher requirements for comprehensive performance due to the complexity of the application scenarios. The salient features of traction batteries in EV applications are [7]:

1. High energy density with temperature tolerance to provide a long driving range under one deep charge opportunity at various temperatures,
2. High power density to attain stable power with deep discharge conditions and provide fast charge capability,
3. Low cost to improve market competitiveness and increase product penetration,

4. Longevity with maintenance-free operation to reduce battery maintenance and replacement frequency,
5. High safety to ensure EV safety and efficiency.

Nevertheless, current traction batteries have distinct advantages and disadvantages [8], [9] (This topic has been reviewed in Chapter 2). Despite lithium-ion (Li-ion) batteries continuing to dominate the EV domain, traction batteries can still not reconcile conflicting requirements for high specific energy, high specific power, low cost, good temperature tolerance performance, and long lifetime. Today's battery systems are typically composed of many cells with a single chemistry type, so designers must compromise the impacts of various performances. This presents significant barriers to original equipment manufacturer (OEM) electrification programs and end-user adoption.

In response, the hybridization of battery systems has been introduced in the research community to overcome the drawbacks of single-chemistry battery systems. These battery systems, composed of two or more types of batteries, are called the hybrid battery system (HBS). The HBS combines complementary advantages of multi-chemistry batteries to mitigate the impacts of individual weaknesses across all key metrics. This concept brings up additional opportunities for utilizing battery potential. However, the proposed HBS hardware structures capable of realizing energy management in the research community and industry are complex, bulky, and expensive. Therefore, the motivation of this project is to explore a novel topology for the HBS that simplifies the electrical architecture capable of realizing energy management.

1.2 Project Aim and Objectives

This project aims to develop a hybrid battery system using a low-complexity structure, simultaneously exploring a feasible battery management approach to allow multiple batteries to be regulated and managed to optimize the overall battery performance. This structure enables flexible power flow allocations between various battery types with simpler hardware complexity and lower cost. The battery management approach performs appropriate control algorithms that allow partial characteristics of battery type to dominate under a given performance constraint and to produce a better system-level performance adaptable to EV applications.

The objectives are listed as follows:

1. Investigating various types of traction batteries and state-of-art HBS technologies.
2. Developing a new HBS structure that is capable of decreasing costs while achieving flexible power regulation between multi-chemistry batteries.
3. Modeling battery from cell to pack level, where the battery datasheet and experimental data parameterize the model.
4. Developing an appropriate management system matching the novel HBS hardware structure.
5. Evaluating the HBS hardware structure and corresponding management system by simulation and experiment.

1.3 Contributions of This Project

In summary, the contributions of this project are listed as follows:

1. A novel discrete-switched structure has been proposed and used in the HBS hardware architecture. This structure can regulate power flow allocations between different battery types by switching cells in and out of series strings based on their states relative to other cells in a battery system.
2. Compared to the proposed HBS in the literature and industry, the power electronics of HBSs using the discrete-switched structure have much lower cost and simpler hardware structure. Besides, this structure can use an "event-based" switching approach, where switching is done by a low-frequency modulation (1~10 Hz).
3. The HBS models from cell to pack level have been developed in MATLAB/Simulink, in which sub-components and lumped models have been all built by Simulink and Simscape toolbox.
4. The heuristic and model-predictive control algorithms have been developed, serving as management system strategies corresponding to HBSs using the discrete-switched structure. The heuristic control algorithm combined a high-level rule-based supervisory control and a low-level near-optimal control. The model-predictive control algorithm comprises a nonlinear cost function, system performance constraints, and a genetic algorithm solver, which can optimize discrete switching operations based on battery states and power demands.
5. Simulations and an experiment with proposed control algorithms have verified the capability of the discrete-switched structure, including flexible power flow allocations between different battery types, optimization of control system operations, and states of charge balancing.

1.4 Thesis Outline

This thesis is a "paper format" style, which is one of the standard formats at Cranfield University. The publication and planned publications have been written in Chapters 4 to 6, including their own abstract, introduction, methodology, results, and conclusion sections. Besides, Contributor Roles Taxonomy (CRediT) is introduced in paper format chapters to explain authors' contributions in each publication [10]. I decided to write an article-based thesis format because the project's achievements had been demonstrated in publications. In order to present the context of the thesis more clearly, except for the article-formatted chapters, other chapters were written from the perspective of the whole project, including the introduction (Chapter 1), literature review (Chapter 2), methodology (Chapter 3), results (Chapter 7), discussion (Chapter 8), and conclusions (Chapter 9). Specifically, this thesis is organized as follows:

Chapter 1 - this chapter presents the project background, aim, objectives, and thesis outline.

Chapter 2 - this chapter investigates the traction battery types for EV applications and reviews state-of-art HBSs. The salient features of various traction batteries have been compared across technical dimensions. Furthermore, the limits of state-of-art HBSs in the literature and industry have been summarized, providing a detailed background for this project.

Chapter 3 - this chapter summarizes this project's methodology, including the developed structure, modeling, control strategies, simulation approaches, experiment embodiment, and future directions.

Chapter 4 - this article-based chapter presents the novel discrete-switched topology for a hybrid battery system. The power electronics of current HBSs are relatively costly due to the use of DC/DC converters. The discrete-switched structure can avoid expensive

DC/DC converters in the HBSs. This structure switches cells in and out of series strings according to the battery states. Using the discrete-switched design, the hybrid battery system successfully allocates the power to two subpack with different battery types and ensures the state of charge remains broadly balanced.

Chapter 5 - this article-based chapter presents an experimental validation for the low-frequency discrete-switched structure. The experiment used a 24 V battery pack for hybrid lead-acid and NMC batteries. This study successfully verifies the capability of power allocations.

Chapter 6 - this article-based chapter presents a novel hybrid battery system (HBS) for an electric vehicle (EV) consisting of Li-S and NCM batteries. The Li-S and NCM batteries in the proposed HBS can fully play the two batteries' energy and power density strengths. The configuration of batteries and hardware in the HBS is optimized to maintain its cheap and lightweight. The energy management system integrates the functions of battery parameter identification, state estimation, and switching control strategy to estimate battery states and allocate power between different batteries. The HBS performances are demonstrated using a simulated model, showing excellent cruising range and maximum power performance. Meanwhile, the simulation results demonstrate estimation and the management strategy robustness under battery degradation.

Chapter 7 - this chapter summarizes the results and key findings of this project.

Chapter 8 - this chapter highlights the primary outcomes based on research objectives. Besides, the discussion point out the limitations relative to my studies to date.

Chapter 9 - this chapter presents an overall conclusion for my PhD project and looks ahead to possible future work.

Appendices - this chapter briefly introduces my work as a research assistant post in the

Chimera and BRAD projects.

1.5 Relationship between the articles and thesis

This section explains how the individual paper chapters (Chapters 4 to 6) connect together to produce a cohesive "paper-format" thesis. Table 1.1 describes how the different publications fit together to visualize the connection between the papers, objectives, and contributions.

Table 1.1: Connection between the papers, objectives and contributions

Objective	Chapter/Section	Contribution
Objective 1: investigating traction batteries and HBSs	Chapter 4: Section 4.1 Chapter 5: Section 5.1 Chapter 6: Section 6.1, Section 6.2	Contribution 1
Objective 2: developing a new HBS structure with cost evaluation	Chapter 4: Section 4.2 Chapter 5: Section 5.2 Chapter 6: Section 6.3	Contribution 2 and 3
Objective 3: modeling	Chapter 4: Section 4.3 Chapter 5: Section 5.3	Contribution 4
Objective 4: battery management system	Chapter 4: Section 4.4 Chapter 5: Section 5.4 Chapter 6: Section 6.5	Contribution 5
Objective 5: evaluation and analysis	Chapter 4: Section 4.5 Chapter 5: Section 5.5, Section 5.6 Chapter 6: Section 6.5	Contribution 6

Each article follows a progressive format from objectives 1 to 5. Since the article in Chapter 4 has elaborated on the modeling process in detail, the article in Chapter 6 omits the model development by citing the article in Chapter 4.

Chapter 2

A Review of Hybrid Battery Systems

In this thesis, a part of the reviews associated with hybrid battery systems has been presented in the introduction sections of Chapters 4 to 6. Still, they are brief because of journal layout limits. This chapter comprehensively reviews various traction battery features and HBS developments. Finally, issues of current HBSs are summarized to explain the research directions of this project in detail.

2.1 Traction Battery Characteristics

Batteries are a type of device that converts chemical energy into electrical energy. It typically consists of one or more electrochemical cells that store chemical energy and release it as electrical energy when a circuit is completed. The components of a typical battery cell are shown in Figure 2.1, where the essential components are briefly introduced as follows [11]:

1. Electrodes: a battery cell has two electrodes, a positive electrode and a negative electrode. These electrodes are usually made of different metals or metal com-

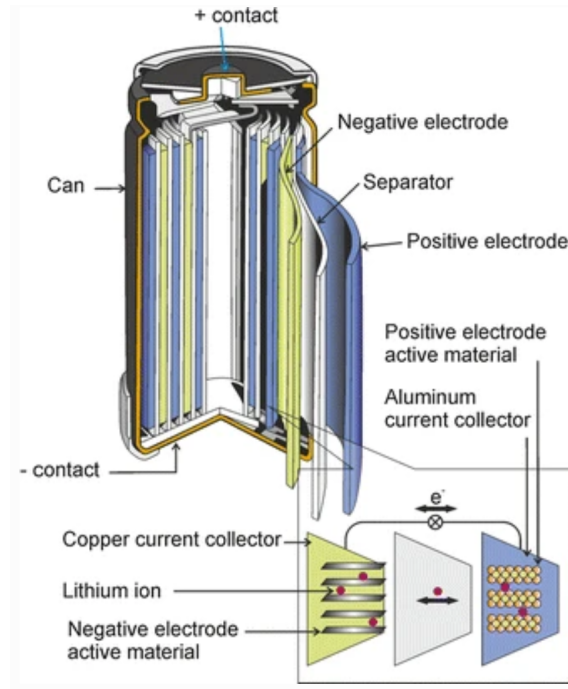


Figure 2.1: Battery components [11]

pounds.

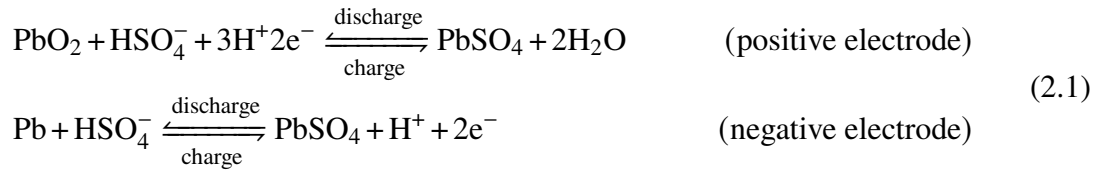
2. Electrolyte: an electrolyte is a substance that can conduct electricity when dissolved in a solvent. In a battery, the electrolyte is usually a liquid or a gel that contains ions that can move between the electrodes.
3. Separator: a separator is a material that keeps the positive and negative electrodes apart in a battery while allowing the flow of ions between them. This prevents short circuits that can damage the battery.

Some batteries may also have additional components such as a casing (can), terminals (+ and - contact), and a vent to release any gas that may be produced during operation.

To date, common battery types in vehicle electrification applications (i.e., HEV, PHEV, and EV) are lead-acid, Nickel-Metal-Hydrate (Ni-MH), Sodium-Nickel Chloride (Na-NiCl), and Li-ion batteries. Their advantages and disadvantages are discussed as follows.

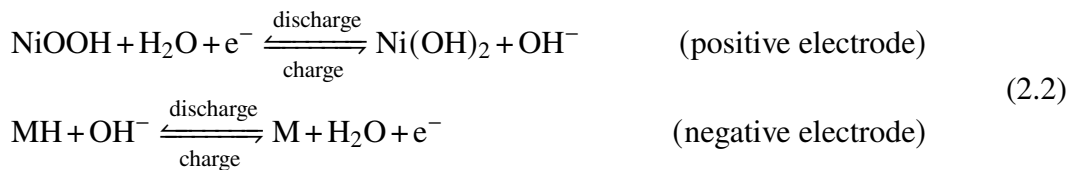
2.1.1 Battery Types in Automotive Applications

Lead-acid batteries, a relatively old technology, are the first rechargeable battery type invented by Gaston Plante in 1859 [12]. Their modern type is the valve-regulated lead-acid (VRLA) batteries, using immobilized electrolytes for maintenance-free [13]. On the electrochemical side, the positive electrode is coated with lead oxide (PbO_2), the negative electrode is made of lead (Pb), and the electrolyte is dilute sulfuric acid (H_2SO_4). The reactions at the positive and negative electrodes are as follows:



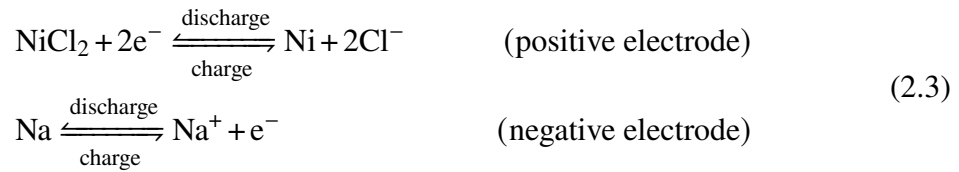
Lead-acid batteries provide inexpensive energy to serve a load, so they are extensively used as starting, lighting, and ignition batteries in vehicles. However, their drawbacks are low specific energy, low lifetime (~ 200 cycles), and inefficiency in high-frequency pulse and high-power load applications [12]. They were applied in early models of hybrid electric vehicles (HEV) since technologies for other traction batteries are immature and costly.

Ni-MH batteries possess better cycle life and energy density but cost more than lead-acid batteries. They were heavily used in HEV applications such as the well-known Toyota Prius model. On the electrochemical side, the positive and negative electrodes are an active material with nickel hydroxide (NiOOH) and hydrogen-absorbing nickel alloys (MH), and the separator uses an alkaline electrolyte (e.g., KOH). The reactions at the positive and negative electrodes are as follows:



One leading drawback of Ni-MH batteries is the severe issue of quick self-discharge without applied loads [13]. Moreover, the theoretical cell voltage is 1.35 V, where the positive and negative electrodes yield 0.52 V and -0.83 V relative to a standard hydrogen electrode, respectively. The relatively low theoretical voltage is one of the issues resulting in the lower energy density than Li-ion batteries. In addition, overcharging is detrimental to their lifespan and inside pressure increases since it can consume water to produce hydrogen, increasing the internal resistance and electrolyte concentration.

Na-NiCl batteries are a type of high-temperature rechargeable battery. They use a nickel chloride electrode (NiCl_2) as the positive electrode, a sodium electrode (Na) as the negative electrode, and a ceramic electrolyte made of beta-alumina [9]. The positive and negative electrode reactions in a Na-NiCl battery are as follows:



One of the critical advantages of Na-NiCl batteries is their high energy density, which can be up to three times higher than lead-acid batteries. They can be recharged thousands of cycles without significant degradation. Meanwhile, they are relatively safe and do not contain toxic materials like lead or cadmium. Their cost is more affordable, although the energy density is lower than Li-ion batteries. Thus, they are particularly well-suited for stationary applications where high energy density, long cycle life, and low cost are essential factors.

However, Na-NiCl batteries need to operate at high temperatures, typically 270 -365 °C, to achieve efficient electrochemical reactions. The critical drawbacks are related to their operation safety with relatively high temperatures and long-term storage in EV applications.

Li-ion batteries occupy a growing market share mainly due to their high energy density, making them attractive for applications of limited weight and volume. Furthermore, they possess longer cycle life (≥ 500 cycles) and slower self-discharge ($\leq 10\%$ /month). Advances in battery chemistries and economies of scale have led to a rapid increase in the cost competitiveness of Li-ion batteries.

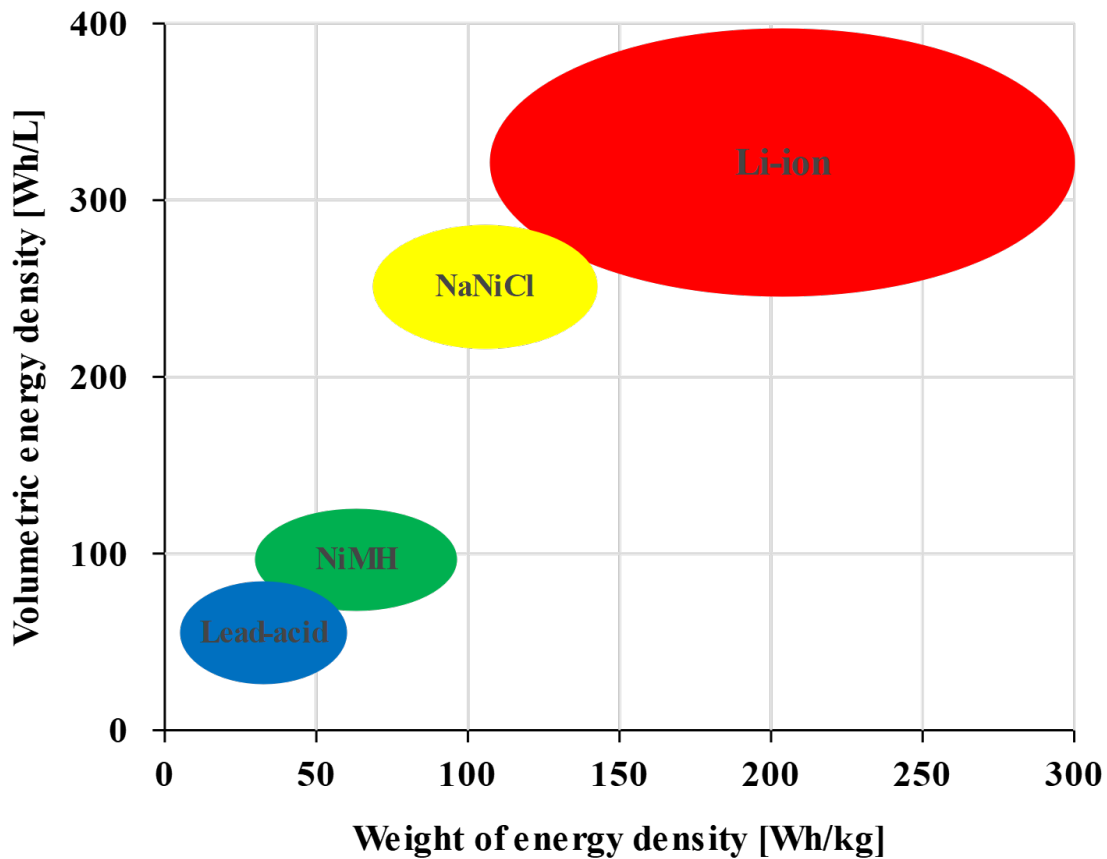


Figure 2.2: Specific energy and power on various energy storage units at cell level [14] and [9]

EV applications are critically sensitive to battery weight and volume, leading to a necessity to configure enough energy under limited weight and volume to meet the extended driving range. As shown in Figure 2.2, among various commercialized traction batteries, including lead-acid, Ni-MH, Na-NiCl, and Li-ion batteries, Li-ion batteries are the most proper technology for fulfilling the EV requirements in energy density [14]. Meanwhile, they have flexibility, high specific power, relatively less pollution, and smaller and lighter cell

designs [15], [16].

Li-ion batteries are a family of battery chemistries with various cathode and anode materials combinations. Since Li-ion batteries are the most prevalent and promising technologies in current and future EV applications, the performances of different Li-ion battery chemistries need to be detailed and compared to understand their specific features, including energy and power density, cost, lifetime, and safety. Thus, the commercialized and advanced Li-ion battery types are briefly reviewed in the following part.

2.1.2 Li-ion Batteries

To date, the prevalent automotive Li-ion chemistries include LiFePO_4 (LFP), LiMn_2O_4 (LMO), $\text{LiNi}_{0.8}\text{Co}_{0.15}\text{Al}_{0.05}\text{O}_2$ (NCA), $\text{Li}_4\text{Ti}_5\text{O}_{12}$ (LTO), and $\text{LiNi}_{1-x-y}\text{Co}_x\text{Mn}_y\text{O}_2$ (NMC). Each combination has particular advantages and weaknesses.

LFP

LFP batteries are a type of Li-ion battery that uses lithium-iron phosphate as the positive electrode, graphite as the negative electrode, the separator of microporous polymer material (e.g., polyethylene and polypropylene), and a non-aqueous electrolyte consisting of a lithium salt dissolved in an organic solvent. Recently, they have received widespread attention and have become popular.

One of the main advantages of LFP batteries is their long cycle life. They can typically be recharged thousands of times without significant degradation, which makes them ideal for applications that require frequent charging and discharging [17]. Compared to other types of lithium-ion batteries, LFP batteries can provide high discharge currents without significant voltage drops. Meanwhile, LFP batteries have excellent tolerance in full-charge conditions, overheating and catching fire, which makes them a safe choice for EV

applications.

Despite these advantages, LFP batteries have a relatively low energy density compared to other Li-ion battery types due to the low voltages (typically around 3.2-3.3 V) and theoretical energy density limits. Additionally, LFP battery performance can be significantly affected at low temperatures. Meanwhile, its higher self-discharge characteristic can cause cell balancing and aging issues [18]. Although employing cell balancing systems and using high-quality cells can mitigate these issues, both solutions have to increase the costs of the battery system [13].

LMO

LMO batteries use manganese oxide as their positive electrode instead of the more commonly used cobalt oxide. Similarly, the negative electrode and separator are the graphite and thin microporous polyethylene or polypropylene membrane, respectively.

The critical advantage of LMO batteries is the lowest cost among various Li-ion batteries owing to the cheap electrode materials. Furthermore, they can provide good rate capability and non-toxicity [19]. However, the critical weakness of the LMO is its low energy density. Besides, it suffers from instability at high temperatures, leading to moderate safety. Despite the shortages of the LMO battery, it has a cost-competitive highlight, which is significant for commercial applications.

NCA

NCA batteries use nickel-cobalt-aluminum oxide as their positive electrode material, graphite as the negative electrode, and microporous polymer as the separator. They are commonly used in electric vehicles and other applications that require high power output and long-lasting performance.

The NCA battery exhibits high energy density and high power density due to the excellent

specific capacity of electrode materials. Simultaneously, it possesses excellent cycling stability [20]. However, the NCA battery is easy to expand and contract because of the poor stability of nickel. NCA's performance in cost competitiveness is not satisfactory due to the doping with expensive Co (15 mol%) and synthesis complexity [21].

LTO

Unlike the above Li-ion battery types, the positive electrode in LTO batteries is typically made of lithium-iron phosphate or lithium manganese oxide materials. These materials are chosen for their high stability and safety and have a lower risk of a thermal runaway than other lithium-ion battery chemistries. Moreover, the negative electrode in LTO batteries is made of lithium titanate ($\text{Li}_4\text{Ti}_5\text{O}_{12}$) material, which is highly stable and does not experience the same degradation over time such as graphite. The lithium titanate electrode has a shallow potential for Li-ion intercalation, making it difficult for lithium ions to become trapped within the electrode and cause damage.

Therefore, LTO batteries have a faster charge capability (≥ 10 C-rate) and cycle durability (≥ 6000) than other Li-ion batteries [22]. Additionally, a highlight of the LTO battery is its high-level safety, ensuring abuse tolerances of the battery in complex operations. Nonetheless, its critical disadvantage is a much lower energy density (60-110 Wh/kg) than other Li-ion batteries.

NMC

Similarly, NMC batteries are typically made of 1) the positive electrode of a mixture of lithium, nickel, manganese, and cobalt oxide, 2) the negative electrode of graphite, and 3) the separator of a polymer material (e.g., polyethylene or polypropylene). This mixture of the positive electrode allows for high energy density and good cycle life.

The NMC battery has the highest energy density among the commercialized Li-ion bat-

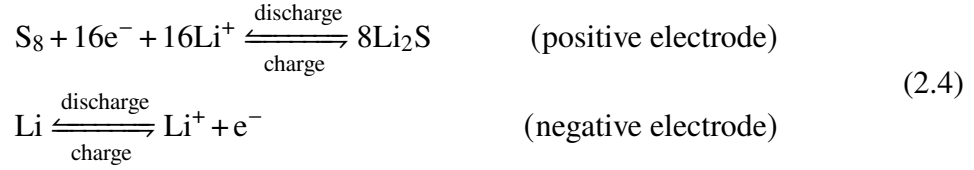
teries. The pre-commercialized NMC battery can even achieve the energy density of 330 Wh/kg at a cell level [23]. Moreover, it has the lowest self-heating rate since manganese has the advantage of forming a spinel structure to reach low internal resistance [19]. Besides, the cost is lower than the NCA battery due to the more effortless blending of nickel, manganese, and cobalt. Nevertheless, although manganese doping improves the stability of the battery, the instability of nickel still has a particular impact on the safety performance.

Li-S

To reach cruising ranges well beyond 500 km, the cell-level energy density must be further increased to more than 300 Wh/kg. In the short term, the performance of the NCM battery can be improved by increasing the nickel content, e.g., the NMC-811 ($\text{LiNi}_{0.8}\text{Co}_{0.1}\text{Mn}_{0.1}\text{O}_2$) battery chemistry with the higher power density and lower cost [24]. Nevertheless, NMC-811 may be a transitional technology as a high-energy battery in EV applications, considering the limitation of the theoretical energy density. In the long term, EV batteries must achieve energy densities of more than 500 Wh/kg at the cell level to overcome EV range anxiety. At this stage, the promising technologies for high-energy battery chemistries include lithium-sulfur batteries (Li-S), lithium-air batteries, and all-solid-state batteries, owing to their higher energy density and lower cost. In this thesis, Li-S batteries are introduced as the case for showing their potential advantage and drawbacks for automotive applications in the future.

Li-S batteries are considered a promising candidate to overcome the energy density limitations of current Li-ion batteries. The working mechanism is complex and needs further research, but the active principle has been revealed. The battery mainly comprises a cathode consisting of sulfur, a carbon-based material and a binder, the lithium metal anode, a polymer separator, and an organic-solvent-based electrolyte. The reaction of the positive

and negative electrodes can be represented as follows [25]:



This battery is well-known for its theoretical energy density of 2500 Wh/kg [26]. To date, the pre-commercial product can achieve more than 400 Wh/kg now and over 600 in several years [27]. Benefiting from the worldwide abundance of sulfur, the cost of the Li-S battery using sulfur as an inexpensive active material is much lower than state-of-the-art batteries [28]. Moreover, it possesses the advantage of abuse tolerance and exhibits a high-level safety [25]. However, the power density of the Li-S battery is rarely performed above 1C due to the complex reaction mechanism. Meanwhile, its cycle life (200 cycles at present) is unsatisfactory owing to the "shuttle effect" and cathode volume expansion [29]. Its poor power density is difficult to improve through electrochemical technology shortly.

2.1.3 Comparison of Various Li-ion Batteries

On the technical aspect, the advantages and disadvantages of various Li-ion batteries can be evaluated across five dimensions: energy density, power density, cost, lifetime, and safety. Figure 2.3 illustrates comparisons of the state-of-art Li-ion batteries. Additionally, Table 4.1 in Chapter 4 lists the specific data of each battery type relative to the five dimensions.

Due to limited weight and volume, EV applications are critically sensitive to energy density to meet the extended driving range. In this dimension, NMC and Li-S batteries are the "best" choices to form EV battery systems now and several years later. Nonetheless, considering other dimensions, they have distinct weaknesses compared to other Li-ion battery types. For example, EVs using NMC batteries have less cost competitiveness and

safety concerns. Alternatively, choosing Li-S batteries have to consider whether their power density and lifetime will affect the performance of battery systems.

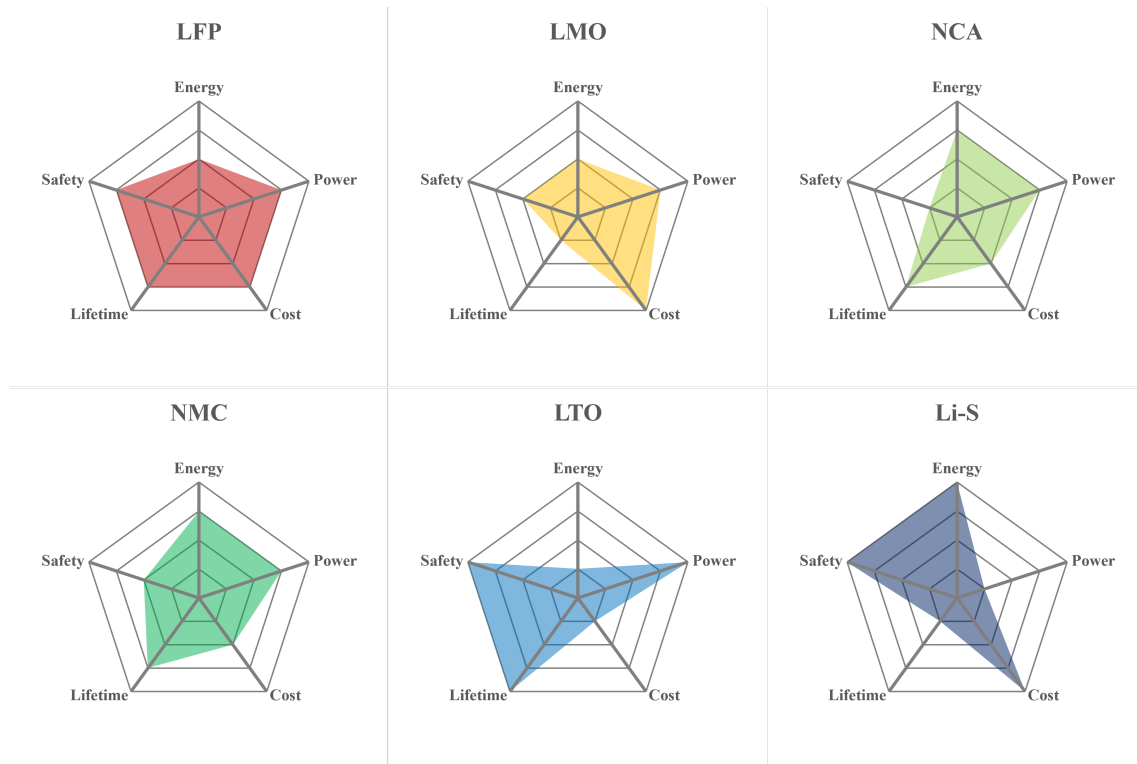


Figure 2.3: Comparison of five performance dimensions on six Li-ion battery chemistries (LFP, LMO, NCA, NMC, LTO, and Li-S) [19].

Across various traction batteries, including the LFP, LMO, NCA, NMC, LTO, and advanced Li-S batteries, no battery chemistries can reconcile requirements for energy density, power density, cost, abuse tolerance, and cycle lifetime. Therefore, the battery system consisting of single battery chemistry has to compromise the impact of various performances.

2.2 Review on Hybrid Battery Systems

2.2.1 Literature and Related Applications

As mentioned, single-chemistry battery systems with a battery type cannot fulfill all salient features in EV applications, hindering end-user adoption and OEM EV programs. The background of the HBS concept is based on existing battery chemistries to alleviate EV problems caused by the lack of electrochemical technologies at the battery pack and system levels. Hybridizing multi-chemistry batteries is a common idea in system engineering: combining various components with distinct advantages and disadvantages to improve the system's overall performance.

The idea of the HBS originated from a hybrid battery-supercapacitor power source in 1999 [30]. This approach combined supercapacitors and lead-acid batteries since Li-ion traction batteries were not yet mature. At that time, lead-acid batteries had high energy density and low self-discharge compared to other storage units but low power density, long charge time, and low cycle life. Despite the disadvantage of having a much lower energy density for supercapacitors, they have an ultrahigh power density and much better cycle life than batteries. In the case of the hybrid battery-supercapacitor power source, lead-acid batteries act as a major energy storage source, while supercapacitors act as a fast power supply source to absorb peak power and allow the batteries to work at lower current levels. Applying the hybrid battery-supercapacitor power source can benefit EV power performance and battery lifetime [31].

Li-ion traction batteries currently face an issue: no battery chemistries are the best in all technical dimensions, including commercialized, pre-commercialized, and promising battery technologies. The most general approach for battery system design is selecting a single battery type to achieve some key design targets but sacrificing other performances. Alternatively, some performances "spill over" to fulfill all design targets, which would raise

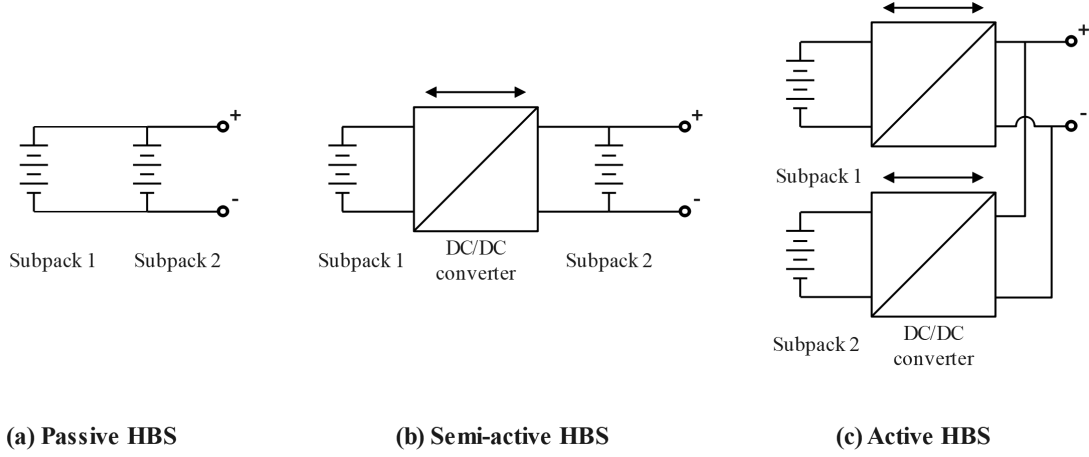


Figure 2.4: HBS topologies: (a) passive HBS, (b) semi-active HBS with a DC-DC converter, and (c) active HBS with two DC-DC converters

the cost issue. Although battery chemistries possess unique advantages and weaknesses, they have complementary advantages in technical dimensions. Hence, in the research community, hybrid battery systems (HBS) have been introduced to potentially mitigate the drawbacks of battery systems of a single-cell type.

On the technical side, there are three typical topologies to manage the power allocation between two or more types of batteries: passive, semi-active, and active [32], as shown in Figure 2.4. Bus contacts "+" and "-" indicate the interface of the battery systems to drive units. In EV applications, they are the inverter and motor. Subpacks 1 and 2 configure different battery types in the system. The passive topology has a comparatively low system complexity since no power electronics are needed to interconnect the subpacks. The passive HBS topology is reported in [33] and [34]. Despite the relatively simple system, the power flow is not controlled between battery subpacks in the passive HBS. Hence, it is necessary for this HBS to carefully adjust subpack size, electrochemical matching of two battery types, and thermal effect of meeting requirements regarding operational constraints, lifespan, and safety.

Further studies address active battery hybridization in EV applications [31]. The semi-

active HBS comprises a DC/DC converter connecting a battery subpacks to another battery subpack and drive units. These effectively decouple the physics and chemistry of the battery subpacks, leading to the power flow can be managed in the semi-active and active HBS. Meanwhile, the battery subpacks can be designed independently based on the requirements. The active HBS comprises two DC/DC converters, which can improve the power capability of the system in addition to the feature of power allocations[35], [36].

Some authors discuss the advantages of the HBS. An HBS applied in plug-in hybrid electric vehicles (PHEV) is developed in [37]. The HBS based on model predictive control can improve fuel efficiency by predicting torque demands. In addition, studies in [38], [39] state that optimizing energy management systems can improve system efficiency and battery current peaks. Most studies on the HBS advantages discuss that the HBS can mitigate battery degradation. A combination of LFP batteries and supercapacitors in EV applications are presented in [31], [40], [41], [42]. The above studies involving battery degradation use the LFP battery aging model proposed in [43]. Results reveal a reduction of LFP battery aging by supercapacitors absorbing peak current and minimizing the root mean square battery current through the LFP batteries.

On the commercialization side, some companies are also exploring hybrid battery approaches. Brill Power releases a pre-commercial product using DC/DC converters in each module to regulate the module's current [44]. MEP Technologies develops a hybrid battery-supercapacitor pack, providing high-impulse buffering [45]. Williams Advanced Engineering presents an adaptive multi-chemistry battery system using module-integrated and bi-directional DC/DC converters [45]. The concept of these pre-commercial battery packs and systems is derived from the semi-active and active HBS topologies.

2.2.2 Limitations

Based on the previous review, it can be found that the DC/DC converter plays a vital role in controlling power allocation in HBSs. Although the research community and industry are actively trying to apply these studies to real-world products, the cost of power electronics is a critical barrier. The key power electronics, DC/DC converters, are expensive and bulky. According to the investigation in [46], the cost of high-power DC/DC converters is approximately \$50.8/kW. In HBS applications, the semi-active and active HBSs need DC/DC converters of more than 50 kW, leading to power electronics being relatively costly in the systems. Based on the specific investigation in Chapters 4 and 6, power electronics for a semi-active HBS cost over \$2000, which is much higher than their cost in a single-chemistry battery system, and even reaches a quarter of the battery cell cost.

Furthermore, insulated-gate bipolar transistors (IGBT) or metal-oxide-semiconductor Field-Effect Transistors (MOSFET), as switching components in DC/DC converters, will generate massive heat at high-frequency operations, leading to increased power consumption and reduced performance [47]. Therefore, it is necessary to consider further the heat dissipation of DC/DC converters in thermal management systems, apart from the heat dissipation of battery cells, to protect the switching components from unwanted oscillations, instability, and signal distortion.

2.3 Concluding Notes

In this chapter, we have reviewed the technical features of traction batteries and current HBS technologies in EV applications. It is worth noting the following:

1. EV applications are critically sensitive to energy density, but power density, cost, lifetime and safety are yet the leading technical dimension to evaluate traction battery

performance. Across comparison of different traction battery types, no battery type can reach comprehensive advantages in all dimensions.

2. The concept of the hybrid battery system is derived from system engineering: combining various battery types with distinct advantages and disadvantages to improve the system's overall performance. The literature has proposed two topologies to regulate power flow allocation between different types of batteries, verified their better performance than single-chemistry battery systems, and proposed corresponding control strategies.
3. The critical barrier for current HBS structure in real-world applications is costly power electronics because of employing DC/DC converters, which leads to much higher hardware costs than single-chemistry battery systems. Another potential issue is the additional heat dissipation requirement generated by high-frequency switching operations of semiconductors in DC/DC converters.

Chapter 3

Methodology

As described in Section 2.3, the limitations for HBS real-world applications are costly power electronics and potentially additional thermal issues - both are side effects derived from employing DC/DC converters. In this project, a novel low-frequency structure has been developed to avoid expensive DC/DC converters. This chapter comprehensively describes the project's methodology from structure development, simulation approaches, experimental embodiment, and future directions. Research methods in this project can be especially summarized as follows:

1. **Structure development:** this project developed the discrete-switched structure used in HBS, which allows cells in and out of series strings in a battery pack. This structure in system-level applications has also been presented in Sections 4.2 and 6.3. In addition, the cost comparisons of power electronics in various HBS structures have been investigated in Sections 4.2 and 6.3.
2. **Modeling:** HBS using the discrete-switched structure have been modeled from battery cells to the battery systems based on the hardware structure and various battery features. Modeling approaches have been demonstrated in Sections 4.3 and 5.2.

3. **Control development:** this project proposed two approaches, heuristic and model predictive control algorithms, to regulate discrete-switched modules based on their states relative to other modules in the pack. The heuristic control algorithm has been presented in Sections 4.4 and 5.2. The model predictive control algorithm has been depicted in Section 6.5.
4. **Simulation approach:** simulation approaches have been designed to verify the capability of the discrete-switched structure, where conditions of case studies are close to real-world EV applications. Simulation results have been shown in Sections 4.5 and Section 6.5.
5. **Experimental embodiment:** simulation approaches have been designed to verify the capability of the discrete-switched structure, where conditions of case studies are close to real-world EV applications. The experimental embodiment (presented in Chapter 5) uses a module-level hybrid battery pack comprised of two different battery types to validate the capability of the discrete-switched structure.
6. **Future applications:** this project further explores the future applications for the HBS comprised of NMC and Li-S batteries using the discrete-switched structure. Details have been included in Chapter 6. Research approaches include an investigation of the development trend of the two batteries, optimization of the HBS configuration, and a case study.

3.1 Structure Development

Figure 3.1 shows a module-level discrete-switched structure. The battery module comprises several cells, a main switch, and a bypass switch. The positive and negative terminals of the battery cells are connected in parallel. The main switch is directly connected to the positive terminal of the parallel cell string. The bypass switch is electrically

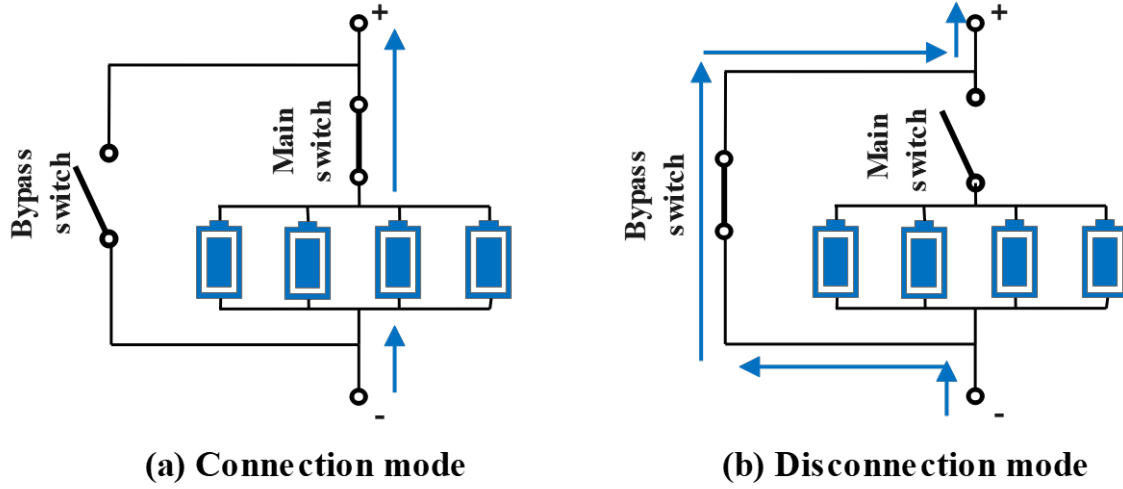


Figure 3.1: Operation modes of a module: (a) connection mode and (b) disconnection mode.

connected to the positive terminal of the circuit and the negative terminal of the parallel cell string. Here, the circuits with main and bypass switches are the main and bypass circuits, respectively. Moreover, an interlock is used in the two switches to protect them from simultaneous switching on or off. The operations of the module contain two modes, as listed below.

1. **Connection mode** - the main switch is switched on, and the bypass switch is switched off. Current flows through the main circuit, and the cells can participate in the overall charging/discharging processes.
2. **Disconnection mode** - the main switch is switched off, and the bypass switch is switched on. Current flows through the bypass circuit, and the cells can be isolated to the overall charging/discharging processes.

The HBS architecture using discrete-switched modules is illustrated in Figure 3.2. Subpacks 1 and 2 comprise different battery types, i.e., subpack 1 uses battery type 1, and subpack 2 uses battery type 2. The power contacts "+" and "-" interface with the high-

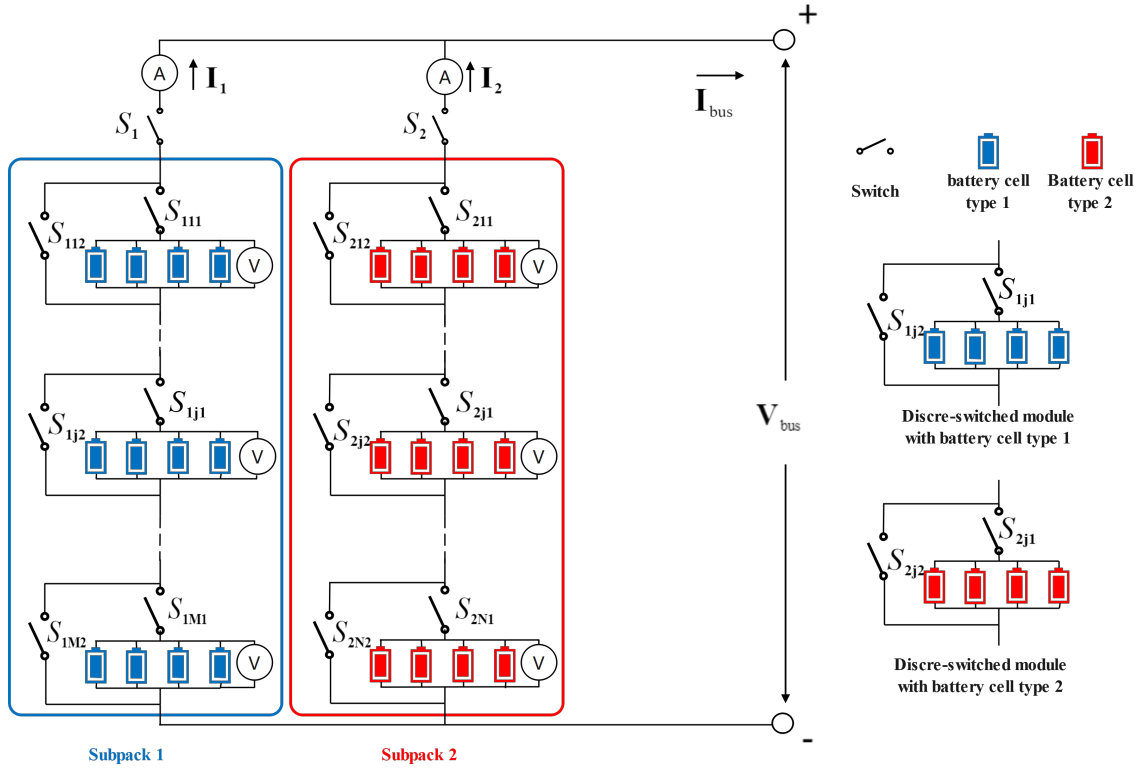


Figure 3.2: The HBS architecture using discrete-switched modules.

voltage bus in EV applications. The two subpacks are connected in parallel via pack-level switches S_1 and S_2 , where S_1 and S_2 regulate the two battery subpack to participate in the overall charging/discharging processes. A subpack contains many discrete-switched modules in series, which can switch in and out of the subpack during operating processes. Meanwhile, the operation of the discrete-switched modules can regulate the currents through subpack 1 and 2, I_1 and I_2 , and terminal voltage of the battery system V_{bus} , to achieve the power flow allocations between the two subpacks.

Currently, a typical HBS requires one or two high-power DC/DC converters to regulate power allocations between the two subpacks. Based on the pulse width modulated technique, switching in DC/DC converters must manipulate thousands of times per second and cope with a system-level terminal voltage. The discrete-switched structure applied in the HBS is not the case. The switching operation utilizes the "event-based" method for power demands and battery states. Hence, the low-frequency switching control can be used for

this structure compared to the converter-based HBS.

Moreover, switching manipulates close to a cell voltage, approximately 2-4 V, based on cell types and states. These advantages enable the discrete-switch-based HBS to use cheaper low-voltage power field-effect transistors (FET) as switches to manage the power allocations. In this thesis, the cost of system-level power electronics has been analyzed in Chapters 4 and 6 to verify the cost competitiveness of the discrete-switch-based HBS.

Nonetheless, the discrete-switch-based HBS has to pay a cost regarding control complexity. This HBS requires a complicated control algorithm to regulate the operations of all switches, compared to operating several high-frequency switches by a modulate-pulse-width method in DC/DC converters. Furthermore, control strategies involve complex optimization problems (e.g., integer conditions and constraints) due to discrete switching. Regarding the control complexity, I have developed corresponding control algorithms in Chapters 4 to 6 to overcome them.

3.2 Battery System Modeling

This section mainly focuses on modeling the HBS with the discrete-switched structure from cell to system levels. For battery cell modeling, the article format chapters (Chapters 4 to 6) only provide their dynamic behaviors and state-space equations of the equivalent circuit models (ECMs) without their explanation. Additionally, ideas associated with system modeling have to be simplified in Chapters 4 to 6 due to journal layout limitations. Hence, this section presents them in detail.

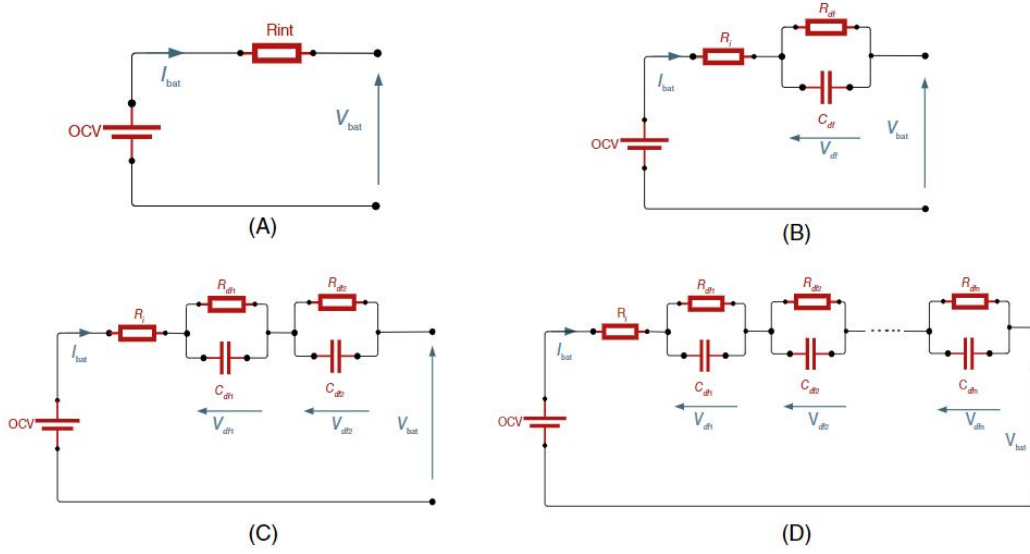


Figure 3.3: Battery cell equivalent circuit models (A) Rint model, (B) first-order RC model (C) second-order RC model (D) n th-order RC model [48]

3.2.1 Cell Modeling

The ECMs are a general approach since it only considers describing the apparent electrical behavior of the battery. The ECM consists of electrical components (DC voltage source, resistors capacitor, etc.) to simulate battery behaviors under operation conditions (e.g., temperature). Compared to electrochemical models, the ECMs have acceptable accuracy, but much lower computing power [48]. Hence, these advantages make the ECMs suited to model large-scale battery packs and be embedded in battery management systems (BMSs).

Figure 3.3 illustrates the various equivalent electrical circuit models applied in the battery (A discharge-positive current convention is used), including the Rint model, first-order model, second-order model, and n th-order model as detailed as follows:

- (A) The Rint model is the simplest ECM, comprising an ideal voltage source and an internal resistor.
- (B) The first-order RC model consists of a voltage source modeling the open circuit

voltage (OCV), an ohmic resistor representing the internal resistance (also known as ohmic polarization), and an RC network describing the diffusion process (also known as concentration polarization). RC network is composed of a capacitance C_{df} and a resistance R_{df} , describing the metal electrodes' polarization and the contact of the electrolyte with the electrodes, respectively.

(C) Apart from the above polarizations, the activation polarization due to the electrochemical reactions on the electrodes' surface is considered in the second-order RC model. Compared to the first-order RC model, this model adds an RC network representing activation polarization.

(D) The precision increases with increasing the order of the model, which can simulate the diffusion of Li-ion more precisely with increasing the number of RC networks. There is, of course, a cost to pay for implementing complexity.

The first-order and second-order RC models are widely used because they balance accuracy and computing complexity [49], [50]. In this project, the battery model uses the first-order or second-order RC model depending on the battery type. The dynamic behavior of the battery for the first-order RC model can be described as follows:

$$\begin{aligned}\dot{V}_{df} &= -\frac{V_{df}}{R_{df}C_{df}} + \frac{I_{bat}}{C_{df}} \\ V_{bat} &= V_{oc} - V_{df} - I_{bat}R_i\end{aligned}\tag{3.1}$$

where V_{oc} is the OCV, and other symbols have the same meaning in Figure 3.3(C). Furthermore, the dynamic behavior for the second-order RC model can be depicted as follows:

$$\begin{aligned}\dot{V}_{df1} &= -\frac{V_{df1}}{R_{df1}C_{df1}} + \frac{I_{bat}}{C_{df1}} \\ \dot{V}_{df2} &= -\frac{V_{df2}}{R_{df2}C_{df2}} + \frac{I_{bat}}{C_{df2}} \\ V_{bat} &= V_{oc} - V_{df1} - V_{df2} - I_{bat}R_i\end{aligned}\tag{3.2}$$

The Columbo counting method can describe these battery models' state of charge (SOC). The equation can be depicted as follows:

$$SOC = -\frac{I_{bat}}{3600Q_{bat}} \quad (3.3)$$

where Q_{bat} is the battery capacity (Ah). The parameters of ECMs are modeled as being dependent on the SOC. Generally, the parameters in the ECMs use a lookup table-based or polynomial fitting method concerning the SOC. Figure 4.5 shows the trends of the parameters concerning the SOC.

3.2.2 Module Modeling

This part introduces the discrete-switched module modeling, taking the first-order RC ECM as an example. On the mathematical side, an equivalent circuit method is used to deduce the state-space function for the module. This approach mainly serves as the control algorithm to estimate the battery states.

The module has connection and disconnection modes, so a piecewise function is used to represent the states of the module, as shown following:

$$u_{mod} = \begin{cases} 1 & \text{connection mode} \\ 0 & \text{disconnection mode} \end{cases} \quad (3.4)$$

This project assumes the modules' cells are almost uniform since commercial batteries generally maintain good uniformity while the paralleled battery cells in the module can naturally self-balancing [13], [51]. Hence, the parameters of the battery module composed

of the cell level can be expressed as follows:

$$\begin{aligned}
Q_{\text{mod}} &= Q_{\text{bat}} N_p \\
V_{oc,\text{mod}} &= V_{oc} \\
R_{o,\text{mod}} &= R_i / N_p \\
R_{p,\text{mod}} &= R_{df} / N_p \\
C_{p,\text{mod}} &= C_{df} N_p,
\end{aligned} \tag{3.5}$$

where N_p is the number of cells in the module. In the module level, Q_{mod} is the capacity, $V_{oc,\text{mod}}$ is the OCV, $R_{o,\text{mod}}$ is the ohmic resistance, $R_{p,\text{mod}}$ and $C_{p,\text{mod}}$ is the RC pair parameters. Considering the control modes of the module-level discrete-switched structure, the state-space function of the module is depicted as follows:

$$\begin{aligned}
\dot{V}_{p,\text{mod}} &= -\frac{V_{p,\text{mod}}}{R_{p,\text{mod}} C_{p,\text{mod}}} + \frac{I_{\text{bat}}}{C_{p,\text{mod}}} u_{\text{mod}} \\
V_{\text{mod}} &= V_{oc,\text{mod}} - V_{p,\text{mod}} - I_{\text{bat}} (R_{\text{mod}} + R_s) u_{\text{mod}} \\
\text{SOC}_{\text{mod}} &= -\frac{I_{\text{mod}}}{3600 Q_{\text{mod}}} u_{\text{mod}}
\end{aligned} \tag{3.6}$$

where $V_{p,\text{mod}}$ is the RC pair voltage drop, and I_{mod} is the current through the module. Since the circuit must pass through the switch, whether it passes through the main or bypass circuit, the switch resistance R_s (despite a quite small resistance) is directly added to the voltage observed equation.

3.2.3 Battery System Modeling

In the dynamic behaviors presented in Equation (3.6), the changes of $V_{p,\text{mod}}$ are ignorable during several digital times (0.1-1 seconds), since the coefficient $\frac{1}{R_{p,\text{mod}} C_{p,\text{mod}}}$ is much greater than the coefficient $\frac{1}{C_{p,\text{mod}}}$. Hence, within one digital time, the transient electromo-

tive force of a module can be integrated as follows:

$$E_{\text{mod}} = V_{oc,\text{mod}} - V_{p,\text{mod}} \quad (3.7)$$

where E_{mod} is the transient electromotive force of the module. The observed function of the terminal voltage for the module can be simplified as follows:

$$V_{\text{mod}} = E_{\text{mod}} - I_{\text{bat}}(R_{\text{mod}} + R_s)u_{\text{mod}} \quad (3.8)$$

Here, subscript symbols i and j are introduced to facilitate the derivation of the expression system model, as shown in Figure 3.2. i indicates the battery subpack i , where Subpack 1 is $i = 1$, and Subpack 2 is $i = 2$. j indicates the module number in subpack i . In the subpack i , a series of parameters for the modules can be integrated as vectors. Taking an example of a subpack i composed of n modules, these vectors are:

$$\begin{aligned} \vec{U}_i &= [u_{i,1}, \dots, u_{i,j}, \dots, u_{i,n}] \\ \vec{E}_i &= [E_{i,1}, \dots, E_{i,j}, \dots, E_{i,n}] \\ \vec{R}_i &= [R_{o,1}, \dots, R_{o,j}, \dots, R_{o,n}] \end{aligned} \quad (3.9)$$

where in the subpack i , $\vec{U}_i$ is the vector comprises all module operation modes, $\vec{E}_i$ is the vector comprises all modules' transient electromotive forces, and $\vec{R}_i$ is the vector comprises all modules' ohmic resistances. The controlled parameters in the subpack i can be depicted as follows:

$$\begin{aligned} E_i &= \vec{E}_i \vec{U}_i^T \\ R_i &= \vec{R}_i \vec{U}_i^T \end{aligned} \quad (3.10)$$

where E_i is the total transient electromotive force of the the subpack i , and R_i is the total ohmic resistance of the the subpack i . The battery system can be simplified by deducing above, as shown in Figure 3.4(A).

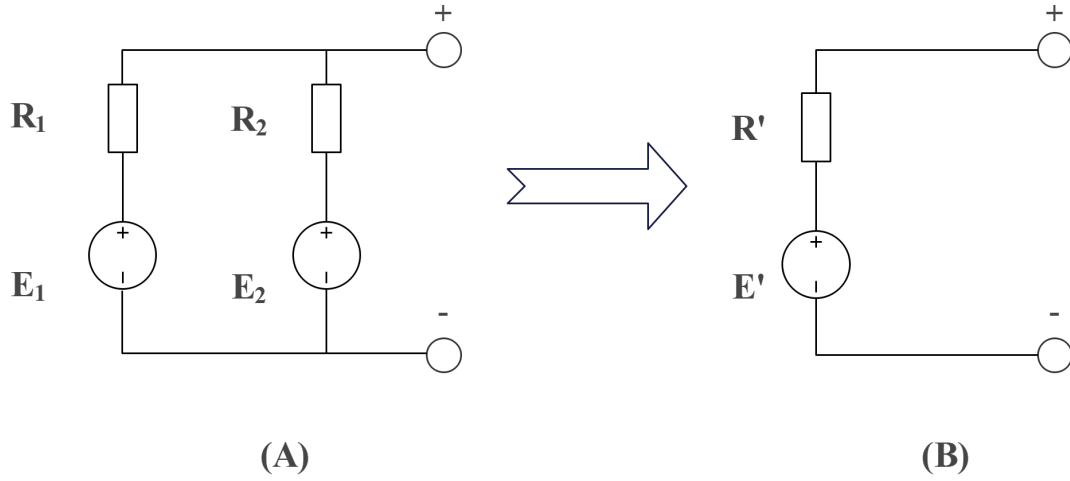


Figure 3.4: Battery module modeling in MATLAB/Simulink.

According to the Kirchhoff laws and Figure 3.4(A), the currents, voltages, and power for the two subpacks and battery system can be depicted as follows:

$$\begin{aligned}
 V_i &= E_i - I_i R_i \\
 I_{\text{bus}} &= \sum_{i=1}^m I_i \\
 V_{\text{bus}} &= V_i \\
 P_{\text{bus}} &= I_{\text{bus}} V_{\text{bus}}
 \end{aligned} \tag{3.11}$$

where m is the number of subpacks in parallel (this equation is suitable for multi-subpack systems, here $m = 2$). The system model can be further simplified based on the Equation (3.11), obtaining the model shown in Figure 3.4(B), the battery system can be expressed as follows:

$$E' - R' I_{\text{bus}} = V_{\text{bus}} \tag{3.12}$$

where:

$$\begin{aligned}
 E' &= \frac{\sum_{i=1}^2 \frac{E_i}{R_i}}{\sum_{i=1}^2 \frac{1}{R_i}} \\
 R' &= \frac{1}{\sum_{i=1}^2 \frac{1}{R_i}}
 \end{aligned} \tag{3.13}$$

Equation (3.12) can be transferred as:

$$R' I_{\text{bus}}^2 - E' I_{\text{bus}} + P_{\text{bus}} = 0 \quad (3.14)$$

This is a solvable quadratic equation. For the convenience of expression, the symbols in solutions are defined as follows:

$$\begin{aligned} I' &= \frac{E'}{2R'} = \sum_{i=1}^2 \frac{E_i}{2R_i} \\ V' &= \frac{E'}{2} \end{aligned} \quad (3.15)$$

Hence, the solution I_i of Equation (3.14) are shown as follows:

$$I_i = \frac{E_i}{R_i} - \frac{V'}{R_i} \left(1 + \sqrt{1 - \frac{P_{\text{bus}}}{I' R'}} \right) \quad (3.16)$$

Meanwhile, the bus voltage can be obtained under known bus power, as depicted as follows:

$$V_{\text{bus}} = V' \left(1 + \sqrt{1 - \frac{P_{\text{bus}}}{I' R'}} \right) \quad (3.17)$$

Following the above approach, allocations of the current I_i between two battery subpacks can be estimated and predicted.

3.3 Control Strategy

This section briefly demonstrates the control strategies used in this project due to the details introduced in Chapters 4 to 6. The control system of the discrete-switched-based HBS comprises three parts: battery state estimations, battery balancing, and power allocation control.

For battery state estimation techniques, Chapter 4 applied the Coulomb counting method to estimate the SOC of each module, which is implemented based on Equation (3.3) and Equation (3.6). Nevertheless, this method is prone to significant cumulative errors in the case of long-term operations. Hence, the extended Kalman filter (EKF) and adaptive extended Kalman filter (AEKF) based on ECM models were applied in case studies of Chapters 5 and 6 to make estimations more accurate.

For battery parameters in ECMs, the component parameters relative to SOC in Chapters 4 and 5 were from the literature and analysis of experimental results. Simultaneously, a lookup table method combined with an interpolated approach was utilized to obtain the parameters in the dynamic behaviors of batteries, i.e., Equation (3.6). This approach for obtaining the parameters is an offline process, i.e., once the parameters are entered in the estimator, the parameters are no longer changed under the actual aging of the battery. Hence, such techniques require an intricate set of initial data for parameterization, and their accuracy is greatly affected by battery aging [52]. To improve those issues, an online forgetting factor recursive least square (FFRLS) method is applied in the case study of Chapter 6 to obtain robust parameter estimations.

The SOC balancing process has been described in Chapters 4 and 6. In short, all modules in each subpack participate in rolling discharge and idle states by regulating the operating modes of the discrete switching to achieve the SOC of the modules remaining broadly balanced.

As mentioned above, the discrete-switch-based HBS has to pay a cost regarding control complexity, although system-level power electronics are much cheaper. Due to the discrete-switched structure, the control algorithms must involve quadratic or nonlinear programming problems with integer control variables and inequality constraints (demonstrated in Chapters 4 and 6). Active-set, Lemke, and path-tracking methods are standard techniques to solve the quadratic programming problem with inequality constraints.

However, none of these algorithms work for this programming with integer variables. Therefore, this project adopts three approaches to overcome algorithm complexity, as follows:

- **Chapter 4** - the overall control strategy in this study is composed of a rule-based supervisory control to achieve high-level aims (shown in Table 4.4), together with a near-optimal control to optimize the performance at coordinate operations of two battery types. In the near-optimal control, this study structures a cost function and adopts a "special" enumeration algorithm to solve the optimization problem. This approach first utilized inequality constraints to reduce the candidate control variables significantly. The size of the candidate control variables was from $2^{113 \times 160}$ to only several hundred. The optimal solution was then obtained by enumeration.
- **Chapter 5** - A simple enumeration method was used to predict power flow allocations between two battery types and decide on switching operations due to only three switching states needing to be enumerated.
- **Chapter 6** - this study structures a cost function in the model-predictive control algorithm with constraints from battery performances, which optimizes the algorithm's integer control variables from hundreds to only two. The genetic algorithm is then applied to calculate the optimal solution.

EV pack-level approaches used in Chapters 4 and 6 have good computing performances, where the computing speeds are approximately 0.4 and 0.1 seconds per operation on a personal computer (Processor: Intel(R) Core(TM) i7-9700 CPU), respectively. Comparing the two approaches, the model predictive control algorithm performs much better calculation speed. It is good enough for the typical sample time requirements of 0.2 seconds in EV battery system applications. Furthermore, the computing time would be further improved with the development of near-future automotive chip technologies.

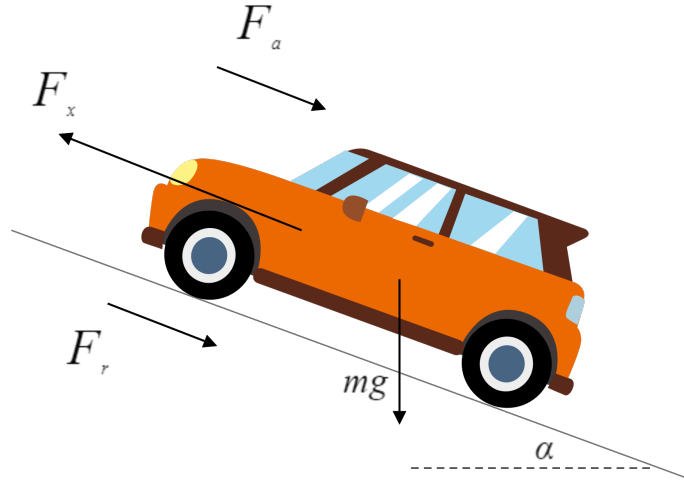


Figure 3.5: Longitudinal dynamics of a typical vehicle.

3.4 Simulation Approach

This section demonstrates the modeling processes from battery cells to discrete-switched battery modules and HBSs. The software used in this project is MATLAB/Simulink.

3.4.1 Simulation Environment

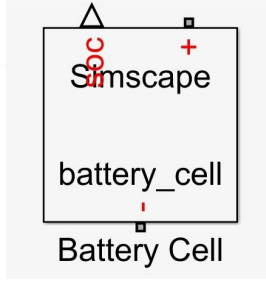
Chapters 4 and 6 used a simple modeling method based on vehicle longitudinal dynamics to obtain the power demands of battery systems. The velocity and acceleration data were from the Worldwide Harmonized Light Vehicles Test Procedure (WLTP) for Class 3 (shown in Figure 4.6). The longitudinal dynamics of a typical vehicle are shown in Figure 3.5. The relationships of various forces are depicted as follows:

$$m\dot{v} = F_x - F_r - F_{aero} - mg\sin\alpha \quad (3.18)$$

where

$$F_{aero} = \frac{1}{2}\rho C_d A v^2$$

$$F_r = mgf\cos\alpha$$



(A)

NAME	DESCRIPTION	VALUE
Main		
Temperature		293.15 K
SOC breakpoints (Mx1 array)		[0, 5, 1]
Temperature breakpoints (1xN array)		[278.15, 293.15, 313.15] K
Capacity breakpoints depended on T		[4.1, 4.2, 4.3] A*hr
Open circuit voltage breakpoints (Mx1 array)		[3.2, 3.4, 3.6, 3.2, 3.4, 3.6, 3.2] V
Internal resistance breakpoints (MxN)		[0.01 * ones(3, 3)] Ohm
SOC initial value (normalized, 0-1)		1
Dynamics		
Change dynamics		First order RC model
First polarization resistance breakpoint		[0.01 * ones(3, 3)] Ohm
First polarization capacity breakpoint		[1000 * ones(3, 3)] F
Initial Targets		
Current (positive in)		☐
Nominal Values		
Current (positive in)		☐

(B)

```

component battery_cell
% Battery Cell
% This block implements a battery cell dynamic model based on tabulated
% characteristics as functions of state of charge (soc) and optional
% temperature (T). In parameter data, N is soc lookup data breakpoint
% vector with N dimensions, and N is temperature lookup data breakpoint
% vector with N dimensions.

outputs
soc = [1, '1']; % soc
end

% parameters on dialog box
parameters
    battery_dynamics = BatteryDynamics.No; % Charge dynamics
end

nodes
    p = foundation.electrical.electrical; % +
    n = foundation.electrical.electrical; % -
end

annotations
    [soc, p] : Side = top;
    [n] : Side = bottom;
end

parameters
    T = (293.15, 'K'); % Temperature
    soc_init = (1, '1'); % soc initial value (normalized, 0-1)
    soc_LUT = [0, 0.5, 1]; % soc breakpoints (1xN array)
    T_LUT = [278.15, 293.15, 313.15]; % Temperature breakpoints (1xN array)
    Ah_LUT = [4.1, 4.2, 4.3]; % Capacity breakpoints depended on temperature (1xN array)
    Bm_LUT = [3.2, 3.4, 3.6, 3.2, 3.4, 3.6, 3.2]; % Open circuit voltage breakpoints (1xN array)
    Rp_LUT = [0.01*ones(3,3)]; % Internal resistance breakpoints (NxB array)
    Rp1_LUT = [0.01*ones(3,3)]; % First polarization resistance breakpoints (NxB array)
    Cp1_LUT = [1000*ones(3,3)]; % First polarization capacity breakpoints (NxB array)
    Rp2_LUT = [0.01*ones(3,3)]; % Second polarization resistance breakpoints (NxB array)
    Cp2_LUT = [1000*ones(3,3)]; % Second polarization capacity breakpoints (NxB array)
end

```

(C)

Figure 3.6: Battery cell modeling in MATLAB/Simulink: (A) customized Simscape block, (B) interface dialog box, and (C) codes of battery cell model in the block.

In Equation 3.18, F_x is the vehicle's traction. m is the mass (kg), C_d is aerodynamic coefficient, A is the front area (m^2), ρ is the air density, g is the gravitational acceleration (kg/m^2), α is the slope angle ($^\circ$), f is the rolling resistance coefficient, and v is the velocity. F_{aero} and F_r are the aerodynamic and fraction resistances, respectively. The power demand P_{dem} can be expressed as:

$$P_{dem} = \frac{v F_x}{\sigma} \quad (3.19)$$

where σ is the drivetrain efficiency (0-100%). The acceleration can be calculated by differentiating the velocity. Hence, this simple model can obtain the power demand of battery system P_{dem} .

In Chapter 5, the power records of quad bike driving trails were directly used as the power profile (shown in Figure 5.6). The driving profile comprises high-speed driving on the road, working on the farm, and dragging a small cargo on the farm.

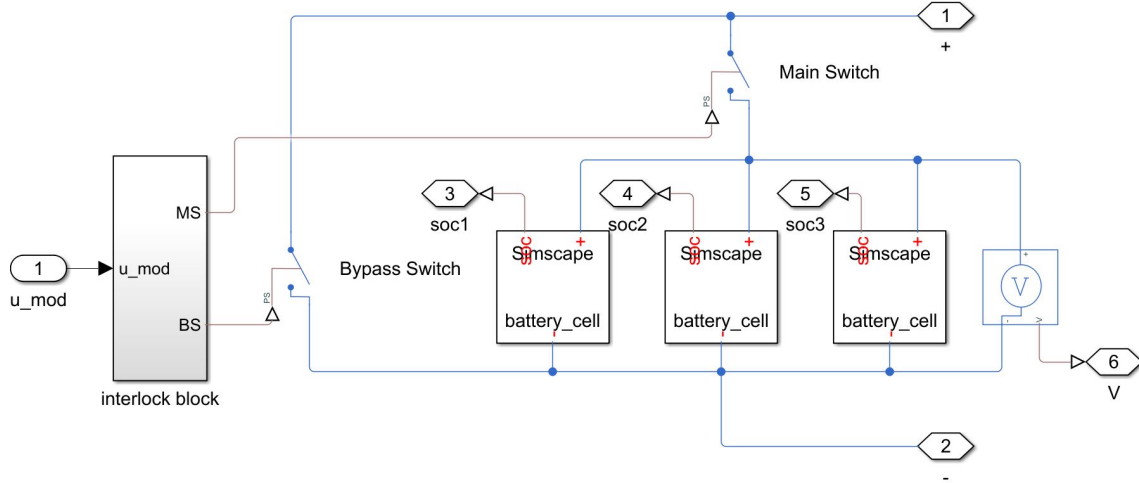


Figure 3.7: Battery module modeling in MATLAB/Simulink.

3.4.2 Modeling in MATLAB/Simulink

In this project, battery cell modeling using the customized block method of the Simscape toolbox in MATLAB/Simulink is shown in Figure 3.6. This block comprises three ports: "+" indicates the positive electric terminal, "-" denotes the electric negative terminal, and "soc" is the SOC output of the battery cell. The interface dialog box is established to adjust the given battery cell's parameters conveniently. This customized block can select the ECM types, including Rint, first-order and second-order ECM, and type in the corresponding parameters. The lookup table-based parameters can be used in this block.

The Simscape toolbox provides an intuitive circuit-building approach. Taking an example of 3 paralleled cells in a module, the discrete-switched module can be modeled in Figure 3.7. Similarly, "+" and "-" indicates the positive and negative electric terminals, respectively. "soc1" to "soc1" are the SOC's of each battery cell. "u_mod" is the mode signal represented in Equation (3.4). "V" is the measured voltage from the voltage sensor.

Since there are too many discrete-switched modules in a subpack, I used the programming method to connect all subpack's modules and generated a customized Simscape block, as shown in Figure 3.8. This block comprises three ports: "+" indicates the positive electric

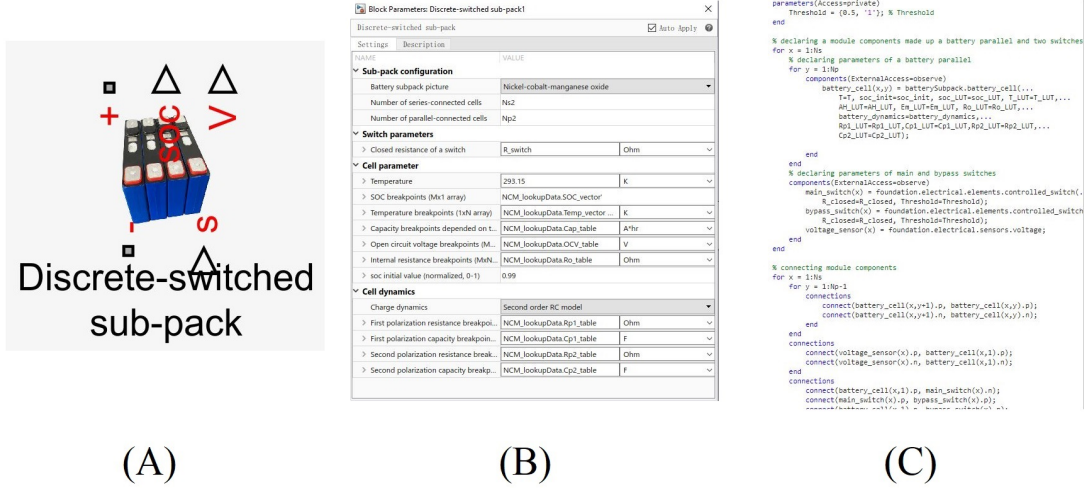


Figure 3.8: Battery subpack modeling in MATLAB/Simulink: (A) customized Simscape block, (B) interface dialog box, and (C) codes of battery subpack model in the block.

terminal, "-" denotes the electric negative terminal, and "soc" is the SOC output of all battery cells in the subpack. The interface dialog box is established to conveniently adjust the given battery cell's parameters and subpack configurations.

Battery system modeling in the Simulink is illustrated in Figure 3.9. The structure of the model is similar to Figure 3.2. "Sn1" and "Sn2" are the control signals of module modes for subpacks 1 and 2 from a controller, respectively; "Vm1" and "Vm2" are the terminal voltages of all modules in subpacks 1 and 2, respectively; "SOC1" and "SOC2" are the SOC of all cells in subpacks 1 and 2, respectively; "I1" and "I2" are the subpacks currents.

Figure 3.10 is this project's lumped battery system model. There are three main parts: System model, control algorithm block, and power demand calculation. In addition, the "Module estimation and SOC balancing" part is used to record and plot simulation results. The system model has been detailed above, and it connects to the power load, where the power load model can be found in [53].

The power demand first generates the power demands and input to the power load. The system model simulates the battery states and current allocations between two subpacks.

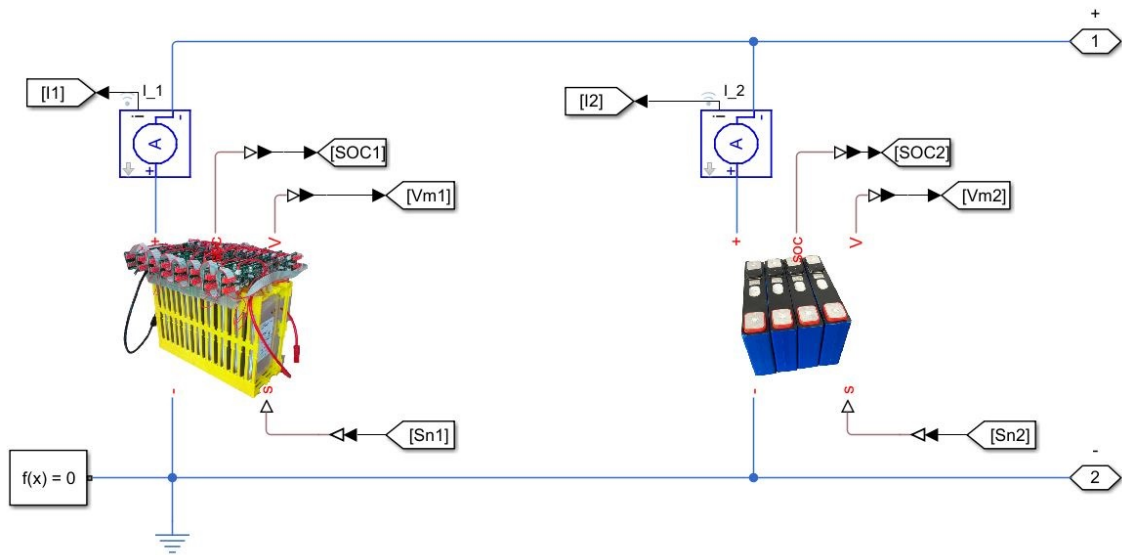


Figure 3.9: Battery system modeling in MATLAB/Simulink.

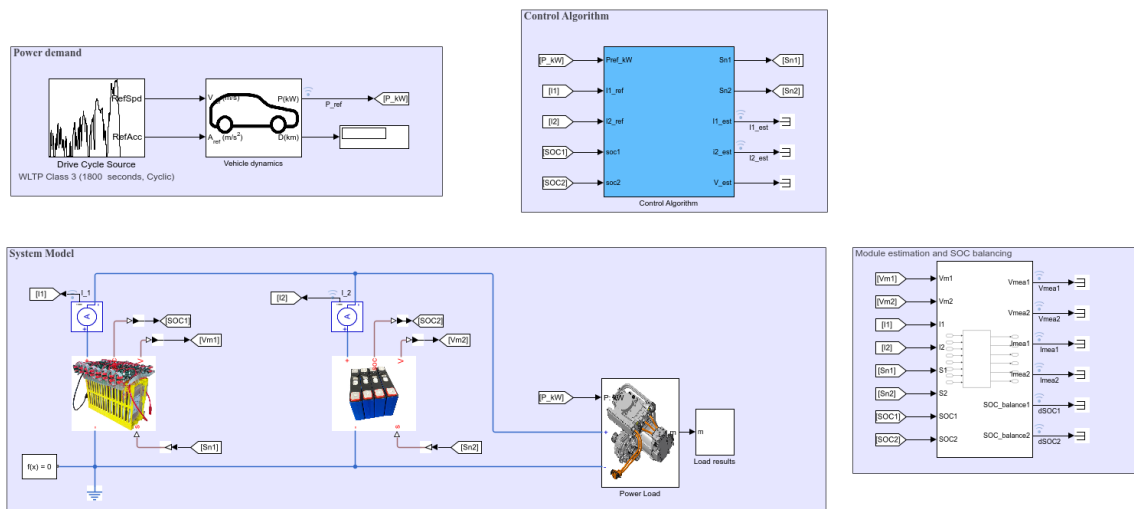


Figure 3.10: Lumped battery system model in MATLAB/Simulink

Simultaneously, the SOC_s, measured voltages, and measured currents are inputted into the control algorithm. It is worth noting that the SOC_s shown in the figure are only served as benchmarks, and the SOC_s are estimated by battery state estimators lumped in the control algorithm. The optimal variables (i.e. module switching) are input to the two subpacks as the switching operation signals at the following digital time.

3.5 Experimental Embodiment

To verify the feasibility of the proposed structure in practical applications, we designed a module-level experiment, which combined an NCM battery module configured with a discrete-switched structure and a battery module composed of two lead-acid batteries. Figure 3.11 shows the prototype hybrid battery pack experimental settings and battery pack structure. Details of the experiment design have been demonstrated in Chapter 5. It is worth noting that at this stage, the prototype battery pack configured a discrete-switched structure in the NMC module. Besides, a heuristic control algorithm was generated as an embedded C code and used in the controller.

The optimal approach of the experiment is to replicate the battery system structure outlined in Chapter 4, which pertains to the high-voltage electric vehicle (EV) pack-level experiment. However, this replication involves substantial expenses related to experimental instruments, equipment, and safety measures. Given that the primary objective of the experiment is to verify the ability to allocate power flow between two different battery types, a decision was made to conduct a module-level experiment at 24 V, thereby offering cost-saving advantages. Figure 5.10 in Chapter 5 depicts the results associated with operations and power flow allocations.

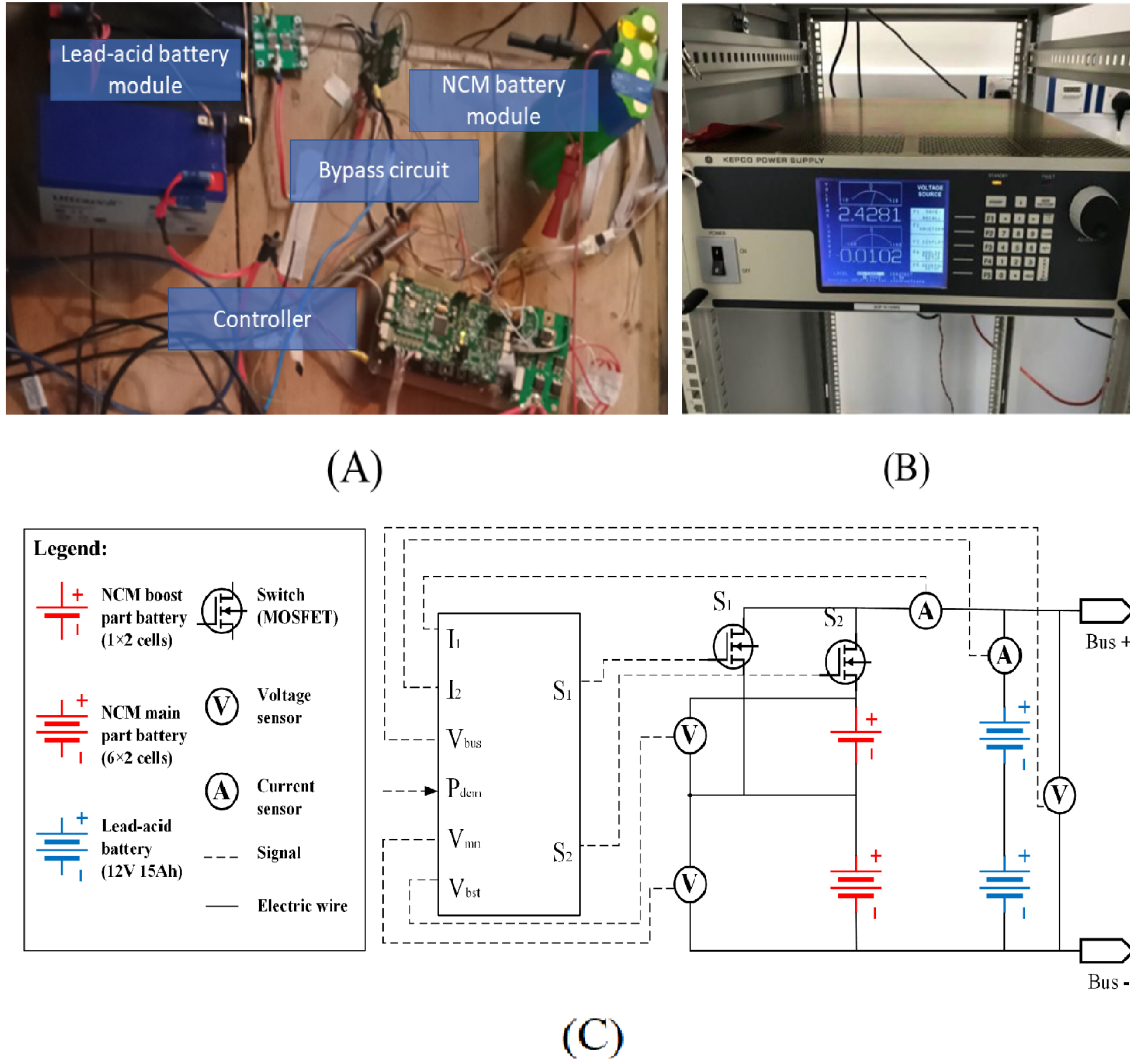


Figure 3.11: Prototype hybrid battery pack: (A) experimental settings, (B) DC power supply, and (C) a diagram of the prototype battery pack structure

3.6 Future Applications

Stand in the near future, critical anxiety of EV ranges can be overcome with the gradual maturity of Li-S battery technologies, which possess ultrahigh energy density, abuse resistance, and relatively cheap cost of electrode materials. Advanced electrochemical technologies are gradually improving the aging issue. However, the power density of the Li-S battery is poor due to its complex full reaction mechanism. Thus, hybridizing the Li-S and high-power battery types is a promising concept for performing a novel EV battery

system with a long cruising range and powerful power capability. In addition, the new HBS's feasibility must be investigated across cost, electric architecture, and performance. Chapter 7 has explored those dimensions and developed an advanced control algorithm to regulate the switching operation in the HBS.

3.7 Concluding Notes

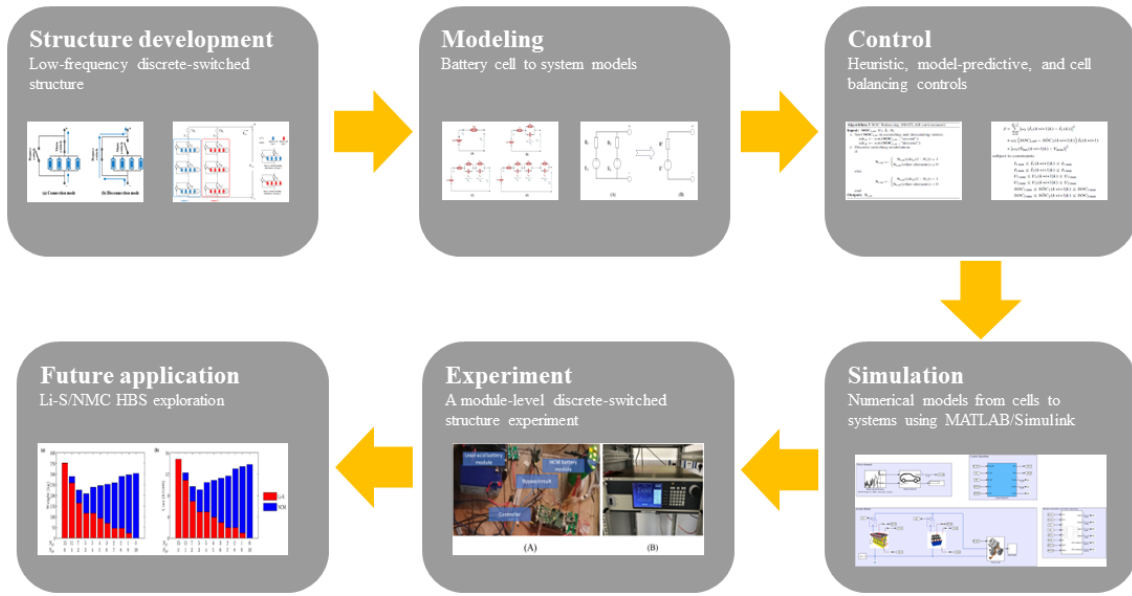


Figure 3.12: A graphical summary of the methodologies in this project.

The methodology of this project is summarized in Figure 3.12. The discrete-switched structure design is the critical innovation in my PhD. We modeled this structure in HBSs from battery cells to systems to verify the feasibility and develop corresponding control algorithms. Although the structure is simple, a cost has to pay in terms of operational complexity. Thus, corresponding control algorithms, including heuristic and model-predictive controls, have been developed to reach the controllability of complex operations. The validated methods were simulations and an experiment. Finally, based on the versatility and scalability of this structure, the future application for a Li-S/NMC HBS has been explored.

Chapter 4

A New Topology for Electric All-Terrain Vehicle Hybrid Battery System Using Low-Frequency Discrete Cell Switching

Abstract

This article presents an investigation into the feasibility of a novel discrete-switched topology for an electric all-terrain vehicle (e-ATV) hybrid battery system (HBS) that avoids expensive and bulky dc–dc converters using a simpler discrete-switched structure together with an intelligent low-frequency switching algorithm. Hardware is simplified at the expense of more complex control. The algorithm switches cells in and out of series strings, based on their state of charge relative to other cells in the pack and the power being drawn from the pack. The principles are demonstrated using a simulated model combining lithium-titanate-oxide (LTO) and lithium-iron-phosphate (LFP) cells together in an e-ATV battery pack. Despite its simplicity, the intelligent switching algorithm successfully allocates power to different elements of the battery and ensures that the state

of charge remains broadly balanced throughout discharge, with the pack ending up in good balance: the LFP cells are in balance to within 0.01% of each other and the LTO cells within 0.1% of each other. While the article focuses on the essential feasibility of the concept, it also identifies future research for including thermal effects, uncertainties in state estimation, cell aging and nonuniformly, and consideration of other powertrain components, for example, motor and power electronics.

Author Statement

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Author contribution: *You Gong:* Writing-Original draft preparation, Conceptualization, Methodology, Software, Investigation, Formal analysis. *Daniel. J. Auger:* Supervision, Conceptualization, Software, Resource, Writing-Reviewing and Editing, Project administration, Funding acquisition. *Abbas Fotouhi:* Supervision, Writing-Reviewing and Editing. *Christopher J. Hale:* Project administration, Funding acquisition.

4.1 Introduction

Battery systems play a vital role in the technological development of electric vehicles (EVs). To be viable in the market, the battery system in an EV must provide adequate safety, high energy density, high power density, long lifespan, and low cost [54], [55]. At present, the post-popular battery chemistries for EVs are variants of lithium-ion. Each of the battery chemistries in the Li-ion battery family has distinct advantages and weaknesses [8].

A comparison of Li-ion battery characteristics is shown in Table 4.1. Lithium-iron-

Table 4.1: Comparison of Characteristics of Li-ion Batteries

Material	Energy (Wh/kg)	Charge (C)	Discharge (C)	Safety	Cycle life
LCO	110–190	0.5	1	Low	500–1000
LMO	100–120	1	2	Medium	1000
NCA	100–150	1	2	Low	2000–3000
NMC	100–170	0.5	1	Medium	2000–3000
LFP	90–115	0.5–1	1–5	High	3000
LTO	60–75	5–10	10	High	5000–20000

phosphate (LFP) batteries are safe and have good specific energy and a relatively low price [56], [57], [58]. However, LFP is not particularly strong in terms of specific power (charge and discharge C-rate) and it is vulnerable to rapid battery degradation under high power demand [55], [43]. By contrast, lithium-titanate-oxide (LTO) has fast charge/discharge ability, wide working temperature ($-35^{\circ}\text{C} \sim 55^{\circ}\text{C}$), a long life-span (approximately 20000 cycles) and excellent safety [8], [57], [22]. Nevertheless, low specific energy hinders its large-scale application [59]. Other battery chemistries such as lithium-nickel-manganese-cobalt (NMC), lithium-manganese spinel (LMO), lithium-nickel-cobalt-aluminum (NCA), and lithium cobalt oxide (LCO) batteries have high specific energy but are less satisfactory in terms of specific power, safety and lifespan. There is no single battery chemistry that is ‘best’ in all categories. The battery designer can either select a single chemistry that is ‘good enough’ and is the most widespread approach today. However, an alternative approach is a mixed-chemistry battery, using a hybrid energy storage system (HESS) with two types of energy storage, which has been proposed to prolong the service life of the system and better manage the conflicting requirements of energy and power density [60].

In the literature, a common approach to EV HESS is to combine supercapacitors and li-ion batteries [55], [41], [31]. Despite being relatively bulky, supercapacitors have higher specific power and better cycle life than li-ion batteries [61], [62]. A HESS like this uses supercapacitors as an auxiliary power source to absorb the power peaks and allow the battery to operate with lower discharge/charge rates. There are three typical topologies in

the literature: passive, semi-active, and active [31], [63]. The difference between them is whether the DC/DC converters are utilized to regulate the power allocation (passive and semi-active topology) and the number of DC/DC converters in the system (semi-active and active topology). Each topology exists studies on the sizing optimization and management strategy for optimized weight, cost, and minimization of battery degradation. However, due to supercapacitors' poor specific energy ($3.5 \sim 4.5$ Wh/kg), supercapacitors in the HESS are only operated in urban environments or short-range driving, but have less effective in medium and long-distance driving scenarios [60], [64].

LTO batteries offer – qualitatively at least – similar advantages to supercapacitors: they support fast charge/discharge, have a wide working temperature envelope, and last for a high cycle life. However, compared to supercapacitors, LTO batteries are cheaper and have a higher specific energy. Hybrid battery systems combining multiple battery types were proposed in [65], where different chemistry batteries in the system are used separately under various power requirements. High and low power demands are provided by the chemistry battery with high and low specific power, respectively. A hybrid battery system (HBS) with LFP and LTO batteries in the electric buses has been proposed in [34], where a passive topology is used with the two battery types working simultaneously, with the allocation of power depending on the inherent characteristics of two batteries. These two systems have the advantages of simple structure and low cost, but the power allocation of the battery systems cannot be regulated. An HBS using individually switched modules has been proposed in [66], where a module comprises a plurality of series and parallel battery cells. However, it did not demonstrate methods of flexible power allocation regulation and SOC balancing. In [67], a deep reinforcement learning-based energy management strategy for an HBS was proposed, but this method also used a semi-active topology. Another solution is to use a DC/DC converter in each module to manage each module's current [44]; this solution has flexible current regulation for each module, but it also has to compromise on hardware complexity and cost.

Approaches to flexible power allocation with a semi-active topology have been proposed in the literature [68], [69]: DC/DC converters can be used to regulate the power allocation between LTO and LFP batteries, with control strategies based on either a low-pass filter or fuzzy logic. These effectively completely decouple the physics and chemistry of the battery elements from the power allocation strategy. However, these strategies require high-power DC/DC converters, which, while effective, adversely affect system cost, weight, and bulk. Consequently, existing HBSs have the following drawbacks: 1) existing passive topologies have simple structures and low cost but cannot flexibly regulate power allocation. 2) existing semi-active and active topologies can flexibly allocate power but are expensive and bulky. Considering whether a similar topology could use cheaper (if less capable) power electronics to achieve a less perfect but still ‘reasonable’ balance between allocation flexibility and system cost is interesting.

The contributions of this study are as follows:

1. A novel HBS topology is proposed, using a discrete-switched structure to regulate power allocation between two types of batteries. The structure switches cells in and out of series strings based on their state of charge relative to other cells in the pack and the power requirement, as shown in Figure 4.2. (More detail will be presented in section II.)
2. A benchmark control algorithm is demonstrated using high-level rules with lower-level near-optimal control.
3. The costs are compared to a conventional hybrid battery system and are shown to be lower.

For this study, two battery chemistries within the Li-ion battery family, namely LFP and LTO batteries, have been selected for this study. These were chosen with an industrial application in mind: they are safe, and they have complementary advantages in specific

power, energy, and lifespan. However, the method is potentially suitable for any similar situation with two or more battery types, or indeed other electrical energy storage systems.

To the authors' knowledge, no existing systems exist with this topology. Battery systems derived from this approach are being developed as part of publicly-funded research projects in the UK, of which the authors are part [70], [71].

The paper is organized as follows. In Section 4.2, the novel topology is illustrated, and the relative costs are explored. In Section 4.3, the battery cell and the topology system are modeled. In Section 4.4, referring to existing management strategies, the energy management strategy for the system is proposed, including power allocation and cell balancing. In Section 4.5, simulation results are presented and analyzed to verify the capabilities of power allocation and SOC balancing. Finally, in Section 4.6, this paper is concluded.

4.2 The Discrete-Switched Topology

Conventional HBS topologies, as explored in [31], [63], [72], are shown in Figure 4.1. Battery sub-packs are connected to high-power DC/DC converters in conventional topologies. By contrast, the discrete-switched topology has a reasonable switch arrangement to achieve power regulation instead of the DC/DC converters in the conventional topologies.

Figure 4.2 illustrates a topology of the proposed HBS for the hybrid LFP-LTO battery source. The LFP and LTO battery sub-packs are connected in parallel via sub-pack switches S_1 and S_2 . Load current and voltage are I_L and V_L , respectively. The currents of the LFP and LTO battery sub-packs are I_1 and I_2 , respectively. S_1 and S_2 control the connection and disconnection of two battery sub-packs to the load. In each battery sub-pack, a parallel string composed of battery cells in parallel and two switches is defined

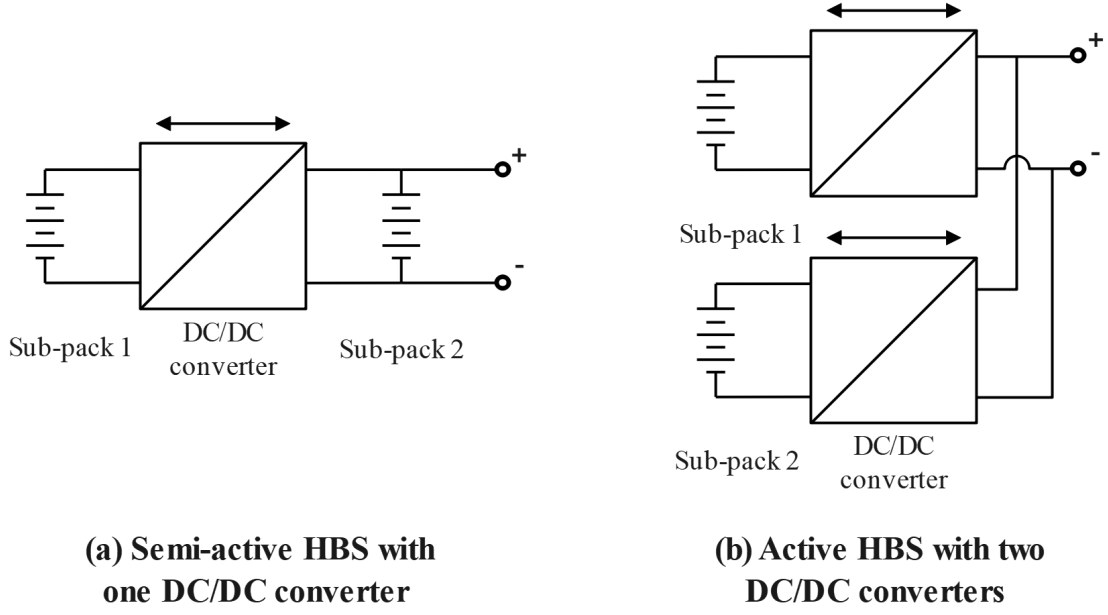


Figure 4.1: Conventional HBS topologies.

as a module. LFP and LTO sub-packs have M and N battery modules, respectively. Each module has two switches: the main switch and the bypass switch. These switches enable module cells to switch in and out of series strings in a sub-pack. Main switches are indicated as S_{ij1} , and bypass switches are indicated as S_{ij2} , where i is the battery type, $i = 1$ and $i = 2$ represent the LFP and LTO battery sub-packs, respectively, and j is the module number in battery sub-pack i . Voltage sensors are connected in each battery module, and current sensors are connected in each battery sub-pack.

The battery module structure and operation modes are shown in Figure 4.3. A battery module has a main circuit and a bypass circuit. The main and bypass switches are on the main and bypass circuit, respectively, to control the connection and disconnection of the circuit. An interlock is applied between the two switches to avoid simultaneous switch-on or switch-off. Operation modes are manipulated by main and bypass switches, where each module contains two operation modes: ‘connection’ and ‘disconnection’. For the ‘connection’, the main switch is closed, and the bypass switch is opened; current can flow through the module and participate in the overall charging and discharging process.

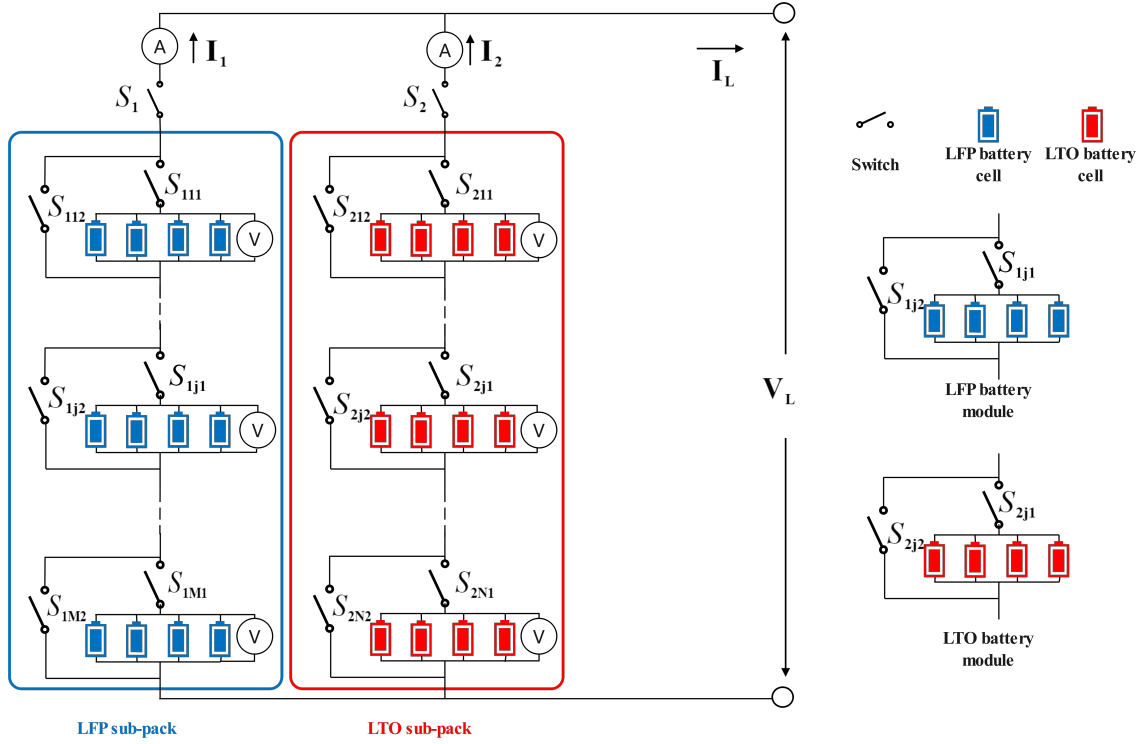


Figure 4.2: The discrete-switched topology of the HBS with LTO and LFP batteries. LFP and LTO sub-packs have M and N battery modules, respectively. In this case study, LFP sub-pack has 113 serials and 12 parallels, and LTO sub-pack has 160 serials and 4 parallels.

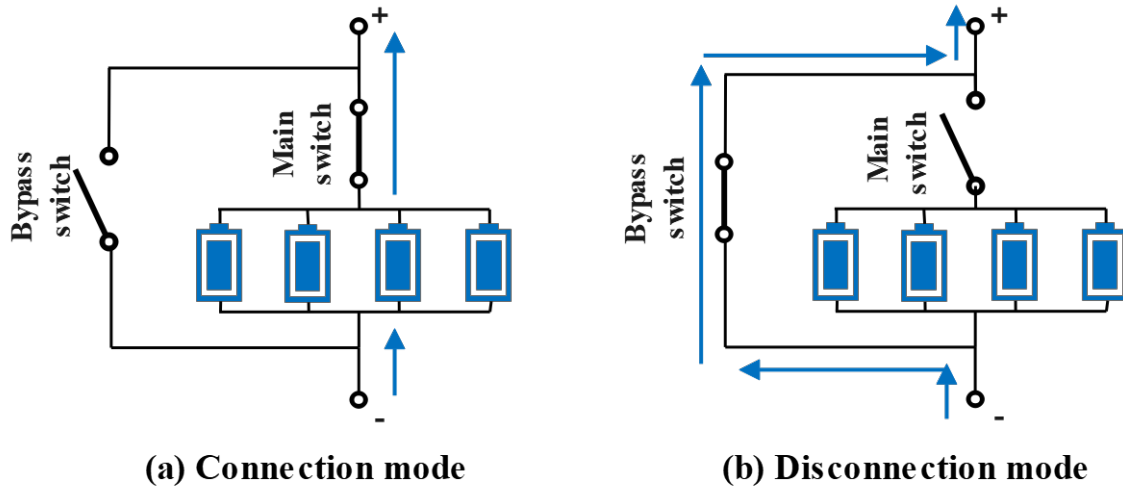


Figure 4.3: Operation modes of a module (blue lines with an arrow represent current direction): (a) Connection mode, and (b) Disconnection mode.

Conversely, for the 'disconnection', the switches have the opposite settings; current can still flow through the module via the low-resistance bypass circuit, but the battery's cells

are disconnected. The cells within each module remain connected to each other as usual, enabling natural self-balancing to continue [13].

In a typical hybrid battery system, switching is done by pulse-width modulated DC-DC converters and must operate thousands of times a second and cope with the full voltage of the pack. This is not the case in the discrete-switched topology. The idea here is to use ‘event based’ switching based on driving power requirements and battery states. Switching also operates at or close to cell voltage (typically 2 – 4 V).

To give an idea of likely cost, the costs of a conventional semi-active hybrid battery system are compared to the costs of this paper’s proposed system – detailed in the case study in section V. The costs considered include a high-power DC/DC converter and bypass structures for cell balancing with MOSFET switches[13]. The cost of a DC/DC is approximately £40.5/kW, and the semi-active system needs a DC/DC converter of about 50 kW [46]. Thus, the DC/DC converter is around £2025. The cost comparison is given in Table 4.2. This shows that the power electronics used in a conventional system cost over £2200, but the proposed topology costs under £400; in the proposed topology, the MOSFET switching is comparable in cost and complexity to a ‘standard’ cell balancing system, and there there is no need for a full-voltage DC/DC converter.

Table 4.2: Comparison of Costs: Proposed System vs Conventional Semi-Active Topology

Parameters	Proposed topology	Conventional semi-active topology
LFP series number		113
LTO series number		160
Switch price (£/per MOS-FET)		0.7
Switch number	548 (Module and sub-pack switches)	273 (Cell balancing switches)
Total switch price (£)	383.6	191.1
DC-DC converter price (£)	0	Approx.2025
Total power electric price (£)	383.6	2216.1

There is, of course, a cost to pay in terms of operational complexity: a discrete-switched topology will need a complex algorithm to decide which switches to operate and, as switching is discrete, it is unlikely that the exact ‘optimal’ conditions (details will be described in Section IV and V).

The first stage in designing a switching algorithm for the hybrid-switched topology is to mathematically describe such a system’s behavior. In the following section, we present the development of an appropriate model set for addressing this.

4.3 Model Development

4.3.1 Cell-Level Modelling

The cells within the battery are modeled using first-order RC equivalent-circuit networks, i.e. state-dependent ‘Thevenin’ models; the format is illustrated in Figure 4.4. Here, $V_{oc,cell}$ is cell open-circuit voltage (V), $R_{o,cell}$ is cell internal resistance (Ω), $R_{p,cell}$ and $C_{p,cell}$ are a ‘polarisation’ resistance (Ω) and capacitance (F) describing transient response; $V_{p,cell}$ is the polarisation voltage (V), and V_{cell} is the terminal voltage (V) of the cell. The parameters of the LFP and LTO cells are listed in Table 4.3 [34], [73], [74], [50]. A discharge-positive current convention is used. The parameters of the cells are modeled as being dependent on their state of charge, and follow the trends shown in Figure 4.5 [73], [75]. The dynamic behaviors of the battery cell are described by Equation (4.1):

$$\mathcal{S}_{cell} \begin{cases} \dot{X}_{cell}(t) = -\frac{1}{3600 Q_{cell}} I_{cell}(t) \\ \dot{V}_{p,cell}(t) = -\frac{1}{R_{p,cell} C_{p,cell}} V_{p,cell}(t) + \frac{1}{C_{p,cell}} I_{cell}(t) \\ V_{cell}(t) = V_{oc,cell} - V_{p,cell}(t) - R_{o,cell} I_{cell}(t) \end{cases} \quad (4.1)$$

where χ_{cell} is the state of charge for the battery cell (normalized from 0 to 1), I_{cell} is the current through the cell (A), and Q_{cell} is the cell capacity (Ah).

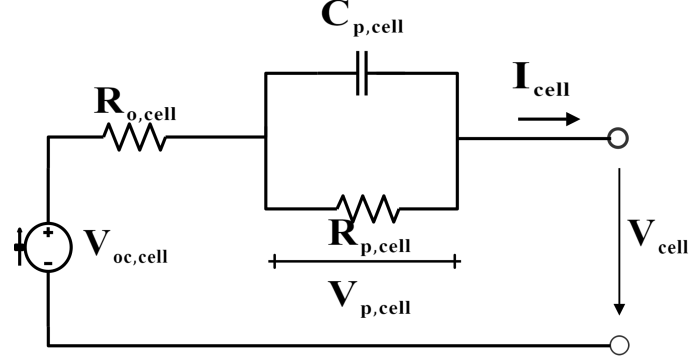


Figure 4.4: First-order RC model of LFP and LTO

Table 4.3: Basic Parameters of the Selected LFP and LTO Battery Cells

Battery type	LFP	LTO
Nominal voltage (V)	3.2	2.3
Capacity (Ah)	10	13
Maximum discharge rate (C)	1	10
Maximum charge rate (C)	1	10
Cycle life (Cycle, 80% DOD)	3000	30000

4.3.2 Battery Sub-pack and System Model

The battery sub-packs switches and the module operation modes are represented by piece-wise function as Equation (4.2) to explain conveniently.

$$S_i = \begin{cases} 1 & \text{connection} \\ 0 & \text{disconnection} \end{cases} \quad M_{(i,j)} = \begin{cases} 1 & \text{connection mode} \\ 0 & \text{disconnection mode} \end{cases} \quad (4.2)$$

where subscript i and j indicate the same meaning as Figure 4.2. S_i represent the sub-pack switch i , and $M_{(i,j)}$ represent the module operation mode of the j module in the battery sub-pack i .

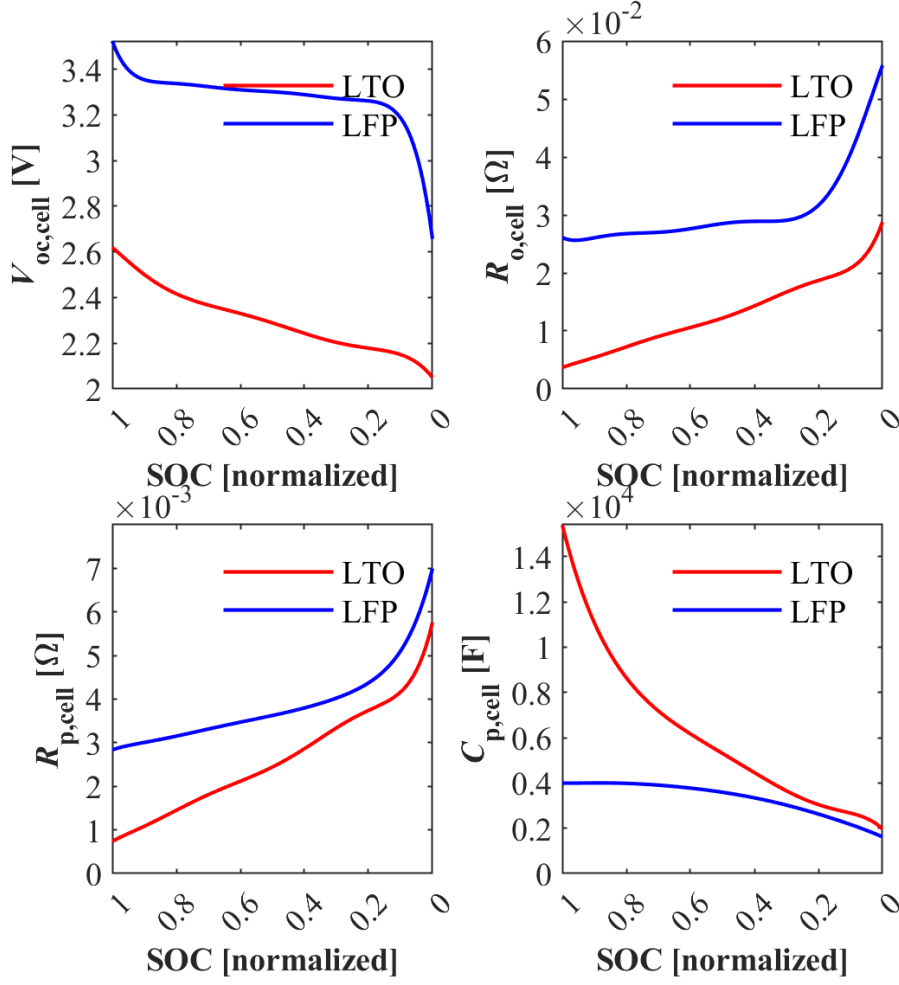


Figure 4.5: Variation of case-study cell parameters with respect to state of charge (25°C)

It is assumed that the battery cells in each module are almost uniform. (This is not necessarily true in practice, and non-uniformity will be explored in future work.) In a module, the relationship between a battery module and the cells made up of the module is depicted as Equation (4.3).

$$\begin{aligned}
 Q_{(i,j)} &= Q_{\text{cell}} N_p \\
 V_{oc,(i,j)} &= V_{oc,\text{cell}} \\
 R_{o,(i,j)} &= \frac{R_{o,\text{cell}}}{N_p} \\
 R_{p,(i,j)} &= \frac{R_{p,\text{cell}}}{N_p} \\
 C_{p,(i,j)} &= C_{p,\text{cell}} N_p
 \end{aligned} \tag{4.3}$$

where N_p is the number of cells in the module, $Q_{(i,j)}$ is the module capacity, $V_{oc,(i,j)}$ is module terminal voltage, $R_{o,(i,j)}$ is module internal resistance, $R_{p,(i,j)}$ and $C_{p,(i,j)}$ are the module polarisation resistance and capacity for the module transient responds, respectively. Since the impact of module operation mode on states of the module is reflected in the current throughout the module, the state of the module can be expressed as Equation (4.4) based on Equation (4.1)).

$$\begin{aligned}\dot{\chi}_{(i,j)} &= -\frac{M_{(i,j)}I_i}{3600Q_{(i,j)}} \\ \dot{V}_{p,(i,j)} &= -\frac{V_{p,(i,j)}}{R_{p,(i,j)}C_{p,(i,j)}} + \frac{M_{(i,j)}I_i}{C_{p,(i,j)}} \\ E_{(i,j)} &= V_{oc,(i,j)} - V_{p,(i,j)}\end{aligned}\quad (4.4)$$

where the I_i is the current throughout sub-pack i , $\dot{\chi}_{(i,j)}$ is the differential of the module SOC, and $E_{(i,j)}$ is the transient electromotive force of the module. $M_{(i,j)}I_i$ is the current through the battery module. For the battery sub-pack i , the module states and switches can be depicted as vectors, as shown in Equation (4.5).

$$\begin{aligned}\vec{M}_i &= [M_{(i,1)}, \quad \dots, \quad M_{(i,j)}, \quad \dots, \quad M_{(i,n)}] \\ \vec{E}_i &= [E_{(i,1)}, \quad \dots, \quad E_{(i,j)}, \quad \dots, \quad E_{(i,n)}] \\ \vec{R}_i &= [R_{o,(i,1)}, \quad \dots, \quad R_{o,(i,j)}, \quad \dots, \quad R_{o,(i,n)}]\end{aligned}\quad (4.5)$$

where n is number of modules in a sub-pack, $\vec{M}_i$ is the vector of operation modes of the modules in a sub-pack, $\vec{E}_i$ is the vector of transient electromotive forces of the modules in a sub-pack, $\vec{R}_i$ is the vector of the internal resistances of the modules in a sub-pack. Thus, the transient electromotive force E_i and internal resistance R_i of sub-pack i can be represented as Equation (4.6).

$$\begin{aligned}E_i &= \vec{M}_i \vec{E}_i^T \\ R_i &= \vec{M}_i \vec{R}_i^T\end{aligned}\quad (4.6)$$

where E_i and R_i are the transient electromotive force and the internal resistance in sub-pack i .

In Equation (4.6), transient E_i can be regulated by operating $\vec{M}_i$, but R_i is also changed with the change of $\vec{M}_i$. The essential objective for the system is to control $\vec{M}_i$ so that the power input and output of the two battery sub-packs can be reasonably allocated. Based on the Equation (4.6) and Kirchhoff laws, the relationship between sub-packs and system level can be expressed as Equation (4.7).

$$\begin{aligned} I_L &= \sum_{i=1}^2 I_i \\ V_L &= V_i = E_i - I_i R_i \\ P_L &= V_L I_L = \sum_{i=1}^2 P_i \end{aligned} \quad (4.7)$$

where I_L and V_L are load current and voltage (V), P_L is the total power demand of the system (W), and P_i is the output power of the battery pack i (W). To deduce the power allocation functions conveniently in the context, the symbols used in the functions are defined as Equation (4.8).

$$\begin{aligned} I_s &= \sum_{i=1}^2 \frac{S_i E_i}{2R_i} \\ R_s &= \left(\sum_{i=1}^2 \frac{S_i}{R_i} \right)^{-1} \\ V_s &= I_s R_s \end{aligned} \quad (4.8)$$

During driving processes, it is worth noting that the S_1 and S_2 can not equal 0 simultaneously, which is in line with the actual situation that the system must be connected to the load. Furthermore, the battery system power allocation satisfies (4.9) according to Equations (4.7) and (4.8).

$$R_s I_L^2 - 2V_s I_L + P_L = 0 \quad (4.9)$$

Finally, load current I_L , load voltage V_L , sub-pack current I_i and power P_i can be solved

by Equations (4.7) and (4.9).

$$\begin{aligned}
I_L &= I_s (1 - \phi) \\
V_L &= V_s (1 + \phi) \\
I_i &= \frac{E_i}{R_i} + \frac{V_s}{R_i} (1 + \phi) \\
P_i &= -\frac{V_s^2}{R_i} (1 + \phi)^2 + \frac{E_i V_s}{R_i} (1 + \phi)
\end{aligned} \tag{4.10}$$

where

$$\phi = \sqrt{1 - \frac{P_L}{I_s^2 R_s}}$$

Consequently, the power allocation can be expressed as Equation (4.11).

$$\begin{aligned}
P_1 &= f_1(\mathbf{X}_{\text{sys}}, \mathbf{U}_{\text{sys}}, P_L) \\
P_2 &= f_2(\mathbf{X}_{\text{sys}}, \mathbf{U}_{\text{sys}}, P_L)
\end{aligned} \tag{4.11}$$

where $\mathbf{X}_{\text{sys}}$ is all states of the system from measurement and estimation, and the control input is $\mathbf{U}_{\text{sys}}$ including module modes and battery sub-pack switches. $\mathbf{X}_{\text{sys}}$ and $\mathbf{U}_{\text{sys}}$ can be expressed as Equation (4.12).

$$\begin{aligned}
\mathbf{X}_{\text{sys}} &= \{\vec{E}_1, \vec{R}_1, \vec{E}_2, \vec{R}_2\} \\
\mathbf{U}_{\text{sys}} &= \{\vec{M}_1, \vec{M}_2, S_1, S_2\}
\end{aligned} \tag{4.12}$$

Thus, the power allocation between battery sub-packs on the different control inputs can be estimated through known power demand and system states.

4.4 HBS Energy Management

4.4.1 Description

Section II and III have developed and modeled the discrete-switched topology. The overall control strategy for this system consists of a rule-based supervisory controller designed to achieve high-level aims, together with a low-level control algorithm designed to optimize performance in achieving the objectives of the supervisory rules. A filtration-based algorithm is then used to create a target reference for power allocation. A low-level controller to approximate this is then calculated optimally. This controller is intended as a benchmark and also to be suitable for real-time execution on today's industry-standard hardware. Several simplifying assumptions are made, such as reasonable homogeneity of cells and modules, uniform temperature distributions, and the availability of accurate state-of-charge estimates. (In the conclusions, these are noted as areas for future work.)

Equations (4.11) and (4.12), describe how power allocation responds to switch positions described by the vectors $\vec{M}_1$ and $\vec{M}_2$ and the main sub-pack switches S_1 and S_2 . The currents in the modules are determined by these switch positions and the current state of each cell in the battery. The module SOC's would unbalance without proper control, and a management strategy is needed to achieve the desired outcome. A management strategy aims:

1. To flexibly allocate power between two battery sub-packs (providing a similar capability to the semi-active or active HBSs), and
2. To keep module SOC's broadly balanced throughout operating processes.

Sub-pack currents and SOC's may need to be constrained according to the batteries' intended operating envelopes, e.g. to preserve lifespan. As the switches are discrete, the

control algorithm to determine the instantaneous values of $\vec{M}_1$ and $\vec{M}_2$ takes the form of an integer optimization control with inequality constraints. This is more complicated than the algorithms required for existing topologies.

The energy management for the proposed topology combines two control strategies to solve switching decisions: rule-based and filtration-based strategies. The filtration-based strategy is implemented to provide the power allocation reference. Power demands with rapid fluctuations are filtered through a low-pass filter to smooth values as power references of the LFP sub-pack. The control algorithm of subsection C will regulate U_{sys} to fit as close as possible to the power references, and the LTO sub-pack absorbs power peaks. However, only a filtration-based strategy cannot avoid the possibility of overcharging and over-discharging sub-packs. Thus, the rule-based strategy mainly protects two battery sub-packs from overcharging or over-discharging. Therefore, energy management is divided into two steps to implement. For the first step, the rule-based strategy decides the sub-pack switches S_1 and S_2 based on the LFP and LTO battery sub-packs SOC_s. For the second step, the filtration-based strategy decides the module switches $\vec{M}_1$ and $\vec{M}_2$ when the two sub-packs coordinately work.

Table 4.4: The Operation Modes for the HBS in Driving Process

Operation mode	$SOC_{LFP}(\%)$	$SOC_{LTO}(\%)$	S_1	S_2	LFP state	LTO state
Discharge mode I	[0 10]	[0 100]	Off	On	Idle	Discharge
Discharge mode II	[10 100]	[0 10]	On	Off	Discharge	Idle
Discharge mode III	[10 100]	[90 100]	Off	On	Idle	Discharge
Discharge mode IV	[10 100]	[10 90]	On	On	Discharge	Discharge
Mechanical braking	[0 100]	[90 100]	Off	Off	Idle	Idle
Regenerative braking	[0 100]	[0 90]	Off	On	Idle	Charge

Rule-based energy management strategy is first adopted [31], [68], [69]. The detailed system operation modes for a driving process are demonstrated in Table 4.4, in which SOC_{LFP} and SOC_{LTO} (%) are the LFP and LTO battery sub-packs SOC_s, respectively. SOC_{LFP} and SOC_{LTO} are average values of their module SOC_s $\chi_{(i,j)}$ because module SOC_s in a sub-pack remain broadly balanced, and it will be verified in later sections. In the

overall driving process, the SOC_{LFP} and SOC_{LTO} are limited by more than 10% to protect the battery sub-packs from over-discharge at discharge modes. They are restricted by less than 90% to avoid overcharge at regenerative braking modes [34], [68], [69]. Discharge modes I and II can protect the LFP or LTO battery sub-packs from over-discharge. When the SOC_{LTO} exceeds 90%, only the LTO battery sub-pack provides the power to the load, and the system works in discharge mode III. This mode reduces frequently using the LFP battery sub-pack under the high-level SOC_{LTO} to improve its degradation. It is also beneficial to protect the LFP battery sub-pack during a vehicle's 'cold start'. When the SOC_{LFP} and SOC_{LTO} are in the range of 10% ~ 100% and 10% ~ 90%, respectively, the two battery sub-packs are coordinated discharging to meet the power demand, so the system works in discharge mode IV. In this mode, the two battery sub-packs allocate the power demand depending on the power demand and SOC states to reduce the current throughout the LFP battery sub-pack and mitigate the influence of the high or pulse current on the LFP battery aging [43], [41].

For braking modes, the LTO battery sub-pack absorbs the regenerative braking energy to avoid aggravating aging due to recurrent charges to the LFP sub-pack during a driving process, ensuring that the LTO battery sub-pack is charging preferentially. The mechanical braking mode can protect the LTO battery sub-packs from overcharging. Long-term recharging, e.g. from a stationary charger, is not considered in this paper and can be optimized for the two sub-packs separately.

4.4.2 SOC Balancing

A rolling discharge approach is applied to maintain a good SOC balance in the pack. This approach reasonably regulates $\vec{M}_1$ and $\vec{M}_2$ depending on the module SOC $\chi_{(i,j)}$ to achieve them balancing. Its principle is similar to cell balancing [76], [77].

The SOC balancing process is described as follows. A battery state estimator firstly estimates $\chi_{(i,j)}$, $E_{(i,j)}$ and $R_{o,(i,j)}$ of all modules. The battery management system then descendingly sorts $\chi_{(i,j)}$ in each battery sub-pack. The modules with high-level SOC in a sub-pack have higher discharge priority. Control input $\vec{M}_1$ and $\vec{M}_2$ are regulated corresponding to the discharge priority of the modules, and then the current allocations are predicted by Equation (4.9). Simultaneously, the battery management system calculates all possible control input U_{sys} with considering battery system constraints Equation (4.16). These processes can guarantee that the modules with high-levelSOCs operate at connection mode (Figure 4.3a), and the modules with low-level SOC operate at disconnection mode (Figure 4.3b). After a discharge period, the previous modules with high-level SOC would be turned into those with low-level SOC. Conversely, the previous modules with low-level SOC would be turned into those with high-level SOC. All modules will be in a rolling discharge/idle state though recurrent implementation of the processes. Consequently, the module SOC in a sub-pack will be approximately balanced through the rolling discharging approach.

4.4.3 Power Allocation

During discharge mode IV, the power allocation between the two battery sub-packs must be regulated. This study uses the filtration-based control strategy to regulate them further. The filtration-based control strategy was initially developed for the HESS in [78] and extended to the semi-active HBS [68]. This method uses a low-pass filter to allocate the power, as expressed in Equation (4.13).

$$\begin{aligned} \dot{P}_f &= -f_s P_f + f_s P_L \\ P_{\text{ref}} &= P_f + K (SOC_{\text{LTO}} - SOC_{\text{LTO,init}}) \end{aligned} \tag{4.13}$$

where f_s is the frequency of a low-pass filter, P_f is the filter power result (W), $SOC_{LTO,init}$ is the initial SOC of the LTO sub-pack, K is the gain of the difference between SOC_{LTO} and $SOC_{LTO,init}$, and P_{ref} is the LFP sub-pack reference power (W) expected to be achieved for the power allocation. As to the low-pass filter, f_s is represented by 10^{-3} Hz, and the value of K is 3000. Besides, the LFP reference power P_{ref} is limited within $0 \leq P_{ref} \leq P_L$ to avoid sub-packs charging each other.

However, the system configuration determines that the power allocation is discrete by regulating U_{sys} . Thus, the battery management system can be designed to make power allocations fit as close as possible to P_{ref} by regulating U_{sys} . The optimal output power of the LFP sub-pack can be expressed by Equation (4.14).

$$U_{sys}^* = \arg \min_{U_{sys} \in \tilde{U}_{sys}} [f_1(X_{sys}, U_{sys}, P_L) - P_{ref}]^2 \quad (4.14)$$

where U_{sys}^* is the optimal control input, and $\tilde{U}_{sys}$ is the set of control input U_{sys} . Thus, two battery sub-pack power distributions at input U_{sys}^* are shown in Equation (4.15).

$$\begin{aligned} P_1 &= f_1(X_{sys}, U_{sys}^*, P_L) \\ P_2 &= f_2(X_{sys}, U_{sys}^*, P_L) \end{aligned} \quad (4.15)$$

Besides, the states that the battery sub-packs mutual charging need to be avoided to decrease unnecessary thermal energy generated, resulting in reduced battery system efficiency. Meanwhile, the output voltage needs to meet the limitation of the load voltage range to the greatest extent. The constraints of power allocation are expressed as Equation (4.16).

$$\begin{aligned} 0 &\leq I_1 \leq I_{1,max} \\ 0 &\leq I_2 \leq I_{2,max} \\ V_L &\geq V_{L,min} \end{aligned} \quad (4.16)$$

where $I_{1,max}$ and $I_{2,max}$ are the maximum discharge limitations for the LFP and LTO battery

sub-packs, respectively, and $V_{L,\min}$ is the minimum load voltage limitation.

Equation (4.14) is a quadratic programming problem with the constraints Equation (4.16), in which $S_1 = 1$ and $S_2 = 1$. This problem can be expressed as Equation (4.17).

$$\begin{aligned} \mathbf{M}_{\text{sys}}^* &= \arg \min_{\mathbf{M}_{\text{sys}}^* \in \tilde{\mathbf{M}}_{\text{sys}}} \left[f_1(\mathbf{X}_{\text{sys}}, \mathbf{M}_{\text{sys}}, P_L) - P_{\text{ref}} \right]^2 \\ \text{subject to: } &0 \leq I_1 \leq I_{1,\max} \\ &0 \leq I_2 \leq I_{2,\max} \\ &V_L \geq V_{L,\min} \end{aligned} \quad (4.17)$$

where $\mathbf{M}_{\text{sys}} = [\vec{\mathbf{M}}_1^T, \vec{\mathbf{M}}_2^T]^T$, $\mathbf{M}_{\text{sys}}^*$ is the optimal vector of $\mathbf{M}_{\text{sys}}$, and $\tilde{\mathbf{M}}_{\text{sys}}$ is the set of $\mathbf{M}_{\text{sys}}$. However, the elements of the vector $\mathbf{M}_{\text{sys}}$ are integer values because of the discrete-switched topology. Existing algorithms to solve the integer problem are time-consuming while needing a high-performance processor (e.g. genetic algorithm). Here, a 'special' enumeration is applied to solve this problem.

Based on Equation (4.7) and Equation (4.16), solutions have following conditions:

1. Assuming V_{LFP} is the voltage under the known positive power demand and only using the LFP battery sub-pack. Thus, E_2 satisfy $E_2 \geq V_{\text{LFP}}$.
2. $E_1 \geq V_L$ and $E_2 \geq V_L$ under the constraints $I_1 \geq 0$ and $I_2 \geq 0$.
3. E_1 and E_2 also need to be greater than $V_{L,\min}$.

The processes of solving the quadratic programming problem are analyzed as follows. The first step is to reduce the size of $\tilde{\mathbf{M}}_{\text{sys}}$ by the proposed rolling discharging approach method. The second step is to extract $\vec{\mathbf{M}}_1$ and $\vec{\mathbf{M}}_2$, which satisfy condition 3. The third step is to calculate V_{LFP} corresponding to each extracted $\vec{\mathbf{M}}_1$, and each extracted $\vec{\mathbf{M}}_1$ has some $\vec{\mathbf{M}}_2$ which satisfies condition 2. Thus, the V_L , I_1 , I_2 , P_1 for each feasible combination

of $\vec{M}_1$ has some $\vec{M}_2$ can be calculated under filtering from step 1 to 3. Finally, through substituting I_1, I_2, P_1 into objective function Equation (4.17), the optimal solution is the $\vec{M}_1$ and $\vec{M}_2$ which obtain minimum value in Equation (4.17). Although it is still a complex algorithm, the size of $\tilde{M}_{\text{sys}}$ is reduced from $2^{113 \times 160}$ to only several hundred through the processes above. Finally, $J = [f_1(\mathbf{X}_{\text{sys}}, \mathbf{M}_{\text{sys}}, P_L) - P_{\text{ref}}]^2$ can be calculated for each $\tilde{M}_{\text{sys}}$ processed. The $\mathbf{M}_{\text{sys}}^*$, which can obtain the smallest J is selected as the input of $\vec{M}_1$ and $\vec{M}_2$.

4.5 Simulation Results and Analysis

4.5.1 Simulation Environment and System Configuration

In the proposed HBS evaluation of this study, a series of simulations and analyses are performed based on repeated typical EV power demand on Worldwide harmonised Light vehicles Test Cycles (WLTP) for Class 3 vehicles. Its speed profile is shown in Figure 4.6 [79]. Furthermore, parameters of the EV (i.e., Nissan Leaf) are adopted, as listed in Table 4.5 [80]. More details of the dynamics model of the EV can be found in [69].

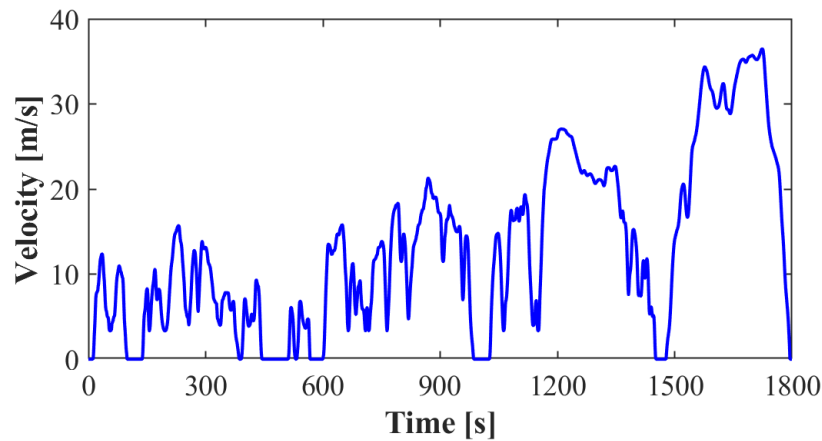


Figure 4.6: Speed profile of the World harmonized Light vehicles Test Cycles (WLTP)

The system's parameters and characteristics of the selected LFP and LTO battery cell are

shown in Table 4.3 and Figure 4.5, respectively. The system adopts a configuration similar to the optimised energy ratios of the LTO and LFP battery sub-packs in [34]. A control group of the LFP battery system is established to compare the performances between the HBS and the LFP system. Furthermore, the nominal and minimum voltages are set as 360 V and 250 V, respectively. The HBS needs to provide energy to satisfy a driving distance of approximately 300 km. The HBS configuration and a control group (only LFP battery system) are listed in Table 4.6, where 'LFP(HBS)' and 'LTO(HBS)' are the configurations of the sub-packs LFP and LTO in the HBS, and 'LFP system' is the only LFP battery system.

Table 4.5: Parameters of the EV

Parameters	Value
Mass (kg)	1580
Width (m)	1.788
Height (m)	1.530
Drag coefficient	0.29
Rolling resistance coefficient	0.015
Vehicle average efficiency	0.85

Table 4.6: The HBS and the LFP System Configurations

Parameters	LFP(HBS)	LTO(HBS)	LFP system
Serial Number	113	160	113
Parallel Number	12	4	16
Nom. voltage (V)	361.6	368	361.6
Capacity (kWh)	43.4	19.1	61.4

Besides, the maximum discharge limitation for $I_{1,\max}$ and $I_{2,\max}$ are 132 A and 434 A, respectively, based on the battery cell characteristics (Table 4.3) and the HBS configuration (Table 4.6). The simulation environment is MATLAB/Simulink.

4.5.2 Simulation Results

Simulation results for power allocation under the WLTP drive cycle are shown in Figure 4.7. Initially, the battery system runs in discharge mode III and mechanical braking mode at high-level SOC_{LFP} and SOC_{LTO} . With a SOC_{LTO} decrease, the system turns into discharge mode IV and regenerative braking mode I. The two battery sub-packs are coordinated discharging, and the LTO battery sub-pack starts to absorb energy from regenerative braking. During the period of coordinated discharging, the LTO sub-pack undertakes most of the power at high power demand, making the LFP sub-pack work within a medium power range. When the SOC_{LFP} and SOC_{LTO} are close to the SOC lower bound, the system still runs in discharge mode IV and regenerative braking mode. Similarly, the LTO sub-pack is allocated a part of power demand at high power requirements. However, the LFP sub-pack output more power during this period. At the end of discharging processes, the system works in discharge modes I or II to protect two battery packs from over-discharges. Meanwhile, when normalising the battery cell current to the C-rate and compared to the single LFP battery system, the LFP battery sub-pack in thg HBS undertakes the lower current, as shown in Figure 4.7(h). Consequently, simulation results verify that this topology can meet the power allocation requirement and decrease the LFP sub-pack power and current at high power demands.

Furthermore, the proposed topology can flexibly allocate the two battery sub-packs' power. In Figure 4.8, the expected powers for the two battery sub-packs are generated by Table 4.4, Equations (4.13) and (4.14)). Figure 4.8(a) and (b) demonstrate that differences of the expected and actual powers in the two battery sub-packs are relatively small. To further compare the errors of the power allocation, Absolute errors between expected and actual power is used to assess its effectiveness, as expressed in Equation (4.18).

$$P_{\text{error}} = |P_{\text{act}} - P_{\text{exp}}| \quad (4.18)$$

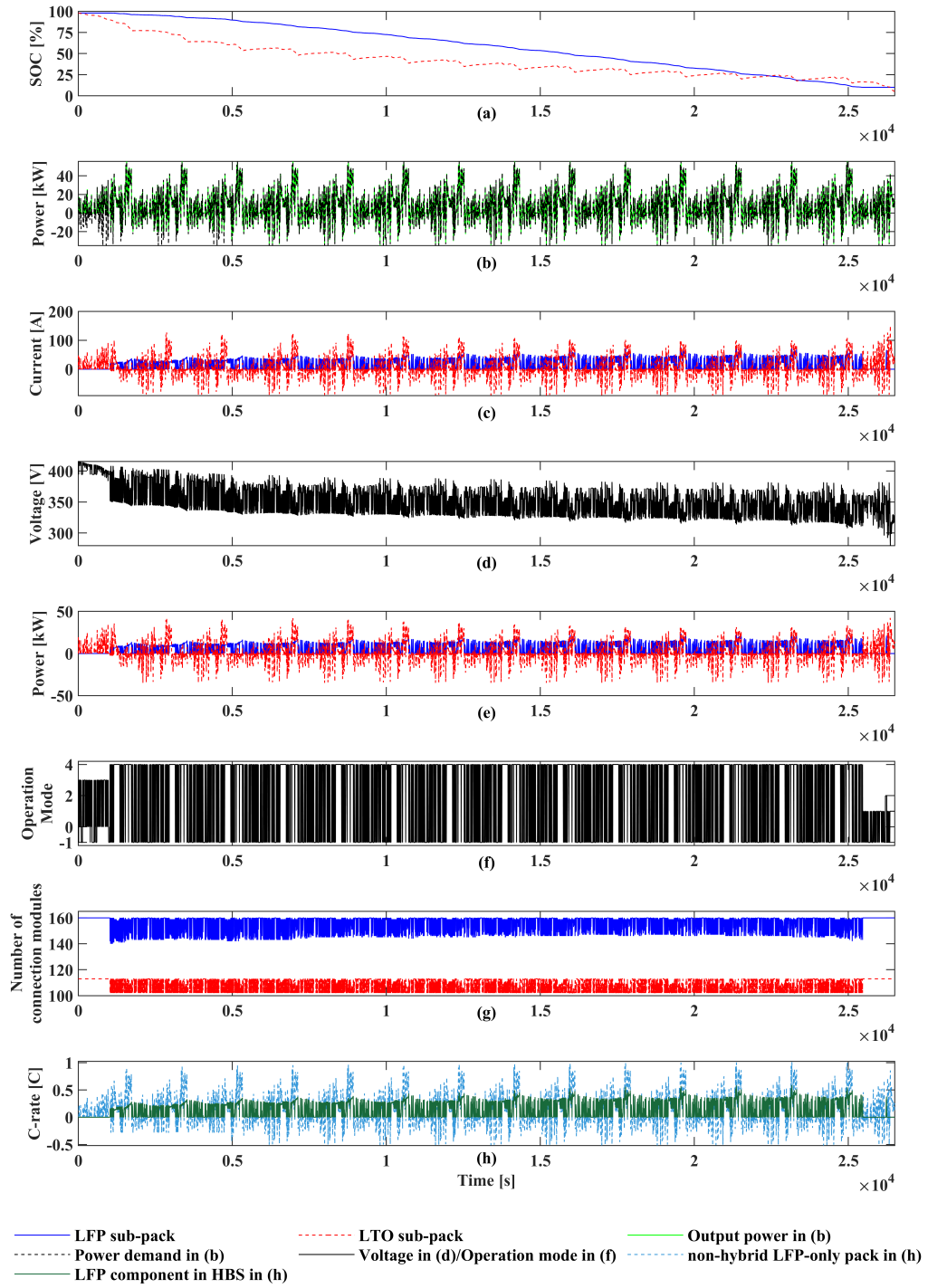


Figure 4.7: Simulation results. (a) SOC for the LFP and LTO battery subpacks. (b) Comparison between power demand and total output power. (c) Current allocations of the two battery subpacks. (d) Battery pack terminal voltage V_L . (e) Power allocations of the two subpacks. (f) Battery system operation mode: The discharge modes are represented by 1 ~ 4, mechanical braking mode is represented by 0, and regenerative braking modes are represented by -1, corresponding to Table 4.4. (g) Number of connection mode modules in the two battery subpacks. (e) Comparison of Charge/discharge rate (C-rate) between the LFP subpack in HBS and the LFP battery system.

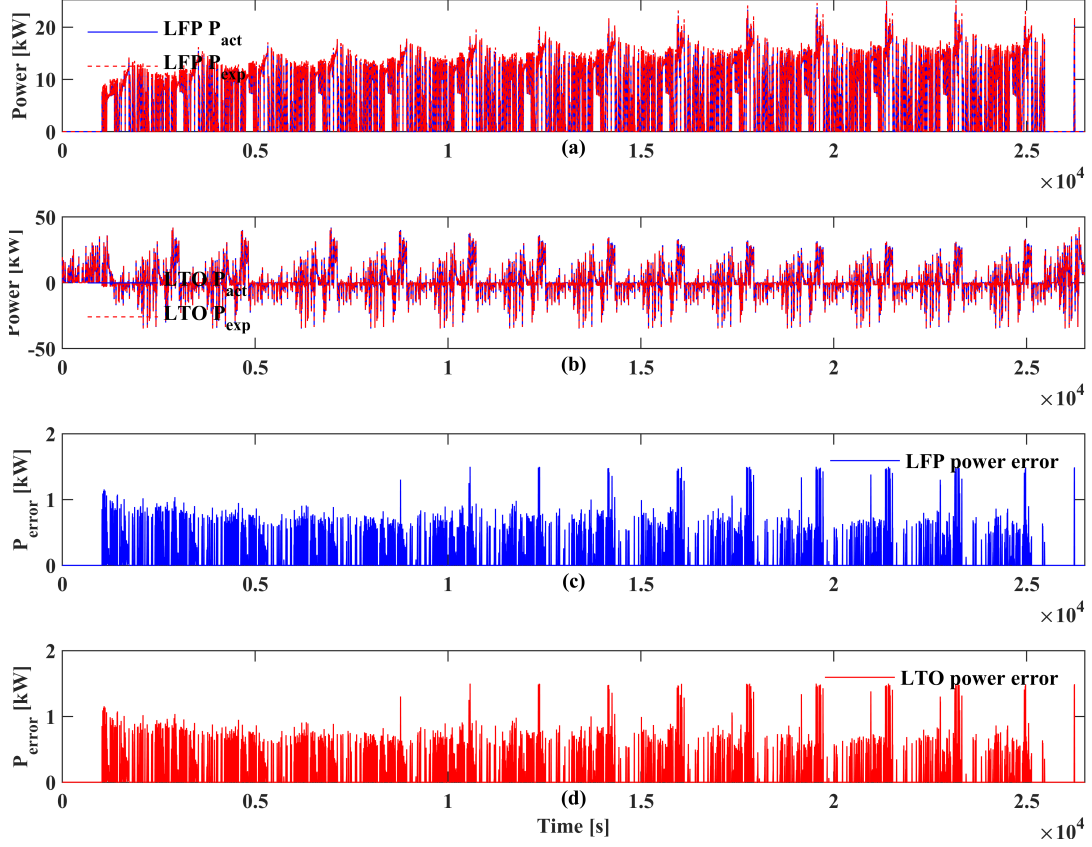


Figure 4.8: Comparison between expected and actual power on: (a) P_{act} and P_{exp} for the LFP battery sub-pack, (b) P_{act} and P_{exp} for the LTO battery sub-pack, (c) P_{error} of the LFP battery sub-pack, (d) P_{error} of the LTO battery sub-pack.

where P_{act} and P_{exp} are the actual power and expected powers (kW), P_{error} is absolute errors between expected power and actual power (kW).

Figure 4.8 (c) and (d) demonstrate P_{error} for LFP and LTO battery sub-packs, respectively. Errors can remain within 1.5 kW while allocating the power between two battery sub-packs. The errors within 1.5 kW are acceptable because the DC/DC converter also has errors within 5% when regulating the power allocation [81]. This means power distribution errors has 0 ~ 2 kW when using DC/DC converter in this battery system. Therefore, the proposed topology has similar performance in flexibly regulating power allocation as the conventional HBS with DC/DC converter.

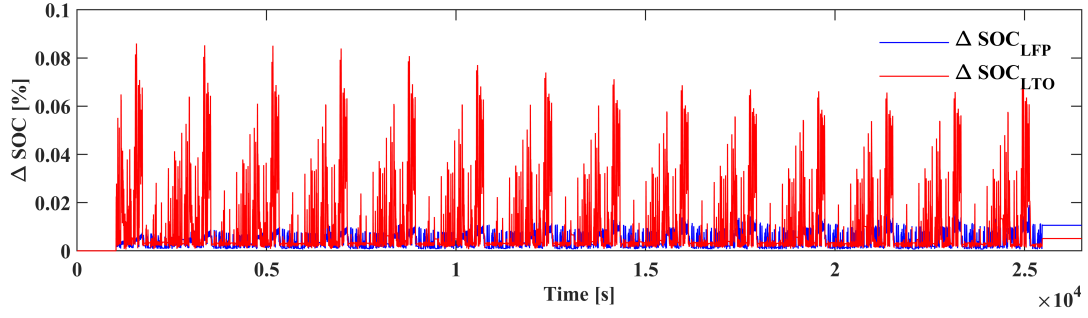


Figure 4.9: The difference between the maximum and minimum SOC of modules in the LFP and LTO battery sub-packs

4.5.3 SOC Balancing

The results of SOC balancing processes are demonstrated in Figure 4.9, where differences between the maximum and minimum SOC of modules in the LFP and LTO battery sub-packs are defined as ΔSOC_{LFP} and ΔSOC_{LTO} , respectively. The battery system initially runs in discharge mode III and mechanical braking mode, and only the LTO battery sub-pack participates in the operation, and all modules in the LTO battery sub-pack are discharged or charged. Thus, SOC_{LFP} and SOC_{LTO} maintain balance. Then, the module switches start allocating power (discharge mode IV), resulting in an unbalanced trend between modules. Simultaneously, the rolling discharging approach controls the module modes $\vec{M}_1$ and $\vec{M}_2$ to prevent the unbalanced trend from continuing to expand and maintains ΔSOC fluctuating within a small range. The simulation results show that ΔSOC_{LFP} and ΔSOC_{LTO} fluctuate within $0 \sim 0.01\%$ and $0 \sim 0.1\%$ in the LFP and LTO battery sub-packs, respectively. It is verified that the topology can maintain the SOC balancing between modules in a sub-pack when the module currents are inconsistent.

The system can also balance the modules in battery sub-packs under initial module SOC that are unbalanced. It is assumed that initial module SOC $\chi_{(i,j)}$ are randomly distributed within the range of 10% based on 80% of initial SOC_{LFP} and SOC_{LTO} . The results of the SOC balancing process is demonstrated in Figure 4.10. During the SOC balancing process, both ΔSOC_{LFP} and ΔSOC_{LTO} decrease at discharge mode IV. The LTO battery sub-pack

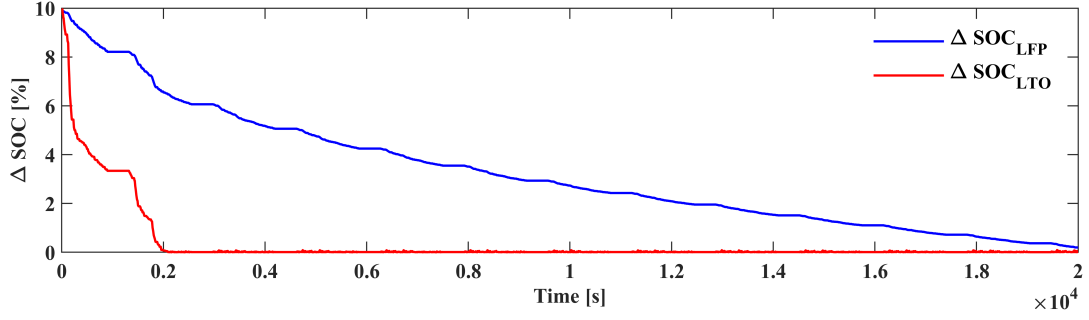


Figure 4.10: Battery active balancing for LFP and LTO battery sub-packs under initial condition of unbalanced module SOC's

first reaches balancing at approximately 2000 seconds and then remains balanced. The LFP battery sub-pack achieves the balancing slowly but can also remain after reaching it. The reason of the LFP battery sub-pack slowly reaching the balancing is the lower current flowing through the LFP batteries. Specifically, the proposed topology utilizes the discrepancy of accumulated electric charge of each battery module by regulating the $\vec{M}_1$ and $\vec{M}_2$ in the two sub-packs to make up for the difference of modules SOC's. Thus, the SOC balancing speed depends on the charging and discharging rate at discharge mode IV.

4.6 Conclusion

A novel discrete-switched topology used in the HBS with LFP and LTO batteries has been proposed in this paper. The proposed topology is to utilize the discrete-switched structure to replace the expensive and bulky DC/DC converter in the semi-active and active topology of the HBS. This study has explored a feasibility approach that simplifies battery system hardware at the expense of a more complex control algorithm. Simulation has verified the topology with a similar performance of regulating power allocation as the existing topology with DC/DC converters, ensuring that SOC's remain broadly balanced throughout discharge.

This study demonstrates the topology in detail, and the system is modeled to explain

the power allocation method. A management strategy is then developed to meet the power allocation regulation between two batteries and balance SOC_s in each sub-pack. A case study with the WLTP Class 3 driving cycle is implemented in MATLAB/Simulink. Simulation results verify that this topology can allocate power flexibly (similar to an HBS with DC/DC converter). In addition to similar features to the conventional HBS, the proposed topology also has the following advantages:

1. The power electronics cost of the proposed topology is much cheaper than the conventional HBS with DC/DC converters. In the case study, the power electronics cost of the proposed topology is £383.6 compared to £2216.1 of the conventional semi-active topology under the same battery system configuration.
2. The topology can integrate two functions of power allocation and SOC balancing. In the case study, the LFP modules are in balance to within 0.01% of each other. The LTO modules are balanced to within 0.1% of each other. SOC_s in the pack end up in good balance with each other.

The intended scope of this work is a description of the novel technology paper only focuses on proposing the novel topology and verifying it has the advantages of cost and flexible power allocation capability. However, in automotive applications, various factors in the HBS need to be considered, including thermal effects, battery state estimations under non-uniform cells, thermal properties, control algorithm optimization and robustness, as well as load properties (e.g. characteristics of motors and inverters). Therefore, these factors in the novel hybrid battery systems will be further explored in the future.

Chapter 5

An Experimental Study for Low-Frequency Discrete Switching Structure of Hybrid Battery System

Abstract

This article designs and implements an experiment of the discrete-switched hybrid battery pack combining nickel cobalt manganese oxide (NCM) and lead-acid batteries to verify the power allocation capability of the discrete-switched structure. The hybrid battery pack is developed in this study, and a benchmarking control algorithm is explored to regulate power allocations between two batteries. Experimental results verify the power allocation capability using the discrete-switched structure. While the article focuses on experimental validation, it also identifies future research such as a higher-level voltage hybrid battery pack experiment to explore results close to EV battery packs.

Author Statement

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Author contribution: *You Gong:* Writing-Original draft preparation, Conceptualization, Methodology, Software, Investigation, Formal analysis. *Daniel. J. Auger:* Supervision, Conceptualization, Software, Resource, Writing-Reviewing and Editing, Project administration, Funding acquisition. *Abbas Fotouhi:* Supervision, Writing-Reviewing and Editing. *Christopher J. Hale:* Resource, Validation, Project administration, Funding acquisition.

5.1 Introduction

Across electrification vehicle applications, the traction battery is critical for vehicle cost and performance. However, despite continuing to dominate the electric vehicle (EV) domain, the traction battery pack based on single chemistry cannot reconcile the conflicting requirements for energy, power, safety, lifespan, and cost [19], [58], [82]. The weaknesses of state-of-art commercialized battery chemistry technologies impact original equipment manufacturer (OEM) electrification programs and end-user adoption.

The research community has proposed hybridizing battery chemistries at a system level to potentially mitigate weaknesses of single-chemistry battery systems [83]. Various approaches employing bi-directional DC/DC converters to manage power flow allocations between various battery types have become mainstream [60], [67] in research projects. Correspondingly, some manufacturers are exploring pre-commercial products using this approach [44], [45], [84]. Nonetheless, those approaches using complex and expensive bi-directional DC/DC converters generate a new issue - there is a trade-off between improving the overall performance of the battery system and significantly increasing the

cost and hardware complexity.

In response, we have developed a modular discrete-switched structure for a hybrid battery system (HBS) [66] [85]. This can integrate and realize real-time power allocations between different batteries containing two or more disparate cell chemistries. Through cost analysis previously investigated, the power electronics of HBSs using this structure are much cheaper than the approaches using the converters. Moreover, HBSs using this structure can reach flexible power allocation through a proper battery management system (BMS). However, the previous study explored the performance of the proposed structure by simulated methods, leading to possibly missing certain unknown factors in real-world applications that would affect the battery system.

In this study, a practical embodiment was implemented to experimentally study this structure based on the concept previously explored. This experiment is a part of publicly-funded research projects in the U.K. of which the authors are part of CHIMERA and BRAD projects.¹² The pre-commercialized module-level product is shown in Figure 5.1. Compared with [85], this study explores a practical embodiment that has a more constrained switching strategy - 'a restricted authority' system, in other words. Specifically, this embodiment reduces controlled degrees of freedom to simplify the hardware complexity: controlling one of the parallel strings instead of all parallel strings. Nevertheless, this experiment does not affect the research on the controllability of power allocations. Correspondingly, the study proposes a control strategy adapted to the hardware structure.

The scope of this study is to experimentally verify the capability of power allocation between two types of batteries using the discrete-switched structure. Accordingly, a module-level prototype battery pack is designed, consisting of a nickel cobalt manganese oxide (NCM) battery module and a lead-acid battery module. The NCM and lead-acid

¹CHIMERA project was supported by Innovate UK [grant number 48727], the project description is shown in Appendix A.

²BRAD project was supported by Innovate UK [grant number 10017550], the project description is shown in Appendix B.

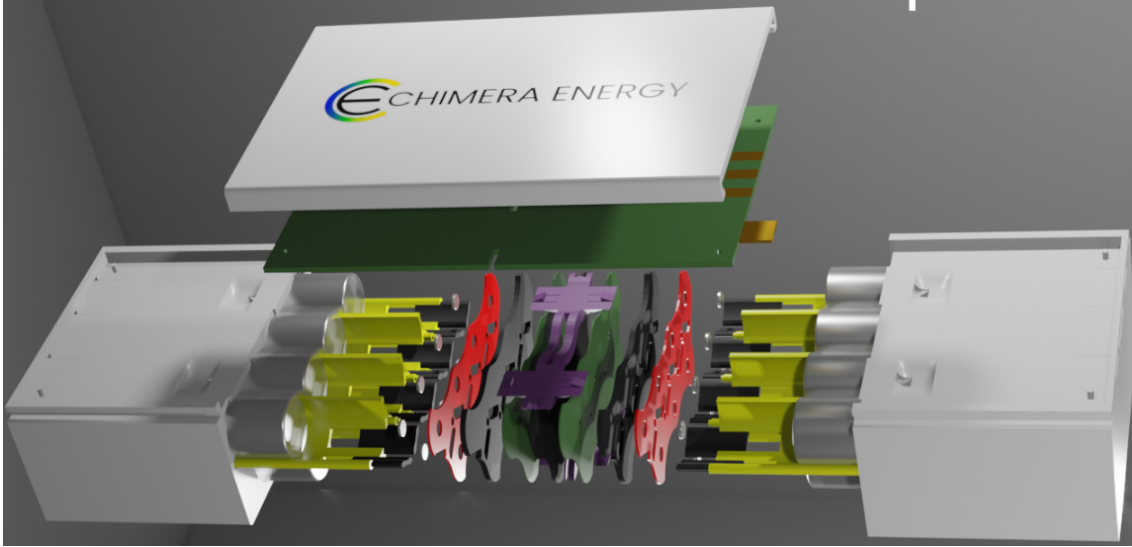


Figure 5.1: The pre-commercialized module-level product

batteries have complementary advantages in improving energy efficiency and cost. The lead-acid battery can provide inexpensive energy to serve a load. Still, one of the drawbacks suffered is inefficiency in high-frequency pulse and high-power load applications [12], [86]. On the other hand, the NCM battery within the lithium-ion battery family has a good efficiency in the above applications but is expensive. Hence, this study aims to reduce the operating time of the lead-acid battery under continuous and instantaneous high currents while sharing a part of the power demand under these conditions.

The contributions of this study are as follows:

1. Conceptual mathematical and simulation models of the restricted authority system are built, where switching is limited to the main packs and their ‘boost’ states. a new control strategy is created by adapting the previously developed control strategy to the new context.
2. Experimental validation of the concept of the discrete-switched structure is designed and implemented to verify its performance of the power allocations between different battery types. The extent to which a discrete-switched HBS with restricted authority

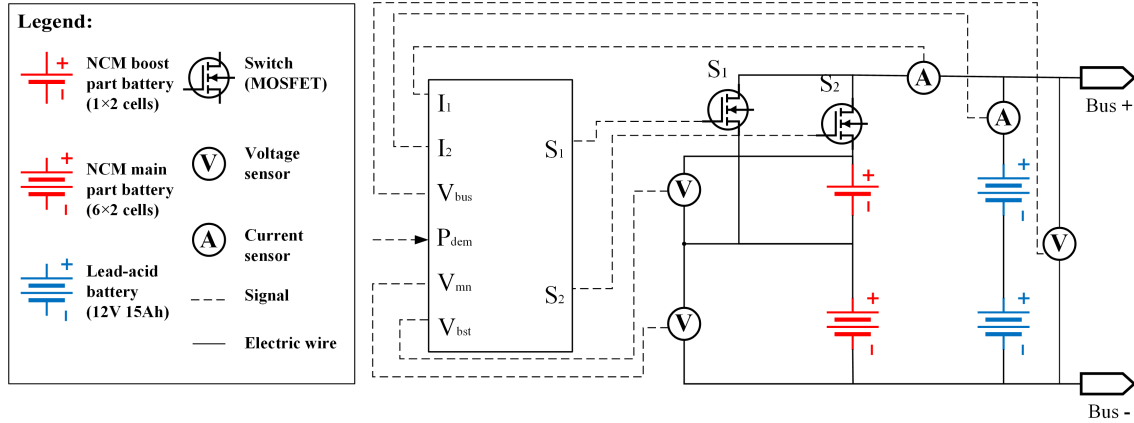


Figure 5.2: A diagram of the prototype battery pack structure

is effective is demonstrated, where its performance to a full-authority system is compared.

3. A practical embodiment with real C code used in the real-world application is developed, allowing the industry partner to maximize their results.

This article is organized as follows. Section 5.2 presents a 'big picture' of experiment design, including battery pack structure, modeling and control strategy, and experiment settings. Section 5.3 demonstrates the modeling of the prototype battery pack. Section 5.4 presents the heuristic control design and the process of real C codeC code generation. Section 5.5 shows the experimental results based on the control strategy and power demands from real-world applications. Section 5.6 discusses the differences between this prototype battery pack and a full-authority HBS previously explored. Finally, Section 5.7 concludes this article.

5.2 Methodology

Figure 5.2 is the block diagram of the prototype battery pack. The battery pack comprises an NCM battery module and a lead-acid battery module. The power contacts "Bus+"

and "Bus-" are the interface of the battery system to a power supply. The NCM and lead-acid battery modules are connected in parallel to simultaneously provide power to a load. Accordingly, the voltage of the NCM battery module tends to equalize with the lead-acid battery module and also equal to the bus voltage V_{bus} . The lead-acid module has two lead-acid batteries (15Ah, 12V) in series. The NCM battery module comprises a main part and a boost part. The main part has 12 battery cells and is the layout of 6 series and 2 parallels. The main part has two battery cells and is the layout of 1 series and 2 parallels. This study employs the discrete-switched structure in the boost part of the NCM battery module. In addition to two battery cells, the boost part comprises a main switch S_1 and a bypass switch S_2 . The main switch is directly connected to the positive terminal of the NCM boost part. In contrast, the bypass switch S_2 is electrically connected to the module circuit and the battery's negative terminal. The NCM boost part can be isolated by opening S_1 and closing S_2 . Conversely, it can participate in the circuit by closing S_1 and opening S_2 . In addition, the whole NCM module can be disconnected from the bus by opening both S_1 and S_2 . In this study, the three switching states callss 'switch-on', 'boost', and 'switch-off' states, respectively.

In the NCM battery module, there are one current sensor and two voltage sensors; I_1 is the measured current; V_{mn} for the measured voltage of the main part; and V_{bst} for the measured voltage of the boost part. Moreover, I_2 is the measured current of the lead-acid battery module, and V_{bus} is the measured voltage of the electrical bus. The battery state estimation and switching control are integrated into the controller. The controller receives power demands and measured values from current and voltage sensors as reference inputs. According to the information, the controller controls the discrete switches S_1 and S_2 to regulate current allocations between the NCM and lead-acid battery modules.

Based on the hardware structure, the pack modeling is developed as demonstrated in Section 5.3. Accordingly, a rule-based control algorithm is developed as a benchmark strategy to verify the power-regulating capability of the low-frequency discrete-switched

Model Structure

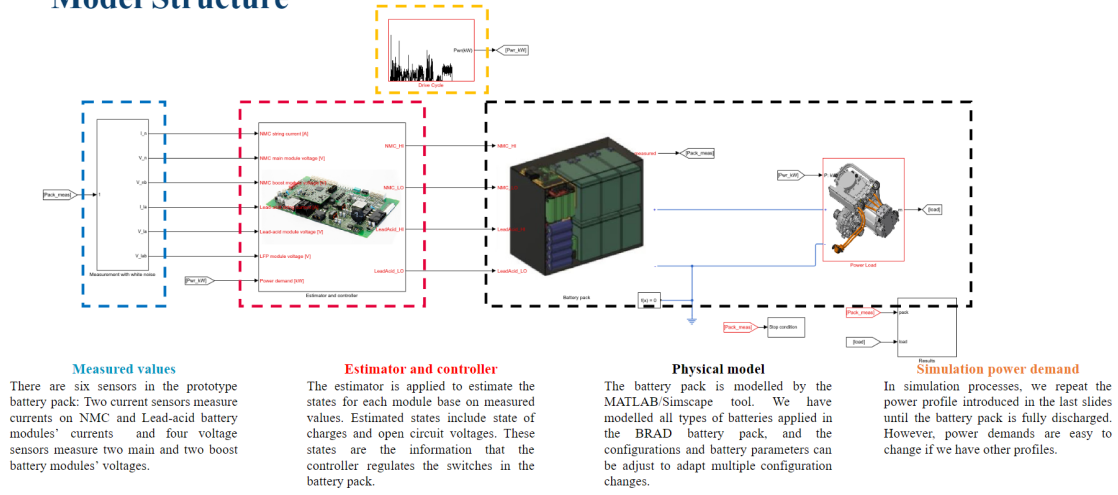


Figure 5.3: Lumped model for this study

structure. A lumped model for this study is shown in Figure 5.3.

The flowchart of the control algorithm is shown in Figure 5.4. The system has three control states of the NCM module: switch-off, switch-on, and boost to respective with the switching states. The current allocation process is operated when the power demand is far greater than the nominal current of the lead-acid battery. Based on the prediction results at the switch-on and boost states, the controller determines the switch-on of the NCM module with or without the boost part participating in the work. Besides, the frequency of the switching control is 0.1 Hz in this study. Details of control design are shown in Section 5.4.

The experimental settings of the prototype battery pack have been established as depicted in Figure 5.5. The batteries used in this study are 4.2Ah Molicel NCM battery cells and 15 Ah Enduroline lead-acid battery cells. The discrete switches are two Vishay P-Channel MOSFETs. The power supply connected to the power contacts "Bus+" and "Bus-" is a KEPCO DC power supply. The power demands in this study adopt a quad bike driving trial, as shown in Figure 5.6. This driving profile includes three parts: driving at high speed on the road, working on the farm, and dragging the small cargo on the farm.

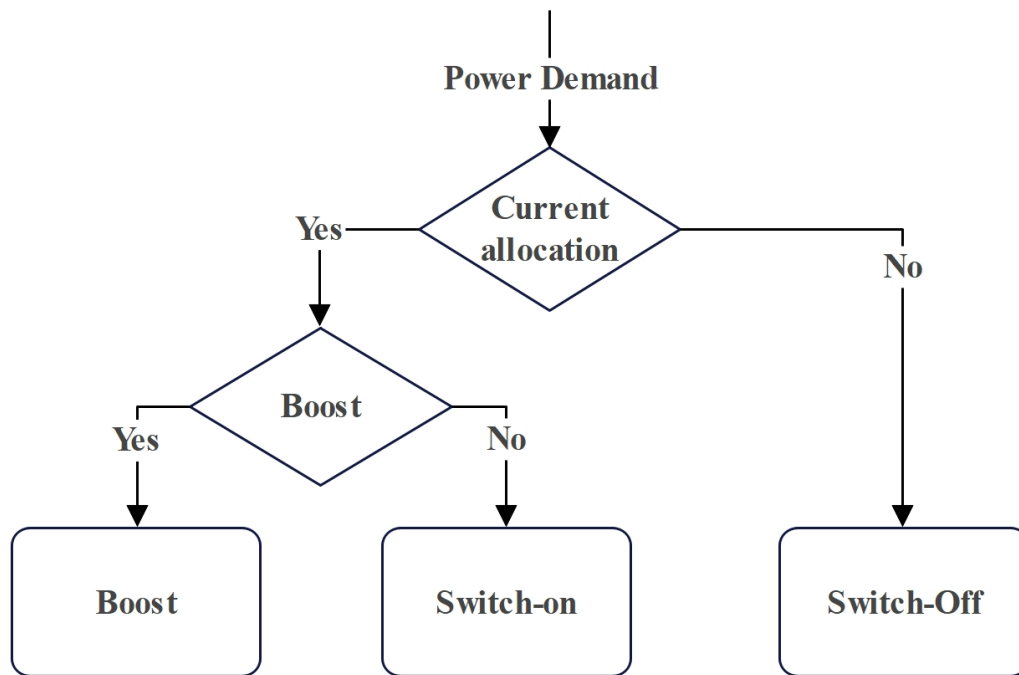
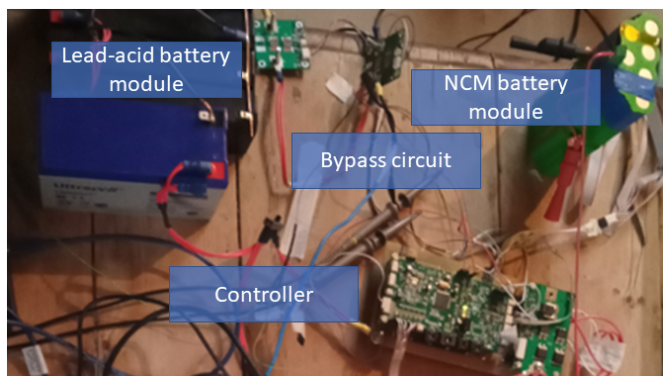


Figure 5.4: Flowchart of the control algorithm



(A)



(B)

Figure 5.5: Experimental settings: (A) the controller, batteries, and electric circuits, and (B) the DC power supply.

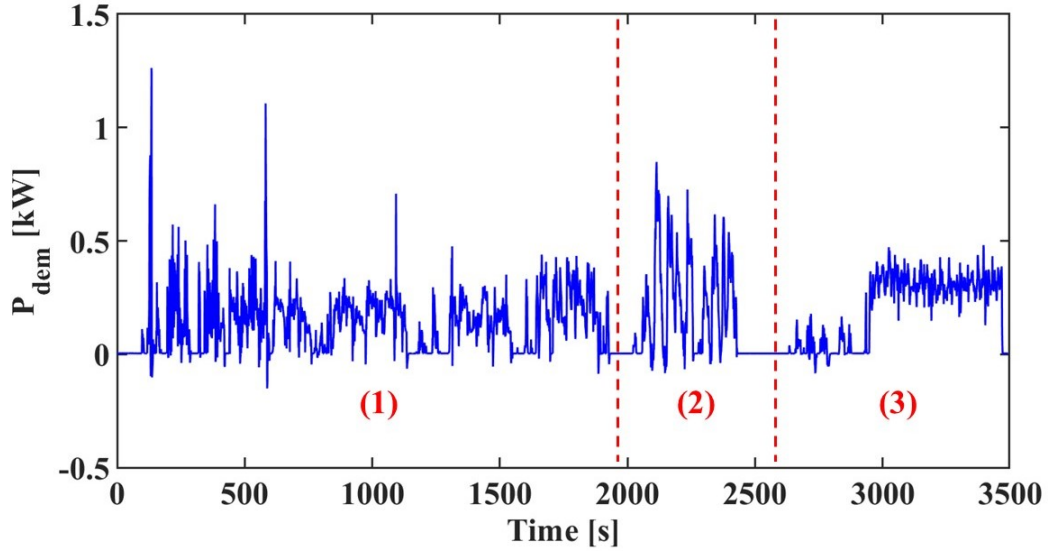


Figure 5.6: Power demand profile: (1) driving at high speed on the road, (2) working on the farm, and (3) dragging the small cargo on the farm

5.3 Modeling

5.3.1 Cell Model

This section details the equivalent circuit models (ECMs) of the NCM and lead-acid batteries used in the controller. The NCM battery uses a second-order resistor-capacitor (2RC) described in [87], while the lead-acid battery uses the remapped Randles' model described in [86].

Figure 5.7(A) shows the 2RC ECM for the NCM battery. It consists of a battery open circuit voltage (OCV), an internal resistance, and two parallel RC pairs. The discrete-time state-space model can be expressed as follows:

$$\begin{aligned}
 \dot{V}_{p1,ncm} &= -\frac{V_{p1,ncm}}{R_{p1,ncm}C_{p1,ncm}} + \frac{I_{ncm}}{C_{p1,ncm}} \\
 \dot{V}_{p2,ncm} &= -\frac{V_{p2,ncm}}{R_{p2,ncm}C_{p2,ncm}} + \frac{I_{ncm}}{C_{p2,ncm}} \\
 V_{ncm} &= V_{oc,ncm} - V_{p1,ncm} - V_{p2,ncm} - I_{ncm}R_{o,ncm},
 \end{aligned} \tag{5.1}$$

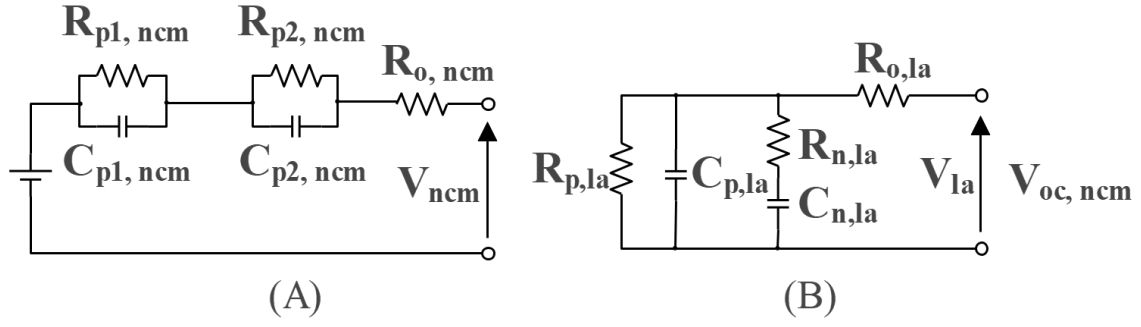


Figure 5.7: Equivalent circuit models for (A) an NCM battery cell and (b) a lead-acid battery cell

where the open circuit voltage (OCV) is $V_{oc,ncm}$, the terminal voltage is V_{ncm} , and the internal resistance is $R_{o,ncm}$. $R_{p,ncm}$ and $C_{p,ncm}$ for the two RC pairs are the polarization resistances and capacitance describing transient response, respectively. Their voltage drops are the $V_{p1,ncm}$ and $V_{p2,ncm}$. The current through all components is I_{ncm} . In this study, the parameters of the NCM battery cell depending on the SOC are shown in Fig. 5.8.

Figure 5.7(B) shows the ECM of the lead-acid battery. This model is obtained by remapping the well-known Randles' model using a star-delta transform. The state-space model can be expressed as:

$$\begin{aligned}\dot{V}_{C_{n,la}} &= -\frac{V_{C_{n,la}}}{R_{n,la}C_{n,la}} + \frac{V_{C_{p,la}}}{R_{n,la}C_{n,la}} \\ \dot{V}_{C_{p,la}} &= \frac{V_{C_{n,la}}}{R_{n,la}C_{p,la}} + \frac{V_{C_{p,la}}}{R_{n,la}C_{p,la}} + \frac{I_{la}}{C_{p,la}} \\ V_{la} &= V_{C_{p,la}} - I_{la}R_{o,la}\end{aligned}\tag{5.2}$$

where $R_{p,la}$ indicates the self-discharge resistance, $C_{p,la}$ and $R_{n,la}$ correspond to the transient effects in the Randles' model, and $R_{o,la}$ represents the internal resistance. V_{la} and I_{la} represent the terminal voltage and throughout current of the battery cell, respectively. The voltage across $C_{n,la}$ that is $V_{C_{n,la}}$, is considered to be an indicator of the state of charge (SOC). In this study, the parameters of the lead-acid battery are listed in Table 5.1.

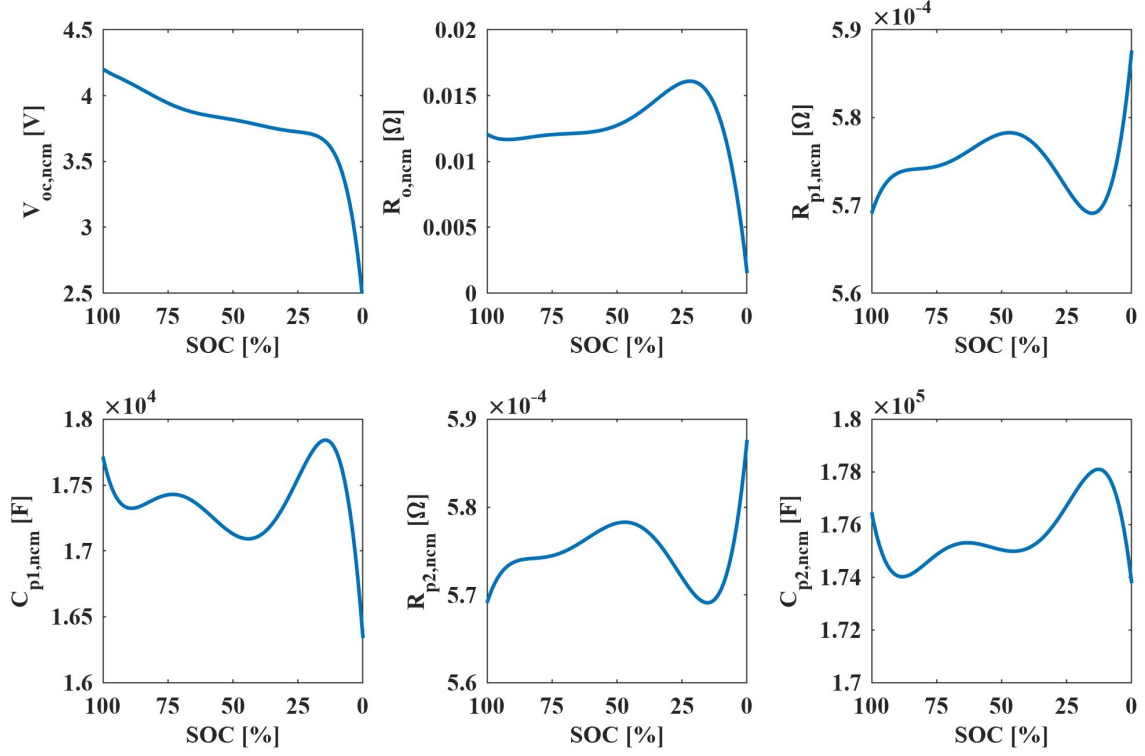


Figure 5.8: NCM battery cell parameters concerning SOC (25 °C) in this study

Table 5.1: Lead-acid battery parameters

$C_{n,la}$	29600 F	$C_{p,la}$	3860 F	$R_{o,la}$	25 mΩ
$R_{n,la}$	27 mΩ	$R_{p,la}$	5 kΩ		

5.3.2 Pack Model

A piece-wise function can define the operation states for the discrete-switched structure to explain conveniently: 1) connecting S_1 and disconnecting S_2 is 1, and 2) connecting S_2 and disconnecting S_1 is 0. The piece-wise function for the operation state u can be depicted as:

$$u = \begin{cases} 1 & \text{boost} \\ 0 & \text{switch-on} \end{cases} . \quad (5.3)$$

Meanwhile, simultaneously opening S_1 and S_2 can disconnect the NCM battery module from the bus.

In this study, all battery cells in the NCM module are almost uniform (The nonuniformity and aging battery cells will be explored in future work). The parameters of the NCM boost part, the NCM main part, and the lead-acid battery series can adopt the "superposition" method as described in [60] and [85]. The main part of the NCM module is depicted as follows:

$$\begin{aligned}
\dot{V}_{p1,mn} &= -\frac{V_{p1,mn}}{R_{p1,mn}C_{p1,mn}} + \frac{I_1}{C_{p1,mn}} \\
\dot{V}_{p2,mn} &= -\frac{V_{p2,mn}}{R_{p2,mn}C_{p2,mn}} + \frac{I_1}{C_{p2,mn}} \\
E_{mn} &= V_{oc,mn} - V_{p1,mn} - V_{p2,mn} \\
V_{mn} &= E_{mn} - I_{mn}R_{o,mn}.
\end{aligned} \tag{5.4}$$

The boost part of the NCM module is depicted as follows:

$$\begin{aligned}
\dot{V}_{p1,bst} &= -\frac{V_{p1,bst}}{R_{p1,bst}C_{p1,bst}} + \frac{I_1}{C_{p1,bst}}u \\
\dot{V}_{p2,bst} &= -\frac{V_{p2,bst}}{R_{p2,bst}C_{p2,bst}} + \frac{I_1}{C_{p2,bst}}u \\
V_{bst} &= V_{oc,bst} - V_{p1,bst} - V_{p2,bst} - I_{bst}R_{o,bst}u.
\end{aligned} \tag{5.5}$$

Meanwhile, the lead-acid battery is depicted as follows:

$$\begin{aligned}
\dot{V}_{C_{n,b}} &= -\frac{V_{C_{n,b}}}{R_{n,b}C_{n,b}} + \frac{V_{C_{p,b}}}{R_{n,b}C_{n,b}} \\
\dot{V}_{C_{p,b}} &= \frac{V_{C_{n,b}}}{R_{n,b}C_{p,b}} + \frac{V_{C_{p,b}}}{R_{n,b}C_{p,b}} + \frac{I_2}{C_{p,b}} \\
V_{bus} &= V_{C_{p,b}} - I_2R_{o,b}.
\end{aligned} \tag{5.6}$$

From Equations (5.4) to (5.6), subscript "mn" indicates the main part of the NCM battery module, the subscript "bst" indicates the boost part of the NCM battery module, and subscript b indicates the lead-acid battery module. Here, the transient electromotive force

and ohmic resistance for the NCM and the lead-acid battery can be described as:

$$\begin{aligned}
E_{mn} &= V_{oc,mn} - V_{p1,mn} - V_{p2,mn} \\
E_{bst} &= V_{oc,bst} - V_{p1,bst} - V_{p2,bst} \\
R_{mn} &= R_{o,mn} \quad R_{bst} = R_{o,bst}
\end{aligned} \tag{5.7}$$

where E_{mn} and E_{bst} are the transient electromotive forces of the main and boost parts of the NCM battery module, respectively. Similarly, R_{mn} and R_{bst} are the ohmic resistances of the two parts. Thus, the transient electromotive forces of the NCM module E_1 , the transient electromotive forces of the lead-acid module E_2 , the ohmic resistances of the NCM module R_1 , and the ohmic resistances of the lead-acid module R_2 can be deduced as:

$$\begin{aligned}
E_1 &= E_{mn} + E_{bst}u \\
R_1 &= R_{mn} + R_{bst}u \\
E_2 &= V_{C_{p,b}} \quad R_2 = R_{o,b}
\end{aligned} \tag{5.8}$$

Based on the Kirchhoff laws, the system-level relationship can be expressed as follows:

$$\begin{aligned}
I_{bus} &= I_1 + I_2 \\
V_{bus} &= E_1 - I_1 R_1 \\
V_{bus} &= E_2 - I_2 R_2 \\
P_{bus} &= I_{bus} V_{bus}
\end{aligned} \tag{5.9}$$

The current allocations between the two modules are thus depicted as follows:

$$\begin{aligned}
I_{bus} &= I_s(1 + \phi) \\
V_{bus} &= V_s(1 + \phi) \\
I_1 &= \frac{E_1}{R_1} - \frac{V_s}{R_1}(1 + \phi) \\
I_2 &= \frac{E_2}{R_2} - \frac{V_s}{R_2}(1 + \phi)
\end{aligned} \tag{5.10}$$

where

$$I_s = \frac{1}{2} \left(\frac{E_1}{R_1} + \frac{E_2}{R_2} \right) \quad R_s = \left(\frac{1}{R_1} + \frac{1}{R_2} \right)^{-1}$$

$$V_s = I_s R_s \quad \phi = \sqrt{1 - \frac{P_{\text{bus}}}{V_s I_s}}.$$

The current allocation between the battery module under different discrete switching modes can be predicted under setting a power demand equal to bus power, i.e., $P_{\text{bus}} = P_{\text{dem}}$. Hence, the predicted current allocation in the system can be expressed by the following equation:

$$Y_{\text{sys}} = f(X_{\text{sys}}, u, P_{\text{dem}}) \quad (5.11)$$

where

$$X_{\text{sys}} = \{E_{\text{mn}}, E_{\text{bst}}, R_{\text{mn}}, R_{\text{bst}}, E_2, R_2\}$$

$$Y_{\text{sys}} = \{I_1, I_2\}$$

5.4 Control Design

This study develops a rule-based control algorithm as a benchmark strategy to verify the power-regulating capability of the low-frequency discrete-switched structure. This section mainly focuses on the benchmark control algorithm, although the controller's functions include battery state estimation and switching control. The model parameter identification and SOC estimation for the lead-acid and NCM battery modules are described in [86] and [87] in detail, respectively, where the extended Kalman filter (EKF) is used for the SOC estimation. The estimation processes are similar to the literature in this study. For brevity, these algorithms in the controller are omitted here.

The system has three control states of the NCM module based on the switching states: switch-off, switch-on, and boost. Currents I_1 and I_2 can be predicted by Equation (5.11)

Embedded Code Generation

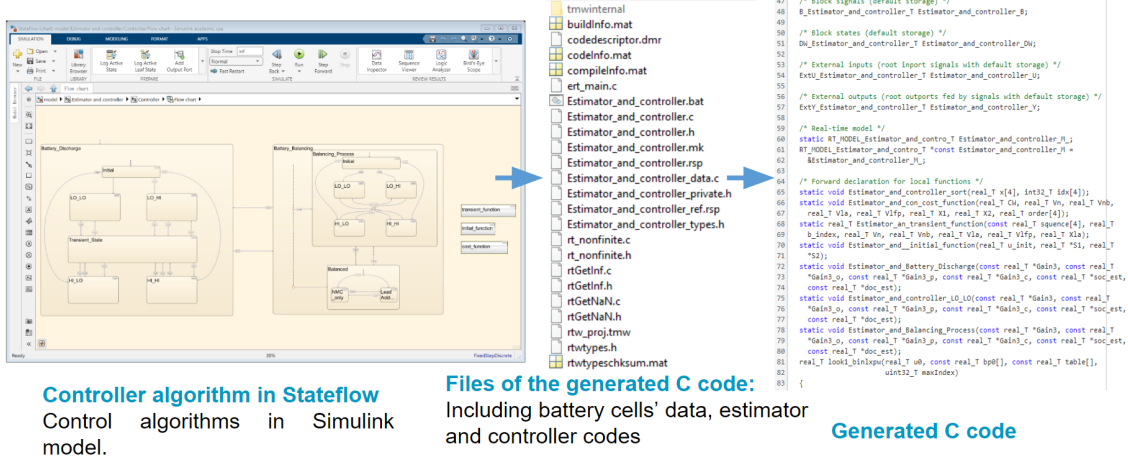


Figure 5.9: C code generation

under various switching states, that is:

$$Y_{sys} = f(X_{sys}, u, P_{dem}) \quad (5.12)$$

where

If (switching state is switch-off)

$$E_{mn} = 0 \quad R_{mn} = \infty \quad u = 0$$

The currents throughout the lead-acid battery module are expected to be no more than ± 7.5 A (0.5 C-rates of the lead-acid battery). Based on the predicted currents I_1 and I_2 , the controller determines whether the NCM module participates in the work, i.e., switch-on or boost states. For example, if the switch-on and boost states cause a relatively large of lead-acid battery current, the switching states will remain 'switch-on'. Conversely, if the lead-acid battery current is limit exceeded, the switch-on and boost states will be considered participating in work. Here, the boost states will be implemented if the predicted current I_1 at the switch-on state is still much greater than the limitations.

Figure 5.9 shows the processes of the embedded C code generation relative to the control algorithm. the control algorithms are developed in the Stateflow tool of MATLAB/Simulink.

A real C-code applied in this experiment is generated by an embedded code application in MATLAB/Simulink.

5.5 Results and Analysis

Figure 5.10 illustrates the experimental results under the quad bike power demands. In Figure 5.10(b), the switching states first relatively frequent changes when driving at high speed on the road due to large fluctuations in the power demands. Meanwhile, during working on the farm and dragging the small cargo, the power is in the medium and high power ranges at most duration, as shown in Figure 5.10. Hence, the system works in the boost state most of the time. In Fig. 5.10(c), the current of the lead-acid battery is broadly stable. The NCM battery can absorb the peak power demands, while the lead-acid battery can charge the NCM battery to remain in the state of charge of the NCM battery.

The results illustrated in Figure 5.10 verify the capability of the current allocations between the two battery modules. This experiment first validates that the currents throughout the two modules can be controllable under a discrete-switched-based battery pack; that is, it is possible to control two battery modules or packs with different battery chemistries for power flow allocations by designing a switching control strategy. Meanwhile, the battery pack exhibits the characteristic of allowing the two modules to exchange energy during discharge. This characteristic can achieve the battery SOC's regulation between different battery chemistries during charging and discharging processes in EV applications.

5.6 Discussion

In this study, the prototype battery pack only applies a discrete-switches structure in the boost part of the NCM module, which makes the battery pack less regulatable. As shown

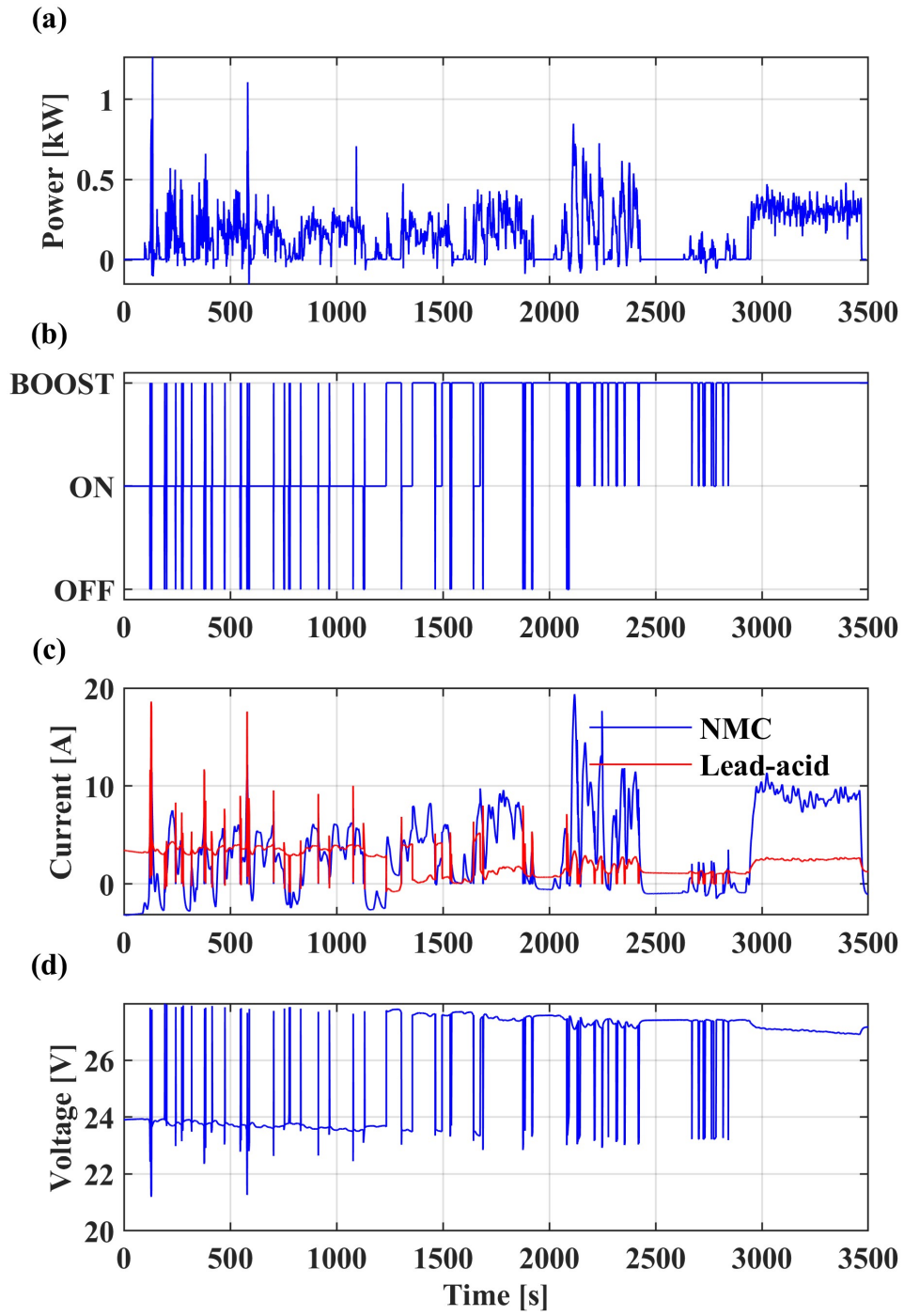


Figure 5.10: Experimental results: (a) bus power P_{bus} , (b) switching states, (c) currents of the NCM and lead-acid module, and (d) bus voltage V_{bus}

in Figure 5.10(b) and (c), although the switching states are adjusted to the "boost" state, the lead-acid battery module still bears relatively high currents at several spike power demands. Nonetheless, by comparing with the research in [85], it can be concluded that the small size of the battery pack (i.e. nominal 24 V battery pack) makes switching the individual parallel string in and out of the series strings have a significant effect on current allocations. Conversely, the operation of each discrete-switch pair has a smaller impact on the current allocations in a high-voltage battery pack with multiple discrete-switched pairs. The regulating processes will be smoother for high-voltage hybrid battery systems with multiple pairs of discrete switches. Hence, the discrete-switched structure performs better in high-voltage battery packs (e.g., EV battery packs).

5.7 Conclusion

To verify the discrete-switched structure used in the hybrid battery pack with multi-chemistry batteries, this article designed and implemented an experiment using the NCM and lead-acid batteries. This study has verified the capability of power allocations between two batteries using a 24-voltage hybrid battery pack. In this study, the hybrid battery pack was designed in detail, and a benchmarking control algorithm was explored to regulate the power allocations between two batteries. Experimental results verify that this structure can allocate power between two batteries.

The intended scope of this work is an experimental validation for the power allocation capability of the discrete-switched structure. Nevertheless, it is challenging to implement experiments on EV battery pack level with discrete-switched structure at this stage due to the limitation of experimental conditions. The article states that the discrete-switched structure performs better in EV battery packs. Therefore, the higher-level voltage hybrid battery pack will be further experimentally explored in the future.

Chapter 6

A Low-Frequency Switched Energy Management for a Li-S/NCM Hybrid Battery System

Abstract

To compete with fossil-fuel vehicles, battery electric vehicles must have an adequate range and ‘driveability’. For the battery system, this means having adequate energy density and power density. In most state-of-the-art vehicles, a single battery chemistry representing the best compromise is used. It is interesting to consider whether two or more chemistries with complementary properties can be combined to benefit from each. Lithium-sulfur (Li-S), for example, offers exceptional gravimetric energy density, but power density is poor; it could be combined with another cell type with good power density, such as nickel cobalt manganese oxide (NCM). This paper proposes such a hybrid battery system. The majority of hybrid battery systems use networks of DC-DC converters, the proposed system uses a low-frequency discrete switching structure with simple and robust power electronics to

control the cells in use at any instant. In the simulation, the system achieves a cruising range in excess of 800 km. Compared to a benchmark, the proposed system is cheaper and lighter. An intelligent energy management strategy is used to control switching. This incorporates real-time state and parameter estimation and uses model-predictive control. The robustness of the system is demonstrated for degraded cells. State of charge estimation for fresh and aged batteries are both within 3%, and the current allocation errors between the two subpacks are 4 A under heavy loading, representing less than 10%. The work assumes heterogeneous cells and good cell cooling; future work is proposed to explore of cell-to-cell variations and extension to thermal effects.

Author Statement

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Author contribution: *You Gong*: Writing-Original draft preparation, Conceptualization, Methodology, Software, Investigation, Formal analysis. *ChengXi Cai*: Writing-Original draft preparation, Methodology, Software, Investigation, Formal analysis. *Thomas Delaney*: Writing-Reviewing and Editing. *Daniel. J. Auger*: Supervision, Conceptualization, Software, Resource, Writing-Reviewing and Editing, Project administration, Funding acquisition. *Abbas Fotouhi*: Supervision, Writing-Reviewing and Editing. *Christopher J. Hale*: Project administration, Funding acquisition.

Notes: *ChengXi Cai* is co-first author, whose contributions are marked in [blue](#).

6.1 Intrduction

Hybrid battery systems (HBSs) combine complementary advantages of two or more types of batteries to mitigate the impacts of individual weaknesses of batteries. In the past

decade, typical EV HBSs in the literature were composed of lithium-titanate-oxide (LTO) and lithium-iron-phosphate (LFP) batteries to prolong the system's lifetime and better manage the conflicting requirements of energy and power density [34], [60], [68], [69]. The LTO battery served as a quick power supply, and the LFP battery functioned as the primary energy storage. The LTO and LFP batteries were chosen considering complementary characteristics: they are safe and have complementary advantages in specific power, specific energy, and lifetime [8], [57]. The LTO battery supports fast charge/discharge (around 10 C-rate) and long service life but suffers from low energy density (60-75 Wh/kg) and high-cost [22]. In contrast, the LFP battery has a higher energy density (90-115 Wh/kg) and low price, but rapid battery degradation under high discharge current [56]. A common approach for hybridizing two batteries is to link two battery subpacks in parallel and allocate power via a high-power dc/dc converter [31], [60], [68], [69]. Another approach is configuring module-level dc/dc converters to regulate the current of each module [44], [63]. Various energy management strategies have been proposed to regulate power flows based on those approaches, ranging from rule-based control to fuzzy logic and deep reinforcement learning [34], [67]–[69].

Nevertheless, with the development of nickel cobalt manganese oxide (NCM), the practicality of the LFP-LTO HBS is being questioned due to the energy densities of the two chemistries being lower than commercialized NCM cells. HBS applications in previous studies were mainly focused on scenarios insensitive to driving ranges or had many charging opportunities, e.g. fixed-line buses and taxis [34], [68]. Meanwhile, the NCM battery has outstanding power density and extended lifespans due to technological breakthroughs in battery chemistry and the battery management system [88]. These advancements lead to a further decline in the lifespan and power density competitiveness of the LFP-LTO HBS relative to the current or near-future NCM battery system. The energy management approach to extend the LFP-LTO HBS lifespan is that the LFP battery operates at a low current during high load discharge, while the LTO battery absorbs most of the peak current

[34], [60]. However, high discharging C-rate is an uncritical factor in the aging of the NCM family batteries [72]. Additionally, high-power or module-level dc/dc converters in the HBS are faced with a substantial increase in the cost of whole battery systems due to the high cost of the dc/dc converters, which undoubtedly weakens the cost competitiveness.

Although the NCM battery has competitive energy and power density compared to other commercial battery chemistries, its energy density is still insufficient to meet the range requirements of some EVs within an accepted pack mass. Lithium-sulfur (Li-S) batteries are a next-generation battery technology aimed at offering a higher gravimetric energy density. They are expected to be commercialized in the next few years [27]. The reason that the Li-S battery is generally considered a technology for addressing range anxiety is its extremely high energy density [28]. The practically achievable specific energy at the cell level will be approximately two times higher than the NCM battery [25]. However, the inadequate specific power of the Li-S battery prevents it from meeting the power density requirements of EV battery systems. Attaining high energy and power density in Li-S battery chemistry is enormously challenging. There is still a long way to go for the Li-S battery to support the high power density of EVs.

The concept of the HBSs brings up additional opportunities for utilizing battery potential on EV battery systems. This paper proposes a next-generation HBS with Li-S and NCM batteries that better manages conflicting energy and power density requirements. To explain further the rationality of the HBS being developed from the perspective of battery characteristics, the energy and power density of the near-future Li-S and NCM batteries are investigated in Section 6.2. In the proposed HBS, the Li-S battery supplies the bulk of the energy with the NCM battery there to deliver the primary peak power supply. In a driving scenario, the NCM battery can undertake most of the power at high power demands (e.g, acceleration and climbing) whereas the Li-S battery is mainly used during mild power demand occasions to maximize range (e.g, cruising). During charging the NCM battery can accept high charge rates to meet the requirement for rapid part charge capability, and

the Li-S part of the pack can be slowly charged when the EV is not in use.

To respond to the high cost of the dc/dc converters, we have proposed a novel HBS topology in [85] and [66]. This topology uses a discrete switching structure that avoids expensive and bulky dc-dc converters. Meanwhile, this topology has the capability to achieve flexible power allocations and better cost competitiveness. The proposed HBS adopts the discrete switching structure, and the cost advantage of using this structure is analyzed in detail in Section 6.2. Nonetheless, some points unconsidered in the previous paper and patent are: 1) battery configuration optimization was not considered and analyzed, 2) no battery state estimations were considered in the power management, and 3) no control system adapted to this topology was developed. These points have been investigated and studied in this paper.

Furthermore, the approach to investigate the performance of the HBS is a simulation study since the Li-S battery is not yet commercially available, and the availability of the Li-S prototype battery is poor. The Li-S and NMC batteries are parameterized and modeled based on the investigations of technological development and their prototypes in this study. The contributions of this study are as follows.

1. A new combination of HBS is proposed, where Li-S and NCM are selected as the main energy and power sources, respectively. Their development trend and achievable energy density in the near future are investigated. The weight and cost are optimized in order to design of battery pack configuration.
2. A new model predictive control system is demonstrated, regulating the cells in and out of series strings based on their state of charge and power requirement. The control system uses a genetic algorithm to solve an objective function with integer variables.
3. Forgetting Factor Recursive Least Square (FFRLS) method is used for identifying the

parameters in the dynamic battery models online. Then Adaptive Extended Kalman Filter (AEKF) is used for state of charge (SOC) estimation. This approach can mitigate the impact of battery aging and inconsistencies on battery state estimations and system power allocations over the system's lifetime.

This paper is organized as follows. Section 6.2 investigates the near-future Li-S and NCM batteries and explores their relative characteristics. Section 6.3 presents the optimal battery configuration and the system structure. Section 6.4 introduces the parameter identification and SOC estimation method. Section 6.5 proposes the new control system from the module to the system. To verify the reliability and accuracy of the proposed battery management framework, the simulation work covers both fresh and aged conditions. Finally, Section 6.6 concludes this paper.

6.2 Development Trends of Li-S and NCM Batteries

The characteristics and the near-future development trends of the Li-S and NCM batteries are first investigated in this study, to illustrate their complementary energy and power density advantages.

To date, the NCM battery is the primary candidate for powering EVs due to its high energy and power density in commercial battery chemistries [24]. The NCM battery is a family of batteries whose cathode is mixed with metal oxides of lithium, nickel, cobalt and manganese in various proportions, expressed as $\text{LiNi}_x\text{Co}_y\text{Mn}_z\text{O}_2$ ($x+y+z=1$). Its development trend of the specific energy is shown as the blue dashed line in Figure 6.1. In commercial products, 2019 is regarded as a watershed because of the introduction of commercial NCM-811 with graphite–silicon anode (e.g. CATL NCM-811 pouch cell and Panasonic cylinder cell). This pushed the specific energy of traction batteries to a new level, reaching 300 Wh/kg at the cell level and 200 Wh/kg at the pack level, but this

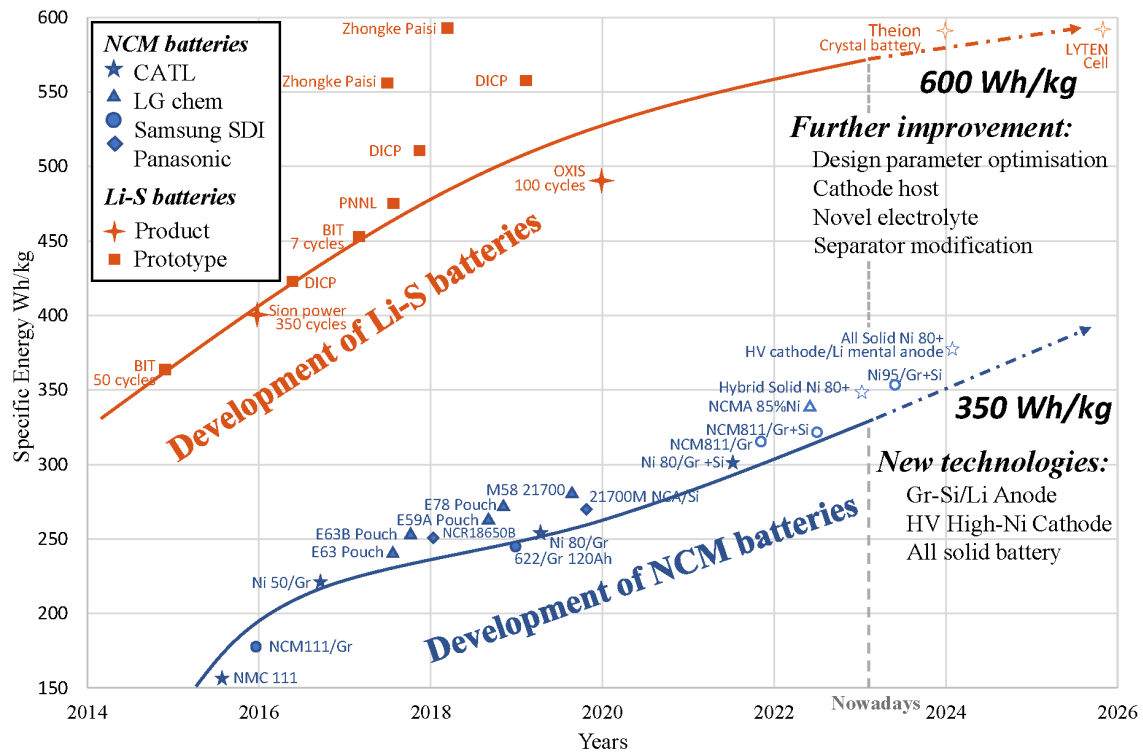


Figure 6.1: Development trends of Li-S and NCM battery specific energies from 2014 to present and near future. Data from [89][90][91][92].

value is still insufficient to satisfy the anticipated energy density for EVs. During the last decade, the energy density has increased mainly because of two methods: increasing the Ni content and expanding cell size. The first method increases the Ni content from 30% (NCM-111) to 50% (NCM-523) and now 80% (NCM-811). With the same Ni content, the large format cell increases the loading of active material and then increases the energy density. Thus the traction battery evolved from 18650 to 21700 and is now a pouch cell. However, the potential of these two methods is reaching their limit to further improve the energy density. In terms of increasing Ni content higher to 90%, the thermal and structural stability is compromised [93], [94]. Further improvement requires the introduction of high energy density anode, high voltage cathode, and solid electrolyte [90], [95]. However, approaching this limitation within the next 10 years is relatively hard, even in a laboratory setting. Before 2025 or sooner, adopting Si-C anode and slightly increasing Ni content can make the specific energy reach approximately 350 Wh/kg and control the

cost at US\$100–175/kWh [89], [96]. Novel strategies from material design and electrode engineering can help stabilize the electrode and, therefore, mitigate the negative effect of hi-Ni content. Furthermore, the breakthrough of asymmetric temperature modulation charging technology enables the NCM battery to support an exceeding 6 C-rate charge while maintaining a cycle life of 2000 times [88].

Li-S battery is well-known for its extremely high cathode specific capacity of 1762 mAh/g, and a theoretically ultrahigh energy density of 2600 Wh/kg [26]. As shown in Figure 6.1, prototype pouch cells currently demonstrated an energy density of 400-500 Wh/kg, and some evidence suggested a possibility to reach 600 Wh/kg shortly [97]–[99]. Benefiting from its cheap raw material, the pouch cell is estimated at around \$ 60–90 per kWh, significantly lower than Li-ion batteries [100]. Moreover, the Li-S battery permits a superior abuse tolerance in terms of overcharging, short circuit resistance and not exploding under the nail piercing test, thus outperforming Li-ion cells in safety [101]. However, commercialization bottlenecks are poor specific power and short lifetimes. The main reason for the poor specific power is the inherently electronic insulation of sulfur and discharged product Li_2S [102]. Specifically, the inactive material causes a significant attenuation of the available energy of the battery at high loads, offsetting the advantage of specific energy. The rate ability will be improved through electrode engineering approaches that can increase the ionic and electronic conductivity, such as carbon coating and conductivity network. Although it is possible to reach a maximum rate ability for EV application at the coin cell level, it is still far from the EV track battery requirements in pouch cell format because of the increasing electrode thickness and active material loading [103]. For aging, the "shuttle effect" caused by the dissolution and migration of intermediate LiPS and significant cathode volume expansion are two main reasons [29], [104]. These issues can be effectively enhanced by electrode engineering, solid-state electrolyte, modified separators, and advanced binder [92], [105]–[109]. The improvement methods will soon be implemented in manufacturing, improving the cycle life to 1000-

Table 6.1: Parameters of the NCM and Li-S Battery Cells

Battery chemistry	Li-S	NCM-811
Package format	Pouch	Pouch
Nominal voltage (V)	2.15	3.7
Maximum voltage (V)	2.6	4.2
Minimum voltage (V)	1.9	3.4
Specific energy (Wh/kg)	600	330
Maximum discharge rate (C)	1	6
Maximum charge rate (C)	0.5	6
Cost (\$/kWh)	60~90	100~175
Cell capacity (Ah)	40	26
Cell weight (kg)	0.141	0.313
Cell cost (\$)	5.9	14.2

2000 cycles [108].

Toward EV application, the NCM and Li-S batteries are in the pouch cell format. The single cell can achieve higher capacity and energy density without a rigid enclosure, which helps reduce the number of cells needed. The cut-off and nominal voltages for the NCM battery cell adopt the nominal parameters of current commercial cells since the high-voltage cathode is not yet sufficiently mature. For the demonstration purpose, the specific energy of Li-S and NCM are set to 600Wh/kg and 330 Wh/kg, respectively. Regarding C-rate ability, the maximum charge/discharge rate for Li-S batteries is 0.5/1 C, and for NCM batteries, it is set as 6 C. The sizes and weights of the Li-S and NCM battery cells used in this study adopt existing commercial and prototype cells in [110] and [111]. Their capacities are calculated according to the investigations above. The costs of the Li-S and NCM batteries are selected as \$70/kWh [100] and \$ 130/kWh [112]. The cell parameters used to form HBS are summarised in Table 6.1.

Table 6.2: Comparison of Tesla Model 3 and proposed HBS targets [115], [116]

Parameter	Tesla Model 3	HBS targets
Maximum power (kW)	208	≥ 208
Capacity (kWh)	60	≥ 98
WLTP Cruising range (km)	490	~ 800

6.3 Battery System Configuration and Structure

6.3.1 Design Target and System Configuration

A limited cruising range of the EVs and lack of charging opportunities have contributed to range anxiety from potential and existing adopters, especially in the 200-500 km range of typical EVs compared to that of a combustion vehicle (typically more than 500 km) [113], [114]. Moreover, EVs require long charging times compared to refueling combustion vehicles. The next-generation battery system should have more energy and faster charging time to respond to these issues derived from range anxiety. In addition to the mileage and peak power, the weight and cost are also the main factors to affect the competitiveness of traction battery systems. Hence, the HBS is expected to be as light and cheap as possible while meeting the energy and power design targets.

Before quantifying the battery weight and cost of the HBS, the proposed HBS should be compatible with the current EV power train and maintain similar performance. A standard-range version Tesla Model 3 is selected as a benchmark. More details of benchmark parameters and HBS design targets can be found in Table 6.2 [115], [116]. Furthermore, the battery pack capacity is calculated depending on the average energy consumption, approximately 0.122 kWh/km, under the Worldwide harmonized Light vehicles Test Procedure (WLTP) for a Class 3 vehicle. The target cruising range requires a battery capacity of more than 98 kWh. The following cost and weight optimization need to satisfy all three design targets shown in Table 6.2.

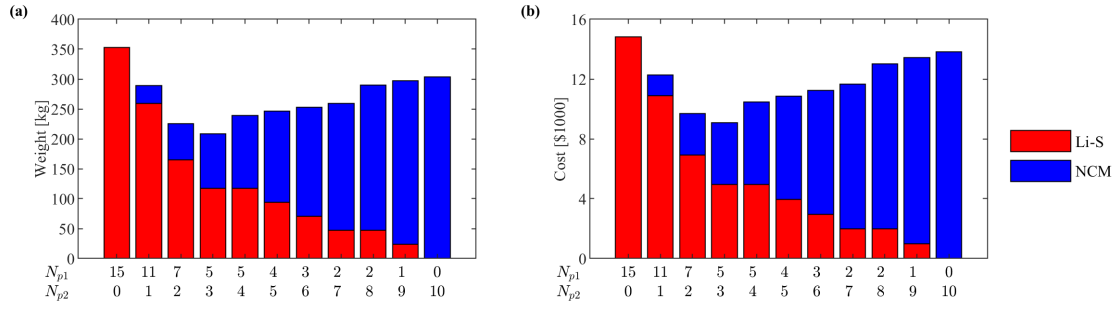


Figure 6.2: Comparison between different battery systems on (a) battery weight, (b) battery cost, and (c) battery plus electronics cost in order to meet the target cruising range and power requirement.

The Li-S and NCM series numbers are designed as 167 and 97 in the HBS, respectively, to fulfill the nominal voltage requirement. Figure 6.2 illustrates cost and weight results. The battery total weight and cost for all the feasible parallel numbers are illustrated in Figure 6.2(a) and 6.2(b). Here, battery systems consisting of a single-cell type are called mono battery systems. The enumerated parallel numbers at the X-axis for the NCM battery (N_{p2}) range from 0 to 10, i.e. from Li-S to NCM mono battery system. The listed parallel numbers for the Li-S battery (N_{p1}) are the minimum numbers corresponding to N_{p2} under meeting the design requirements, i.e. from NCM to Li-S mono battery system. The figures show a first decreasing then increasing total battery weight and cost as the N_{p2} increases. The Li-S mono battery system ($N_{p1} = 15$ and $N_{p2} = 0$) is the most expensive and heaviest battery configuration. Although the Li-S battery has the advantages of high energy density and low cost, it must increase the parallel number to meet the maximum power target, resulting in a high cost and heavy. Simultaneously, the NCM mono battery system ($N_{p1} = 0$ and $N_{p2} = 10$) is also heavier and more expensive than all HBS configurations. The high power density advantage is not highlighted in the system, because it has to compromise with the energy storage target. The battery systems are lighter and cheaper as the mix deepens. This reveals that the HBS configurations can effectively mitigate the conflicting energy and power density requirements between the two battery types. In this case study, the optimal HBS configuration for the weight and cost is 5 Li-S battery parallels and 3 NCM battery parallels, i.e. $N_{p1} = 5$ and $N_{p2} = 3$. Table 6.3 lists the optimal

Table 6.3: Configuration of the optimal HBS

Parameter	Li-S subpack	NCM subpack
Serial Number	167	97
Parallel Number	5	3
Nominal voltage (V)	359.1	358.9
Capacity (kWh)	71.8	28.0
Maximum discharge current (A)	200	468
Maximum charge current (A)	100	468
Battery weight (kg)	117.7	91.1

HBS configuration. Fulfilling all design objectives, HBS achieved lower pure cell weight (208.8kg, without any other battery pack components such as cooling and housing) to Tesla Model 3 (~228kg) by 8.4%.

The HBS requires more costly power electronics than the mono battery system, so the cost evaluation of battery systems needs to consider power electronics. The HBS topologies flexibly regulating power allocation can be divided into those with and without dc/dc converters, namely the semi-active and discrete switching topology. The detail of the semi-active topology can be found in [31], and the discrete switching topology is illustrated in Figure 6.3. Table 6.4 compares the electronics and total battery system costs of various configurations, including the Li-S battery system, NCM battery system, semi-active HBS, and discrete switching HBS. The semi-active HBS requires a 100 kW high-power dc/dc converter and thus costs approximately \$5080 at present [46]. A MOSFET on the passive-balancing bypass circuit of each parallel string is approximately \$0.7 in the Li-S battery system, NCM battery system, and semi-active HBS. The switches in a discrete switching module require passing a larger continuous current on a switch, so the MOSFET cost used in the discrete switching module is \$1.5. The semi-active HBS cost (\$14353.9) is comparable to the costs of the Li-S battery system (\$14951.5) and NCM battery system (\$13882.2) due to the dc-dc converter cost, although its battery cost is lower. Conversely, the power electronics cost of the discrete switching HBS is only \$792 compared to \$5264.8 in the semi-active HBS. The low cost of power electronics of the discrete switching HBS

allows it to remain relatively cost-competitive. Therefore, the proposed HBS uses the discrete switching structure to regulate power allocation flexibly.

Table 6.4: Comparison of Cost: Li-S battery system, NCM battery system, Semi-active HBS and Discrete-switching HBS

Parameters	Single chemistry		Dual chemistry (HBS)	
	Li-S battery system	NCM battery system	Semi-active	Discrete-switched
Li-S series number	167	0	167	167
NCM series number	0	97	97	97
Li-S parallel number	15	0	5	5
NCM parallel number	0	10	3	3
MOSFET number	167	97	264	528
Cost per MOSFET (\$)	0.7	0.7	0.7	1.5
MOSFET cost (\$)	116.9	67.9	184.8	792
DC-DC converter cost (\$)	0	0	5080	0
Power electric cost (\$)	116.9	67.9	5264.8	792
Cell cost (\$)	14834.6	13814.3	9089.2	9089.2
Total cost (\$)	14951.5	13882.2	14354.0	9881.2
Relative cost (%)	108 %	100 %	104 %	71 %

6.3.2 System Structure

Figure 6.3 illustrates the discrete switching HBS composed of Li-S and NCM battery subpacks. The Li-S and NCM battery subpacks are connected in parallel. Bus current and voltage are I_{bus} and V_{bus} , respectively. The currents of the Li-S and NCM battery subpacks are I_1 and I_2 , respectively, measured by two current sensors. In each battery subpack, a module comprises a parallel string of battery cells and two switches. Each module has a voltage sensor to measure the module voltage. According to the configuration of the HBS in Table 6.3, the Li-S battery subpack has 167 Li-S battery modules, each with 5 Li-S battery cells in parallel. Similarly, the NCM battery subpack has 97 Li-S battery modules, each with 3 NCM battery cells in parallel. Two switches in each module are the main and bypass switch. These switches enable module cells to switch in and out of series strings in a subpack. An interlock is used between the switches to avoid simultaneous switch-on

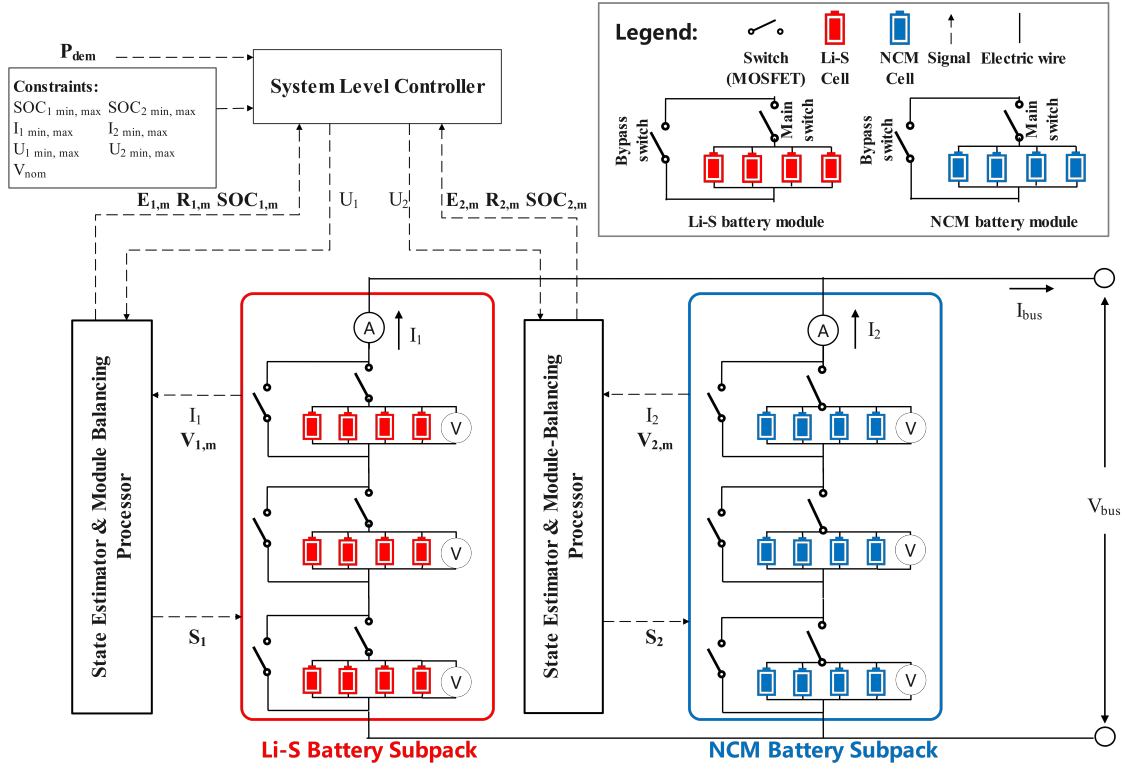


Figure 6.3: Block diagram of the discrete switching HBS with the control system

or switch-off. In the module, when the main switch is closed and the bypass switch is opened, current can flow through the battery cells of the module, and the battery cells participate in the charging and discharging processes. Conversely, two switches have the opposite setting; current flow through the module via the low-resistance bypass circuit, but no current flow through the battery cells. The HBS allocates the Li-S and NCM subpack current by manipulating all modules' discrete switches.

The battery control system integrates three parts: state estimators, module balancing processors, and a system-level controller to manage power allocation between two battery subpacks. The measured and estimated values in Figure 6.3 are defined as follows, to

facilitate the narrative of this paper.

$$\mathbf{V}_{i,m} = [V_{(i,1)}, \dots, V_{(i,j)}, \dots, V_{(i,N_i)}]$$

$$\mathbf{E}_{i,m} = [E_{(i,1)}, \dots, E_{(i,j)}, \dots, E_{(i,N_i)}]$$

$$\mathbf{R}_{i,m} = [R_{(i,1)}, \dots, R_{(i,j)}, \dots, R_{(i,N_i)}]$$

$$\mathbf{SOC}_{i,m} = [SOC_{(i,1)}, \dots, SOC_{(i,j)}, \dots, SOC_{(i,N_i)}]$$

$$\mathbf{S}_{i,m} = [S_{(i,1)}, \dots, S_{(i,j)}, \dots, S_{(i,N_i)}]$$

Here, subscripts i indicate the battery type, $i = 1$ and $i = 2$ represent the Li-S and NCM battery subpacks, respectively. Subscripts j indicate the module number in battery subpack i , N_i is the battery module number in battery subpack i . Besides, $V_{(i,j)}$ is the measured voltages for module j in battery subpack i . Similarly, $E_{(i,j)}$, $R_{(i,j)}$ and $SOC_{(i,j)}$ represent transient electromotive force, internal resistance and SOC of the module (i, j) , respectively. $S_{(i,j)}$ is the module switching states, where 0 and 1 indicate switching out and in of series strings, respectively. The vector $\mathbf{V}_{i,m}$, $\mathbf{E}_{i,m}$, $\mathbf{R}_{i,m}$, $\mathbf{SOC}_{i,m}$ and $\mathbf{S}_{i,m}$ indicate the vectors combined all module values in the subpack i . The control signal U_i is the number of switch-in battery modules for subpack i . The specific meaning of these values is elaborated in Section 6.5.

The state estimators estimate $\mathbf{E}_{i,m}$, $\mathbf{R}_{i,m}$ and $\mathbf{SOC}_{i,m}$ in each battery subpack based on the measured value I_i and $\mathbf{V}_{i,m}$. The algorithm of the estimators is described in Section 6.4. The system-level controller optimizes U_i depending on the estimated states and developed control algorithm in Section 6.5.1. After that, U_i is inputted to the module balancing processor as references of discrete switching modulations. The module balancing processor implements a rolling discharging/charging approach to balance the battery modules in each subpack, detailed in Section 6.5.2. The outputs from the battery control system are the switching sequence $\mathbf{S}_{i,m}$ for the battery modules. The main and bypass switches in all modules implement switches in or out of the modules depending on $\mathbf{S}_{i,m}$.

Further inputs to the system-level controller are $\text{SOC}_{i\min, \max}$, $I_{i\min, \max}$, $U_{i\min, \max}$ and V_{nom} . The constraint $\text{SOC}_{i\min, \max}$ sets the minimum and maximum limits for the SOC of battery subpack i , $I_{i\min, \max}$ for of battery subpack i , $U_{i\min, \max}$ for the switch-in module number of battery subpack i . In addition, V_{nom} sets the nominal bus voltage. These inputs are applied as the constraints and coefficients of the objective function Equation (6.17).

The discrete switching structure uses "event-based" switching depending on the power demands and battery states. Switching operates at a module voltage of typically 2~4 V rather than coping with the full voltage of the system. The electronics achieving the power allocations apply the MOSFETs, and are a lower cost than the high-power dc/dc converter, as shown in Table 6.4. Nonetheless, hundreds of switches in the proposed HBS need to operate during the power allocation process instead of operating the dc/dc converter only by pulse width modulation as in the conventional HBS. Consequently, such operational complexity needs to pay more cost in the control algorithm. The following section presents the appropriate control system to address this problem.

6.4 Module State Estimation

6.4.1 Model and Parameter Identification

The module-level model of the HBS has been developed in [85], but the module state estimation has not been considered. In this study, a module-level equivalent circuit model (ECM) is equivalent to an enlarged battery cell composed of multiple battery cells in parallel when using the estimation algorithm. Although the cell-level estimation can be achieved by adopting a special balance circuit or configuring sensors on each battery cell [117], the additional hardware cost seriously weakens the cost competitiveness of the HBS as same as configuring the dc/dc converter. Meanwhile, the cells in a module

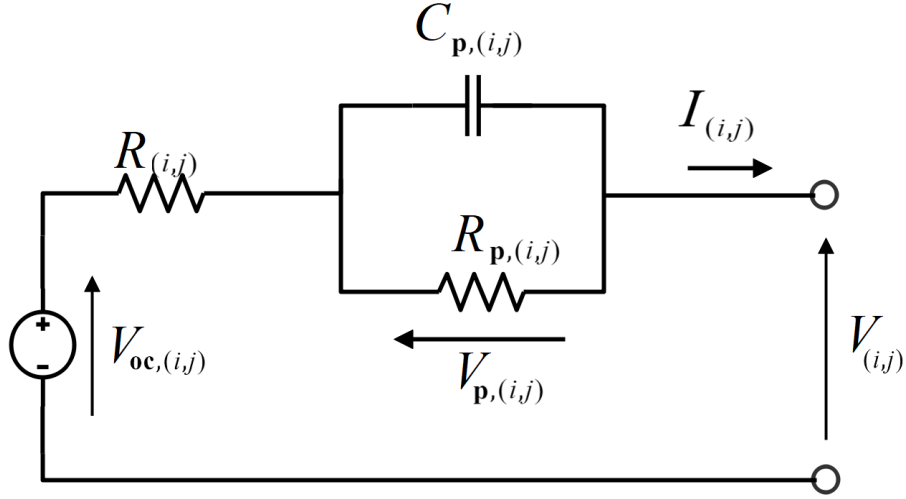


Figure 6.4: First-order RC equivalent circuit model (Thevenin model)

connected to each other in a discrete switching structure can achieve a natural self-balance [13]. In addition, Considering these cells are exposed to almost the same environment, the degradation can be assumed to be almost the same. Finally, the battery cells in each module can achieve almost uniformity through simple screening by the manufacturer. Therefore, the state estimator is developed based on the module-level modeling in the study, where the specific module-level modeling method has been proposed in [60], [69], [85].

The Li-S and NCM modules are modeled using first-order RC ECM (i.e, state-dependent "Thevenin" models), as shown in Figure 6.4. Compared with more complex ECMs (e.g., 2 and 3 RCs), the Thevenin model has a lower computational cost and sufficient precision for this study [118], [119]. More importantly, all the model parameters in the Thevenin model are structurally identifiable [120]. Here, $V_{oc,(i,j)}$ (V) is the open circuit voltage (OCV), $R_{(i,j)}$ is the ohmic resistance (Ω), $R_{p,(i,j)}$ and $C_{p,(i,j)}$ are a "polarization" resistance (Ω) and capacitor (F). $V_{p,(i,j)}$ is the voltage drop of the RC pair. The measured values are discharge-positive current throughout the module $I_{(i,j)}$ (A) and terminal voltage $V_{(i,j)}$ (V). The state function of the Thevenin model is depicted in Equation (6.1), where a discharge-positive

current convention is applied.

$$\begin{cases} V_{(i,j)} = V_{oc,(i,j)} - V_{p,(i,j)} - I_{(i,j)}R_{(i,j)} \\ \frac{dV_{p,(i,j)}}{dt} = \frac{I_{(i,j)}}{C_{p,(i,j)}} - \frac{V_{p,(i,j)}}{R_{p,(i,j)}C_{p,(i,j)}}. \end{cases} \quad (6.1)$$

where

$$I_{(i,j)} = S_{(i,j)}I_i$$

In the previous study of the HBSs, the parameter $V_{oc,(i,j)}$, $R_{(i,j)}$, $R_{p,(i,j)}$ and $C_{p,(i,j)}$ are modeled as being dependent on the battery module SOC. Their changes of dynamic behaviors are derived from fixed look-up tables when implementing estimations. However, $V_{oc,(i,j)}$ and $R_{(i,j)}$ are sensitive to battery health conditions, so the fixed look-up table could only reflect the parameters of a fresh battery module. The estimated accuracy becomes increasingly unreliable as the battery degrades. Considering the various working situations generated by the discrete switching structure, degradation rates may differ between modules. This could cause the trajectories of parameter changes between modules to be different. Therefore, for the proposed estimation algorithm, the model parameters should be identified online to correct parameters in each module. An approach used for model parameter identification and correction is the FFRLS [111]. The FFRLS identifies the model parameters using a recursive least square algorithm with a forgetting factor. This study utilizes this online algorithm for identifying and correcting model parameters.

The transfer function (Equation (6.2)) can first be obtained via Laplace transformation based on the state-space Equation (6.1) for the module model,

$$G(s) = \frac{V_{(i,j)}(s) - V_{oc,(i,j)}(s)}{I_{(i,j)}(s)} = -R_{(i,j)} - \frac{R_{p,(i,j)}}{1 + s\tau_{(i,j)}} \quad (6.2)$$

where

$$\tau_{(i,j)} = R_{p,(i,j)}C_{p,(i,j)}.$$

The trapezoidal discretization method, $s = \frac{2}{T} \frac{1-z}{1+z}$, is adopted at the sampling interval T (second). The discrete transfer function can be written as:

$$G(z^{-1}) = \frac{\theta_2 + \theta_3 z^{-1}}{1 - \theta_1 z^{-1}} \quad (6.3)$$

where

$$\begin{cases} \theta_1 = \frac{2\tau_{(i,j)} - T}{T + 2\tau_{(i,j)}} \\ \theta_2 = -\frac{TR_{(i,j)} + TR_{p,(i,j)} + 2R_{(i,j)}\tau_{(i,j)}}{T + 2\tau_{(i,j)}} \\ \theta_3 = -\frac{TR_{(i,j)} + TR_{p,(i,j)} - 2R_{(i,j)}\tau_{(i,j)}}{T + 2\tau_{(i,j)}} \end{cases}$$

The $V_{oc,(i,j)}$ change in the Thevenin model is a sluggish process during operation because it depends on the module SOC. Thus, this change within several continuous sampling steps can be neglected, i.e. $V_{oc,(i,j)}(k) \approx V_{oc,(i,j)}(k-1) \approx V_{oc,(i,j)}(k-2)$ at time k . The uniform regression form used for parameter identification can be depicted as follows:

$$V_{(i,j)}(k) = \Phi(k)\Theta(k) \quad (6.4)$$

where

$$\begin{aligned} \Phi(k) &= [V_{(i,j)}(k-1) \quad I_{(i,j)}(k) \quad I_{(i,j)}(k-1) \quad 1] \\ \Theta(k) &= [\theta_1 \quad \theta_2 \quad \theta_3 \quad V_{oc,(i,j)}(1 - \theta_1)]^T \end{aligned}$$

Here, $\Phi(k)$ is the input vector that received the measured values, and $\Theta(k)$ is the vector containing the model parameters that need to be identified. The relationships between the state-space model parameters ($V_{oc,(i,j)}$, $R_{(i,j)}$, $R_{p,(i,j)}$ and $C_{p,(i,j)}$) and the transfer function

parameters (θ_1 , θ_2 and θ_3) are depicted as follows:

$$\begin{cases} R_{(i,j)} = \frac{\theta_3 - \theta_2}{1 + \theta_1} \\ R_{p,(i,j)} = -2 \frac{\theta_1 \theta_2 + \theta_3}{1 - \theta_1^2} \\ C_{p,(i,j)} = -\frac{T(1 + \theta_1^2)}{4(\theta_1 \theta_2 + \theta_3)} \\ V_{oc,(i,j)} = \frac{\theta_4}{1 - \theta_1} \end{cases} \quad (6.5)$$

Algorithm 1 FFRLS parameter identification

Input: $\Phi(k)$ $\Theta(k-1)$ $V_{(i,j)}(k)$ $\Upsilon(k-1)$

- 1: $e(k) \leftarrow V_{(i,j)}(k) - \Phi(k) \cdot \Theta(k-1)$
- 2: Gain calculation
 $K(k) \leftarrow \Upsilon(k-1)\Phi^T(k) \cdot [\Phi(k)\Upsilon(k-1)\Phi^T(k) + \lambda]^{-1}$
- 3: Error covariance
 $P_k \leftarrow \frac{1}{\lambda}[1 - K(k)\Phi(k)] \cdot \Upsilon(k-1)$
- 4: Parameter matrix update
 $\Theta(k) \leftarrow \Theta(k-1) + K(k) \cdot e(k)$

Output: $\Theta(k)$

The specific processes of the FFRLS for identifying $\Theta(k)$ are illustrated in Algorithm 1. $\Upsilon(k)$ is the error covariance at time k , and λ is the forgetting factor. The forgetting factor λ represents the effect of historical data on identification. λ ($0 \sim 1$) for Li-S and NCM battery modules are set to 0.95 to achieve the best identification results. Once the new measured values are received at k , the FFRLS can update $\Theta(k)$. The Thevenin model parameters can then be extracted according to Equation (6.5).

6.4.2 Module State Estimation

The core control-related state for the module is the SOC. Following its definition, the most straightforward method is Coulomb counting which directly calculates the accumulated/consumed charges during the charge/discharge process. This method could be highly accurate in the laboratory with high-precision equipment and mature testing procedure.

However, because of cost, less accurate sensors applied in EVs make the Coulomb counting method unreliable. Kalman filter concept is therefore applied to calibrate the $SOC_{(i,j)}$. Considering the non-linear relationship between $V_{(i,j)}$ and $SOC_{(i,j)}$, the AEKF is adopted in this study. Based on the continuous state-space model in Equation (6.1), The discrete state-space model of the battery modules can be expressed as follows:

$$x_{(i,j)}(k) = A_{(i,j)}(k-1) \cdot x_{(i,j)}(k-1) + B_{(i,j)}(k-1) \cdot u_{(i,j)}(k-1) \quad (6.6)$$

where

$$A_{(i,j)}(k) = \begin{bmatrix} 1 & 0 \\ 0 & e^{-\frac{T}{\tau_{(i,j)}}} \end{bmatrix} \quad x_{(i,j)}(k) = \begin{bmatrix} SOC_{(i,j)}(k) \\ V_{p,(i,j)}(k) \end{bmatrix}$$

$$B_{(i,j)}(k) = \begin{bmatrix} -\frac{T}{C} \\ R_{p,(i,j)}(1 - e^{-\frac{T}{\tau_{(i,j)}}}) \end{bmatrix} \quad u_{(i,j)}(k) = I_{(i,j)}(k),$$

and the observation equation is:

$$V_{(i,j)} = V_{oc,(i,j)}(k) - I_{(i,j)}(k)R_{(i,j)}(k) - V_{p,(i,j)}(k). \quad (6.7)$$

The model parameters are from the results of the FFRLS algorithms. Details of the AEKF applied in battery state estimations can be found in [87]. In order to construct the linearized observation equation corresponding to the state $x_{(i,j)}$, $V_{(i,j)}$ used in the AEKF algorithm is a polynomial-fitted function to SOC. Simultaneously, the Taylor expansion is applied to linearize this equation. Therefore, the linearization observation function for Equation (6.7) can be expressed as follows:

$$V_{(i,j)}(k) = C_{(i,j)}(k) \cdot x_{(i,j)}(k) + D_{(i,j)}(k) \cdot u_{(i,j)}(k) \quad (6.8)$$

where

$$C_{(i,j)}(k) = \left. \frac{dV_{oc,(i,j)}}{dSOC_{(i,j)}} \right|_{x(k)=\hat{x}(k)} - 1$$

$$D_{(i,j)}(k) = V_{oc,(i,j)}(k) - V_{p,(i,j)}(k) - R_{(i,j)}(k) \cdot I_{(i,j)}(k) - C_{(i,j)}(k) \cdot x_{(i,j)}(k).$$

The AEKF algorithm is demonstrated in Algorithm 2. Λ and Γ are the covariance matrix of measurement and process noise, respectively. The noise statistic characteristic is calculated from continuous M points so as to adaptive changing environments. An innovation-based adaptive estimator in this algorithm is designed to keep up with noisy variants in the real system [121]. In this way, the AEKF makes the estimations from the state-space function Equation (6.1) and Coulomb counting method well fusion, so as to obtain a more accurate $SOC_{(i,j)}$.

Algorithm 2 AEKF SOC estimation

Input: $x_{(i,j)}(k-1)$ $\Omega_x^+(k-1)$ $\Gamma(k-1)$ $\Lambda(k-1)$

1: Prior prediction

$$x_{(i,j)}^-(k) \leftarrow A_{(i,j)}(k-1) \cdot x_{(i,j)}(k-1) + B_{(i,j)}(k-1) \cdot u_{(i,j)}(k-1)$$

2: Covariance update

$$\Omega_x^-(k) \leftarrow A_{(i,j)}(k-1) \cdot \Omega_x^+(k-1) \cdot A_{(i,j)}^T(k-1) + \Lambda(k-1)$$

3: Predict system output

$$\hat{V}_{(i,j)}(k) \leftarrow C_{(i,j)}(k) \cdot x_{(i,j)}(k) + D_{(i,j)}(k) \cdot u_{(i,j)}(k)$$

$$c(k) = V_{(i,j)}(k) - \hat{V}_{(i,j)}(k)$$

4: Kalman gain calculation

$$L(k) \leftarrow \Omega_x^-(k) C_{(i,j)}^T(k) \cdot \left[C_{(i,j)}(k) \Sigma_x^-(k) C_{(i,j)}^T(k) + \Gamma(k-1) \right]^{-1}$$

5: Adaptive noise matrix

$$H(k) \leftarrow \frac{1}{M} \sum_{q=k-M+1}^k c_q(k) \cdot c_q^T(k)$$

$$\Gamma(k) \leftarrow C_{(i,j)}(k) \Omega_x^-(k) C_{(i,j)}^T(k)$$

$$\Lambda(k) \leftarrow L(k) H(k) H^T(k)$$

6: State estimation update

$$x_{(i,j)}(k) \leftarrow x_{(i,j)}^-(k) + L(k) \cdot e_A(k)$$

7: Covariance update

$$\Omega_x^+(k) \leftarrow [I - L(k) C_{(i,j)}(k)] \cdot \Omega_x^-(k)$$

Output: $x_{(i,j)}(k)$ $\Omega_x^+(k)$ $\Gamma(k)$ $\Lambda(k)$

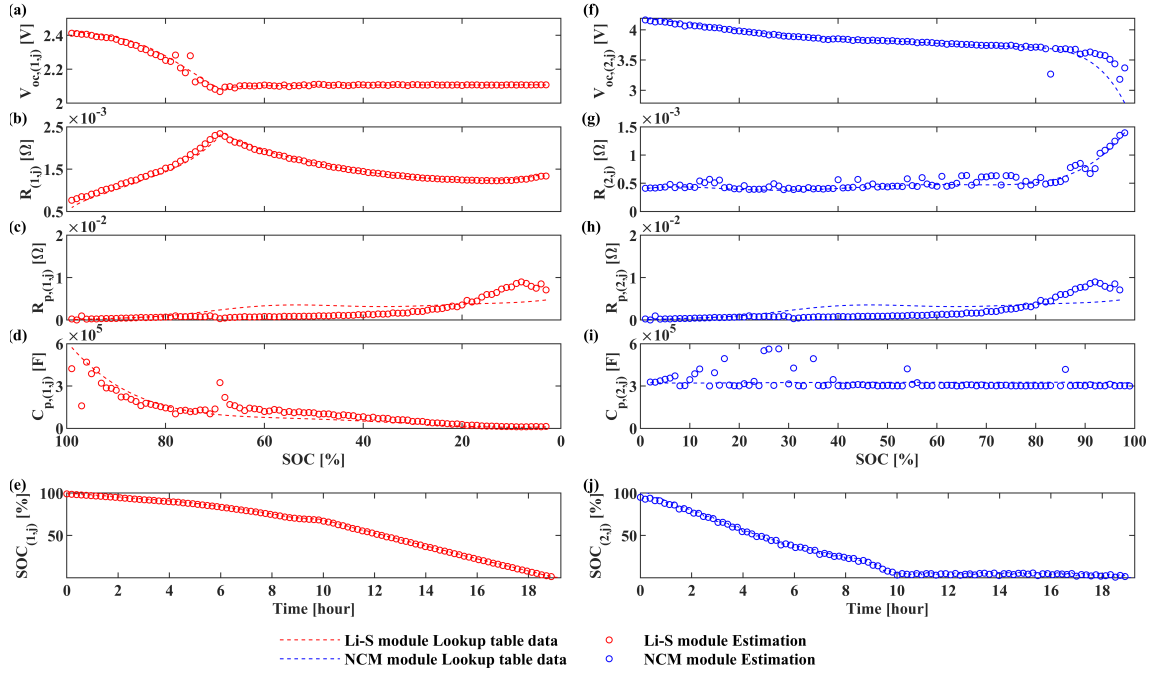


Figure 6.5: Estimation results for the fresh Li-S and NCM battery modules: (a)-(d) parameter identification results for Li-S battery, (e) SOC estimation result of Li-S module, (f)-(i) parameter identification results for NCM, (j) SOC estimation results of NCM module.

In the following section, the transient electromotive force $E_{(i,j)}$ is defined as follows.

$$E_{(i,j)}(k) = V_{oc,(i,j)}(k) - V_{p,(i,j)}(k) \quad (6.9)$$

6.4.3 Module Results

The estimated results of one Li-S and one NCM battery module were randomly selected from the Li-S and NCM subpack, respectively, in the cruising range simulation scenario, to demonstrate the accuracy of the module-level algorithm. The results of the state estimators for the two fresh modules are illustrated in Figure 6.5. Similarly, the results for the two aged modules are illustrated in Figure 6.6. In these figures, circle points represent the mean value during the time region of the SOC change of 1%, and the dash lines are the benchmark look-up table parameter in the battery module model. The results of the

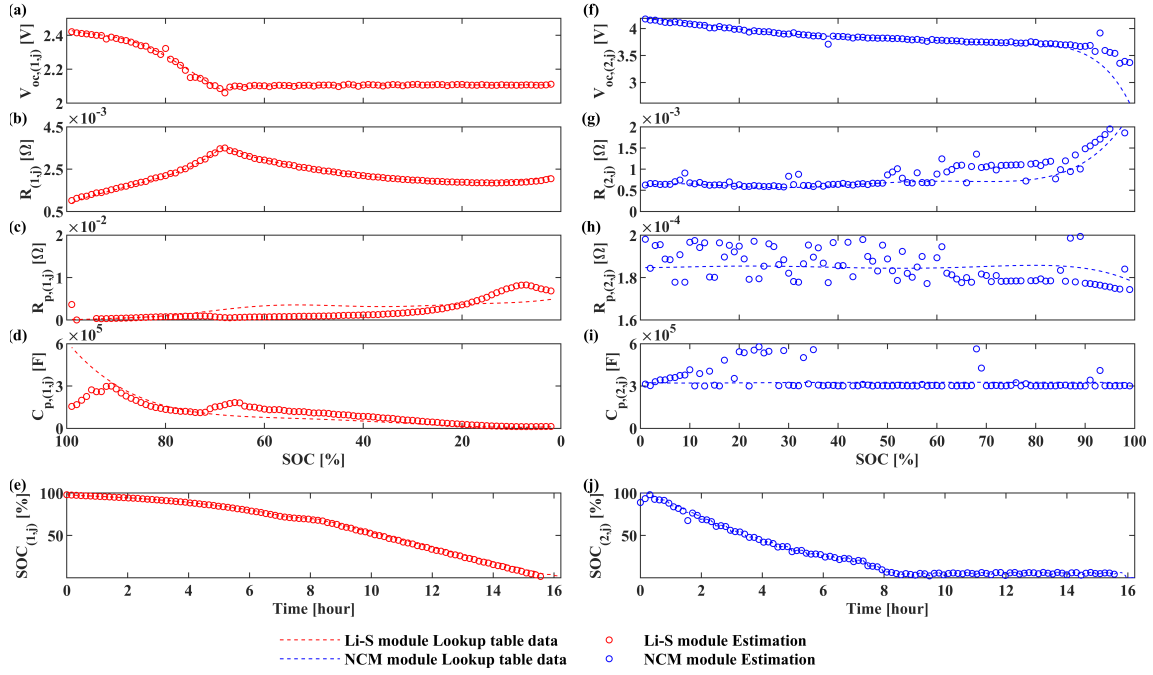


Figure 6.6: Estimation results for the aged Li-S and NCM battery modules: (a)-(d) parameter identification results for Li-S battery, (e) SOC estimation result of Li-S module, (f)-(i) parameter identification results for NCM, (j) SOC estimation results of NCM module.

FFRLS parameter identification are depicted as the first four rows in Figures 6.5 and 6.6, and the SOC are depicted as the last rows in the two figures.

For the FFRLS algorithm, the identifications of the dynamic parameters in the Thevenin model have a difference in sensitivity to current excitation. Large and abrupt excitation changes can cause errors in parameters that depend on dynamic changes. Therefore, The polarization parameters ($R_{p,(i,j)}$ and $C_{p,(i,j)}$) have greater fluctuations than $V_{oc,(i,j)}$ and $R_{(i,j)}$. Nonetheless, the algorithm performs with good accuracy at high current fluctuations, especially for the OCV $V_{oc,(i,j)}$ and internal resistance $R_{(i,j)}$. Also, The SOC estimation results and Section 6.5.4 demonstrate that these errors have little effect on SOC estimation and power allocations. In summary, the algorithm shows good enough capabilities for online parameter identification, under different HBS aging conditions and high current fluctuations.

Table 6.5: RMSE evaluation for SOC estimations

Module type	Fresh module	Aged module
Li-S	0.9%	2.0%
NCM	1.5%	2.4%

Figures 6.5 and 6.6 also illustrate the SOC estimation results for the fresh and aged HBSs, respectively. It is clear that AEKF performs well in both modules regardless of the loading level, whether the battery modules are under high-loading or low-loading conditions, the SOC can be faithfully identified. To quantify SOC estimation performances, the root mean square error (RMSE) method is applied to evaluate the accuracy of SOC estimations. Its equation is expressed as follows:

$$\text{RMSE} = \sqrt{\frac{\sum_{t=1}^T [y(t) - \hat{y}(t)]^2}{T}}. \quad (6.10)$$

where T is the number of data points, $y(t)$ is the t -th measured value. $\hat{y}(t)$ and $\bar{y}(t)$ are estimated and mean values corresponding to $y(t)$, respectively.

The overall RMSE errors for the fresh and aged NCM and Li-S battery modules are listed in Table 6.5. According to the results, the SOC estimations of the aged modules are less accurate compared to the fresh modules. SOC RMSEs of approximately 1% are obtained for the fresh modules whereas the SOC RMSEs for aged modules are approximately 2%. This is a sufficient SOC estimation accuracy in EV applications.

6.5 HBS Management Strategy

6.5.1 System Level Controller

This study proposes a novel system-level control algorithm to regulate the discrete switching modulation. In [85], we have proposed a control algorithm to manage the power al-

location between two battery subpacks. The previous algorithm directly controls module switching, so hundreds of manipulated variables need to be optimized when implementing the algorithm. The complicated online algorithm puts a high-performance requirement on optimizing all variables at a short control step time (0.2-0.5 seconds in the control system). Alternatively, the control step time has to prolong at the expense of the algorithm performance. The algorithm of this study decouples the module-level and system-level optimized variables. Specifically, the system-level controller is only required to optimize two manipulated variables: the number of switch-in modules U_1 and U_2 for the Li-S and NCM subpacks, respectively. The module-balancing processor modulates the module switches according to the SOC of each module and the control signals of the number of switch-in modules.

The fluctuations of dynamic voltage drops for a module are small during several digital times since $\tau_{(i,j)}$ in the Thevenin model is a large constant (10-100 seconds). Although transient electromotive force $E_{(i,j)}$ and internal resistance $R_{(i,j)}$ between battery modules are significant for the module-level estimation, they have little effect on the accuracy of the current allocation estimation. Therefore, the transient electromotive forces and internal resistances are averaged as the equivalent states of a module and assume the average module states at time k and $k+1$ are nearly equal. The average module states can be predicted as follows:

$$\begin{aligned}\bar{E}_{i,m}(k+1) &\approx \bar{E}_{i,m}(k) = \sum_{j=1}^{N_i} \frac{E_{(i,j)}(k)}{N_i} \\ \bar{R}_{i,m}(k+1) &\approx \bar{R}_{i,m}(k) = \sum_{j=1}^{N_i} \frac{R_{(i,j)}(k)}{N_i}\end{aligned}\tag{6.11}$$

where $\bar{E}_{i,m}$ and $\bar{R}_{i,m}$ are the average transient electromotive force and internal resistance of the modules in battery subpack i , respectively. It is worth mentioning that when implementing the algorithm at time $k+1$, the states are recalculated based on the estimated values from the state estimators rather than inheriting the states already predicted in the system level controller at time k . The predicted transient electromotive forces and internal

resistances for two subpacks can be deduced as Equation (6.12),

$$\begin{aligned}\hat{E}_i(k+1) &= U_i(k+1)\bar{E}_{i,m}(k+1) \\ \hat{R}_i(k+1) &= U_i(k+1)\bar{R}_{i,m}(k+1) + N_i R_s\end{aligned}\tag{6.12}$$

where $\hat{E}_i$ and $\hat{R}_i$ are the predicted transient electromotive force and resistance for battery subpacks i , respectively. R_s indicates the resistance of a module switch (Ω). In the discrete switching module, R_s is independent of the module operations (i.e. R_s is a constant value) since the current needs throughout one of the switches in a module at the connection or disconnection mode. According to Kirchhoff's laws, the relationship of predicted states in subpack and system levels can be expressed as follows:

$$\begin{aligned}\hat{I}_{\text{bus}}(k+1) &= \hat{I}_1(k+1) + \hat{I}_2(k+1) \\ \hat{V}_{\text{bus}}(k+1) &= \hat{E}_i(k+1) - \hat{I}_i(k+1)\hat{R}_i(k+1) \\ \hat{P}_{\text{bus}}(k+1) &= \hat{I}_{\text{bus}}(k+1)\hat{V}_{\text{bus}}(k+1)\end{aligned}\tag{6.13}$$

where $\hat{I}_{\text{bus}}$ is the predicted bus current, $\hat{V}_{\text{bus}}$ is the predicted bus voltage, and $\hat{P}_{\text{bus}}$ is the bus power. It is assumed that the rates of change of two battery subpacks per sampling interval in the system-level controller are negligible when implemented digitally. The current allocations between two battery subpack are thus depicted in Equation 6.14,

$$\begin{aligned}\hat{I}_{\text{bus}}(k+1) &= I_s(k+1)[1 + \phi(k+1)] \\ \hat{V}_{\text{bus}}(k+1) &= V_s(k+1)[1 + \phi(k+1)] \\ \hat{I}_i(k+1) &= \frac{\hat{E}_i(k)}{\hat{R}_i(k)} - \frac{V_s(k+1)}{\hat{R}_i(k)}[1 + \phi(k+1)]\end{aligned}\tag{6.14}$$

where

$$\begin{aligned}
I_s(k+1) &= \frac{1}{2} \left[\frac{\bar{E}_{1,m}(k)}{\bar{R}_{1,m}(k)} + \frac{\bar{E}_{2,m}(k)}{\bar{R}_{2,m}(k)} \right] \\
R_s(k+1) &= \left[\frac{1}{\hat{R}_1(k)} + \frac{1}{\hat{R}_2(k)} \right]^{-1} \\
V_s(k+1) &= I_s(k+1)R_s(k+1) \\
\phi(k+1) &= \sqrt{1 - \frac{\hat{P}_{\text{bus}}(k+1)}{V_s(k+1)I_s(k+1)}}.
\end{aligned}$$

The SOC_s after a sample time T can be depicted by (6.15).

$$\hat{SOC}_i(k+1) = \hat{SOC}_i(k) + \frac{U_i(k)\hat{I}_i(k)T}{N_iQ_i} \quad (6.15)$$

where $\hat{SOC}_i$ is the SOC of battery subpack i , only used in battery system controller; Q_i is the capacities of battery subpacks i (Ah), respectively. It is assumed the $P_{\text{dem}}(k) = \hat{P}_{\text{bus}}(k+1)$ to estimate power allocation at time $k+1$. Hence, the equations of predicted current allocation and SOC_s in the battery system controller at time $k+1$ can be integrated and expressed as follows:

$$\mathbf{Y}_{\text{sys}}(k+1) = f[\mathbf{X}_{\text{sys}}(k), \mathbf{U}_{\text{sys}}(k), P_{\text{dem}}(k)] \quad (6.16)$$

where

$$\begin{aligned}
\mathbf{X}_{\text{sys}}(k) &= \{\bar{E}_{1,m}(k), \bar{R}_{1,m}(k), \bar{R}_{1,m}(k), \bar{R}_{2,m}(k)\} \\
\mathbf{U}_{\text{sys}}(k) &= \{U_1(k), U_2(k)\} \\
\mathbf{Y}_{\text{sys}}(k) &= \{\hat{I}_1(k), \hat{I}_2(k), \hat{V}_{\text{bus}}(k), \hat{SOC}_1(k), \hat{SOC}_2(k)\}
\end{aligned}$$

The system state prediction in the battery control system is given by Equation 6.16. The $\mathbf{X}_{\text{sys}}$, $\mathbf{U}_{\text{sys}}$ and $\mathbf{Y}_{\text{sys}}$ represent the system-level states, manipulated variables, and system-level estimations, respectively. The manipulated variables U_1 and U_2 at a time k can be

regulated by minimizing the following objective function:

$$\begin{aligned}
J = & \sum_{i=0}^{p-1} \left| \omega_1 (\hat{I}_1(k+i+1|k) - \hat{I}_1(k)) \right|^2 \\
& + \omega_2 \left(SOC_{2,\text{ref}} - \hat{SOC}_2(k+i+1|k) \right) \hat{I}_2(k+i+1) \\
& + \left| \omega_3 (\hat{V}_{\text{bus}}(k+i+1|k) - V_{\text{nom}}) \right|^2
\end{aligned} \tag{6.17}$$

subject to constraints

$$\begin{aligned}
I_{1\min} & \leq \hat{I}_1(k+i+1|k) \leq I_{1\max} \\
I_{2\min} & \leq \hat{I}_2(k+i+1|k) \leq I_{2\max} \\
U_{1\min} & \leq U_1(k+i+1|k) \leq U_{1\max} \\
U_{2\min} & \leq U_2(k+i+1|k) \leq U_{2\max} \\
SOC_{1\min} & \leq \hat{SOC}_1(k+i+1|k) \leq SOC_{1\max} \\
SOC_{2\min} & \leq \hat{SOC}_2(k+i+1|k) \leq SOC_{2\max}
\end{aligned}$$

where the meaning of the constraint symbols is mentioned in Section 6.3.2. In addition, U_1 and U_2 are the integer values, since the discrete switching structure can only switch integer numbers of modules in the working circuit.

The nonzero value of the weight ω_1 determines the weighting on how much the variation of the Li-S battery subpack current is minimized. The controller more aggressively minimizes the change in the Li-S battery subpack current $\hat{I}_1$ with increasing ω_1 . For the second term on the right side of (6.17), the weighting on the NCM battery subpack current is determined by the nonzero value of the weight ω_2 and the NCM battery subpack state of charge $\hat{SOC}_2$. The controller more aggressively reduces the NCM battery subpack current $\hat{I}_2$ with the $\hat{SOC}_2$ decreased, while the larger the value of ω_2 the more aggressively the controller increases the $\hat{I}_2$ at current allocations. $SOC_{2,\text{ref}}$ is a constant value to regulate the influence of the $\hat{SOC}_2$ change on the $\hat{I}_2$. The nonzero value of the weight ω_3 determines the weighting on the difference between bus voltage $\hat{V}_{\text{bus}}$ and system nominal voltage V_{nom}

is minimized. The controller more aggressively minimizes the gap between both voltages with increasing ω_3 and keeps the bus voltage stable.

The objective function (Equation (6.17)) is nonlinear, and the optimal variable U_1 and U_2 are the integer values. In other words, the system-level control algorithm is a nonlinear model-predictive control (NMPC) with integer variables, where both the objective and state functions are nonlinear. Hence, a genetic algorithm is applied to address this NMPC algorithm, because this algorithm can solve nonlinear programming problems with integer variables. Compared with the power allocation algorithm proposed in [85], this simplified algorithm reduces the computational demand.

6.5.2 Module SOC Balancing

Algorithm 3 SOC Balancing (MATLAB environment)

Input: $\text{SOC}_{i,m}$, U_i , $\hat{I}_i$, N_i

1: Sort $\text{SOC}_{i,m}$ in ascending and descending orders:

$idx_a \leftarrow \text{sort}(\text{SOC}_{i,m}, \text{"ascend"})$

$idx_d \leftarrow \text{sort}(\text{SOC}_{i,m}, \text{"descend"})$

2: Discrete switching modulation:

if $\hat{I}_i \leq 0$

$$\mathbf{S}_{i,m} \leftarrow \begin{cases} \mathbf{S}_{i,m}(idx_a(1 : N_i)) = 1 \\ \mathbf{S}_{i,m}(\text{other elements}) = 0 \end{cases}$$

else

$$\mathbf{S}_{i,m} \leftarrow \begin{cases} \mathbf{S}_{i,m}(idx_d(1 : N_i)) = 1 \\ \mathbf{S}_{i,m}(\text{other elements}) = 0 \end{cases}$$

end

Output: $\mathbf{S}_{i,m}$

Algorithm 3 demonstrates the algorithm of the discrete switching modulation to balance the module SOC's in two battery subpacks, where the symbols indicate the same meaning as the previous. The module-balancing processor firstly ascendingly and descendingly sorts $\text{SOC}_{i,m}$, as described in step 1. The vector elements of $\mathbf{S}_{i,m}$ correspond to the

module numbers one-to-one, and 1 and 0 for the elements indicate module connection and disconnection, respectively. idx_a records the reference number of all modules in battery subpack i from lowest to highest SOC; idx_d records their reference number from highest to lowest SOC. Step 2 describes the discrete switching modulation. At a charge period ($\hat{I}_i \leq 0$), the modules with low-level SOC operate in the connection mode, while the modules with high-level SOC operate in the disconnection mode. The system level controller determines the number of connection modes by U_i . Conversely, at a discharge period ($\hat{I}_i > 0$) the modules with high-level SOC operate in the connection mode, while the modules with low-level SOC operate in the disconnection mode. After a discharge period, the previous modules with high-level SOC would be turned into those with low-level SOC. All modules will be in a rolling discharge/idle state through recurrent implementation of the processes. Hence, the module SOC in a subpack will be approximately balanced through the rolling discharge and charge approaches.

6.5.3 System Simulation

In this study, the parameters of the reference vehicle are adopted as mentioned in Table 6.2. Details of EV modeling and simulation can be found in [122], [123]. WLTP speed profile is depicted in Figure 6.7, which is used to calculate the HBS power demand in the cruising range simulation.

The Li-S and NCM battery cell parameters are shown in Table 6.1. The design targets and configuration of the HBS are demonstrated in Section 6.3. Parameters and coefficients in the control algorithm are shown in Table 6.6. The simulation environment is MATLAB/Simulink, where the model in [53] is applied as the load model. Besides, the model development from cell to system level can be found in [85].

To research the robustness of the estimation and control algorithms proposed in this paper,

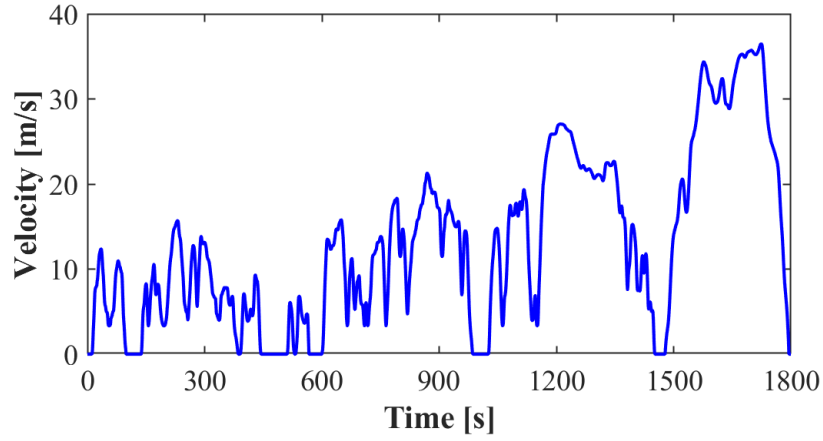


Figure 6.7: Speed profile of the Worldwide harmonized Light vehicle Test Procedure (WLTP) for a Class 3 vehicle.

Table 6.6: Control System Parameters

$I_{1\min}$	0 A	$I_{1\max}$	200 A	$I_{2\min}$	-450 A
$I_{2\max}$	450 A	$\text{SOC}_{1\min}$	0.05	$\text{SOC}_{1\max}$	1
$\text{SOC}_{2\min}$	0.05	$\text{SOC}_{2\max}$	1	$U_{1\min}$	150
$U_{1\max}$	167	$U_{2\min}$	97	$U_{2\max}$	87
N_{s1}	167	N_{s2}	97	p	1
ω_1	20	ω_2	400	ω_3	20
$\text{SOC}_{2\text{ref}}$	0.3	T_s	0.2	R_s	0.5 m Ω

this section illustrates the results for two HBSs with different degrees of aging consisting of fresh and aged batteries, respectively. In the aging HBS case, the aging capacity of Li-S and NCM batteries are set as 15% compared to that of the fresh batteries, i.e. remaining capacities of 85%; The internal resistances of aging batteries are 1.5 times that of the fresh batteries. Results of the cruising range and maximum power are also simulated, responding to the design targets. Besides, the accuracy of the estimation and control algorithms are analyzed to verify their reliability.

The simulations of the cruising range for the fresh and aged HBS are implemented to evaluate the performance of the proposed HBS under the repeated typical EV power demand on the WLTP. Figure 6.8 demonstrates the cruising performance from fully charged (100% SOC) to nearly depleted states (5% SOC) in the fresh Li-S and NCM battery subpacks. The cruising range of the HBS achieves 874 km, meeting the design

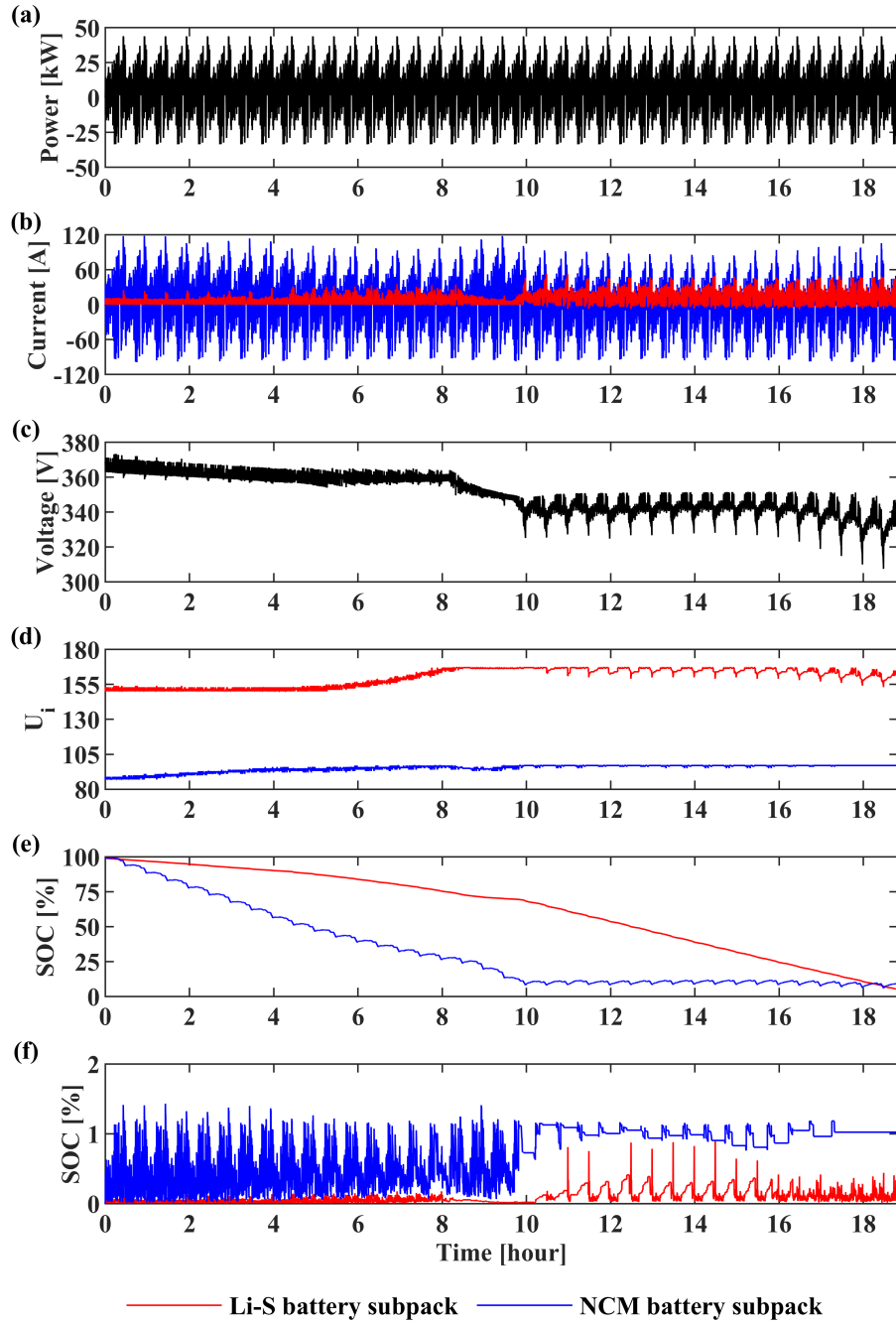


Figure 6.8: The fresh battery HBS under a cruising test: (a) power demand P_{dem} , (b) current I_1 and I_2 for the two battery subpacks, (c) bus voltage V_{bus} , (d) the number of switch-in modules (U_1 and U_2) for the two battery subpacks, (e) SOC of battery subpacks, and (f) maximum SOC difference within subpacks.

requirement of 800 km. This range performance can solve the range anxiety for most drivers. The power demand is illustrated in Figure 6.8(a) based on repeating the speed profile in Figure 6.7. The measured currents of two battery subpacks I_1 and I_2 and

the measured bus voltage V_{bus} are depicted in Figures 6.8(b) and 6.8(c), respectively. Figure 6.8(d) shows the manipulated variables, the number of switch-in modules U_1 and U_2 . Figure 6.8(e) illustrates the estimated SOC of the two battery subpacks. Figure 6.8(f) illustrates the differences between the battery modules with maximum and minimum SOC in the two battery subpacks.

During the cruising simulation, the two battery subpacks are getting discharged in a coordinated way, and the NCM battery subpack absorbs energy from regenerative braking. The NCM battery subpack undertakes more power at high power demand, making the Li-S battery subpack discharge within a comfortable current range. Similarly, the NCM battery subpack also works at low and medium current ranges during the discharging and charging periods, compared to the current constraints of $I_{2\text{min}}$ and $I_{2\text{max}}$. The reasons for such current allocations are that the NCM battery subpack attributes a greater current withstand capability than the Li-S battery subpack, either charging or discharging period. Besides, when designing the weights of the objective function (Equation (6.17)), we make the SOC of the NCM battery subpack decrease faster than that of the Li-S battery subpack at the initial stage, as shown in Figure 6.8(e). The NCM battery subpack can use fast charging opportunities, but Li-S batteries can only charge slowly. This way, fast charging opportunities can be better utilized. Finally, taking into account the module-to-module SOC balance within each subpack, the maximum SOC difference is shown in Figure 6.8(f). The SOC differences between the highest and lowest module within subpacks can be lower than 2%.

Figure 6.9 demonstrates the cruising performance for the aged Li-S and NCM battery subpacks. The cruising range of the HBS is reduced to 768.5 km due to the reduction in the capacities of the Li-S and NCM batteries, but it can still support the mileage requirements of most drivers for a day. The control system can accurately regulate the discrete switching HBS so that the aged HBS can maintain a reasonable current allocation. This proves that the control system can achieve the control capability for batteries in various

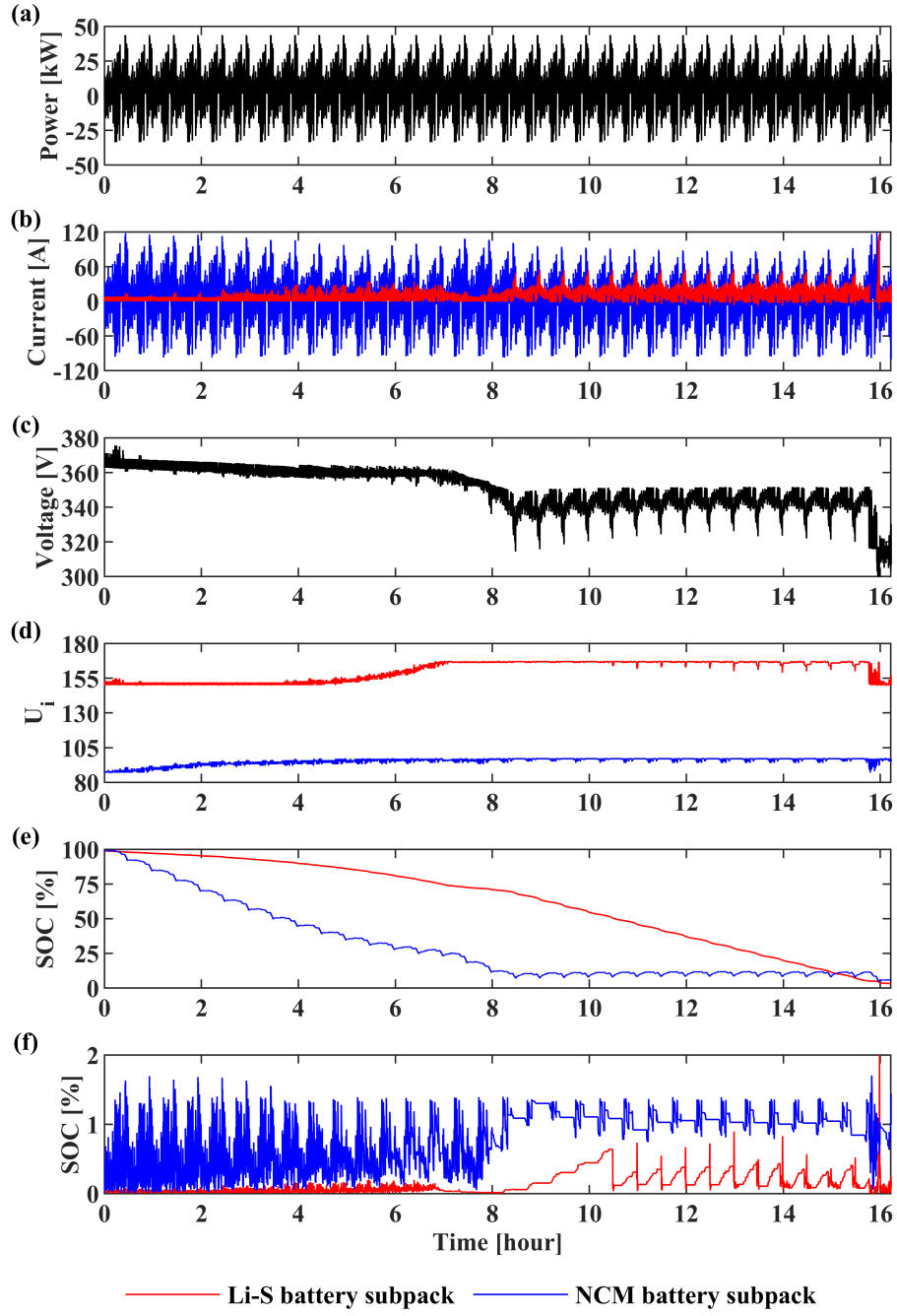


Figure 6.9: The aged battery HBS under a cruising test: (a) power demand P_{dem} , (b) current I_1 and I_2 for the two battery subpacks, (c) bus voltage V_{bus} , (d) the number of switch-in modules (U_1 and U_2) for the two battery subpacks, (e) SOC of battery subpacks, and (f) maximum SOC difference within subpacks.

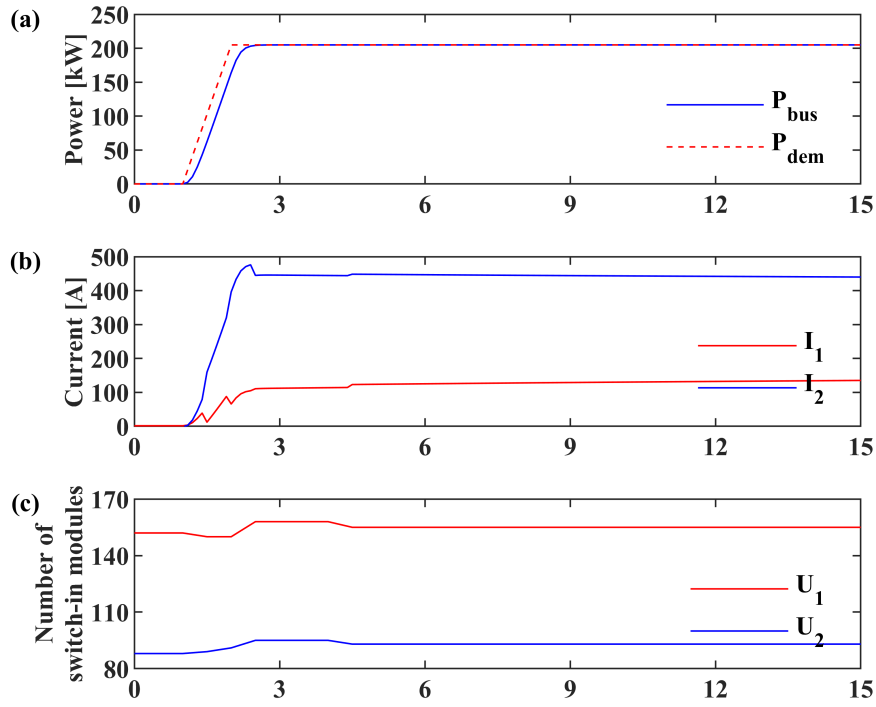


Figure 6.10: The HBS performance under the peak power demand on (a) P_{dem} and P_{bus} , (b) I_1 and I_2 , and (c) U_1 and U_2

degrees of aging HBSs.

Furthermore, a simulation of the maximum power is implemented to validate the peak power performance of the HBS. Figure 6.10 demonstrates the performance under the peak power demand, where the two battery subpacks are fully charged. In the power demand profile to test the peak power capability, the maximum power is set to 208 kW in response to the design target in Section 6.3. As shown in Figure 6.10(a), the power demand P_{dem} increases sharply from 0 to 208 kW from 1st to 2nd second and then keeps the 208 kW power demand until the end of the test. The bus power P_{bus} corresponding to the P_{dem} is also depicted in Figure 6.10(a). The currents of the two battery subpacks are shown in Figure 6.10(b), while the number of switch-in modules (U_1 and U_2) is depicted in Figure 6.10(c). Under the high power and high power change rate, the system can effectively allocate the current of the two battery subpacks by regulating all discrete switches. Simultaneously, the control system can ensure that the current constraints in the HBS are met while power demands change rapidly. These results verify that the HBS

can achieve the target of the maximum power of 208 kW and can adapt in response to significant changes in power demands.

6.5.4 System Level Predictive Accuracy

Considering some assumptions for the system-level controller are proposed in Section 6.5.1, the result accuracy needs to be verified by comparing them to the measured values. The RMSE and Nash-Sutcliffe model efficiency coefficient (NSE) methods are first applied to evaluate the accuracy of estimation of the controller during the whole simulation [124]. Their equations are expressed in (6.10) and (6.18)

$$\text{NSE} = 1 - \frac{\sum_{t=1}^T [y(t) - \hat{y}(t)]^2}{\sum_{t=1}^T [y(t) - \bar{y}(t)]^2}. \quad (6.18)$$

The results of the RMSEs and NSEs are shown in Table 6.7. The RMSE for the fresh and aged battery subpacks are approximately 3 ~ 4 A under the large current fluctuations. The NSEs indicate how well the measured versus predictive data fits. The NSEs for the Li-S battery subpack current, NCM battery subpack current and bus power are close to 1, corresponding to a good match of the model to the measured data.

Furthermore, for a more intuitive comparison of currents and power between measured and estimated values, The results from 10 to 10.5 hours are extracted, as shown in Figure 6.11. In this figure, the left and right columns show the results of the fresh and aged HBSs, respectively. Figures 6.11(a) and 6.11(d) demonstrate the Li-S subpack differences between the measured and estimated currents. Figures 6.11(b) and 6.11(e) demonstrate the NCM subpack differences between the measured and estimated currents. Figures 6.11(c) and 6.11(f) show the errors between the estimated power and power demands.

The results intuitively illustrate that the estimated errors are relatively small, reflecting the reasonableness of the assumption. Besides, the results also explain that selecting the

Table 6.7: Error evaluation between estimated and mean values

HBS type	Measurement	Estimation	RMSE	NSE
Fresh HBS	I_1	$\hat{I}_1$	2.97 A	0.88
	I_2	$\hat{I}_2$	3.01 A	0.98
	P_{dem}	P_{bus}	1.43 kW	0.98
Aged HBS	I_1	$\hat{I}_1$	3.10 A	0.86
	I_2	$\hat{I}_2$	3.87 A	0.96
	P_{dem}	P_{bus}	1.45 kW	0.97

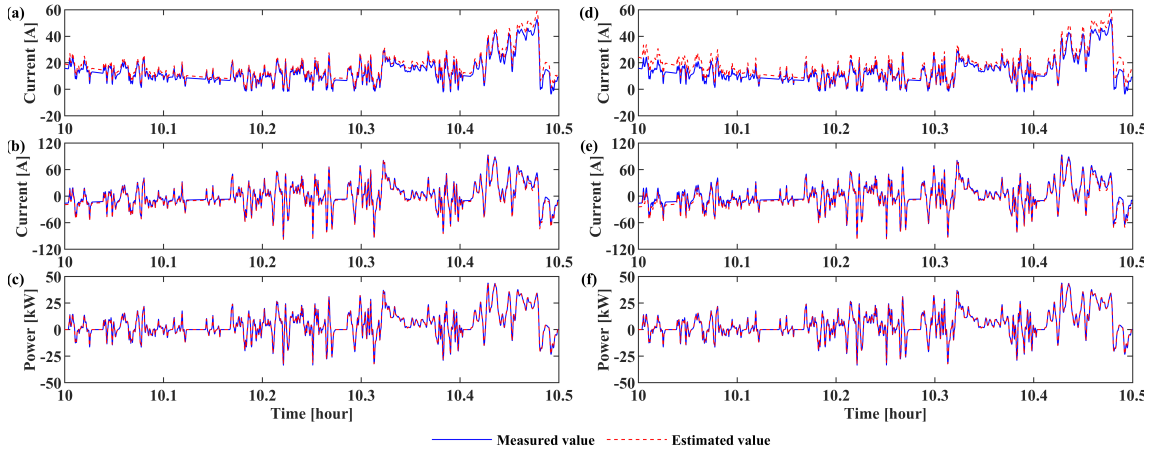


Figure 6.11: Comparison between measured (or expected) and estimated values on (a) $\hat{I}_1$ and I_1 for the fresh Li-S battery subpack, (b) $\hat{I}_2$ and I_2 for the fresh NCM battery subpack, (c) P_{dem} (dash line) and P_{bus} (solid line) for the fresh HBS, (d) $\hat{I}_1$ and I_1 for the aged Li-S battery subpack, (e) $\hat{I}_2$ and I_2 for the aged NCM battery subpack, and (f) P_{dem} (dash line) and P_{bus} (solid line) for the aged HBS.

predictive step $p = 1$ in the objective function (Equation (6.17)) is reasonable because this step size can keep the lowest computational complexity and ensure accurate prediction results.

6.6 Conclusion

This article has proposed a novel HBS for an EV combining Li-S and NCM cells. The proposed HBS uses the complementary advantages of the energy and power density of the two batteries to mitigate the range anxiety and conflicting energy and power requirements

under limited battery system weight. The article started by exploring the complementary advantages of Li-S and NCM batteries and their likely development trends. Battery parameters based on the existing literature have been identified. This information has been used to design an HBS that is lighter and cheaper than a benchmark system. This is achieved in part by adopting a low-frequency discrete switching structure, avoiding the use of expensive and bulky high-power dc/dc converters.

An HBS management framework has been proposed, integrating the state estimators, a system-level controller, and module balancing. The state estimators apply AEKF and FFRLS algorithms to estimate each module's state and parameters online, which mitigates the impact of the module aging and inconsistencies on power allocations over the system's lifetime. The system-level controller regulates power allocations between Li-S and NCM battery subpacks, based on the module's states and power requirements; this uses an NMPC algorithm with integer control variables, optimized using a genetic algorithm. The module balancing processor implements a rolling discharging/charging approach to balance the battery modules in each subpack.

Two case studies, a fresh and an aged HBS, are simulated in Simulink and Simscape to evaluate the performance of the proposed HBS. The fresh and aged HBS have respective cruising ranges of 874 km and 769 km. The maximum power requirement of 208 kW is met, and the system is capable of adapting to large changes in power demands in a short period. This shows that the proposed approach can cover the extremes of daily driving range and maximum power demand for typical EVs. Meanwhile, the estimators perform well in the battery modules. The respective RMSEs for the fresh and aged NCM and Li-S battery SOC are 0.9% and 2.4%. The online parameter identification and SOC estimation are good enough to support the prediction of the system-level controller. The prediction part of the system-level controller can accurately predict the power allocation, and the objective function can regulate the discrete switches to allocate powers between two battery subpacks reasonably, under different aging and power conditions.

In summary, the proposed HBS has the following advantages:

1. While neither the Li-S nor NCM can meet the power and energy density requirements for an EV traction battery alone, the proposed HBS combines the advantages of the two batteries to give full play to their strengths, enabling them to be commercialized in near-future EVs. This provides a route to impact for new battery chemistries, enabling their advantages to be exploited.
2. The proposed control system can accurately predict and reasonably allocate the power between the Li-S and NCM battery subpacks, and remain the SOC's in each subpack broadly balanced. This is implemented without the use of complex power electronics.
3. The proposed estimation framework is robust to aging.

There have been a number of simplifying assumptions in this work: so far, temperature variations and cell-to-cell variations have been assumed insignificant. This assumption may or may not hold in practice, and it would be beneficial to perform further work to assess this. It would also be beneficial to move from simulation to practical implementation. At present, this is not possible as the availability of Li-S cell prototypes is poor, but this should be revisited as the technology develops.

Chapter 7

Overall Results

The main results of the work presented in "paper-format" chapters (Chapters 4-6) are summarized as follows.

Chapter 4 proposed a new topology for HBS using a discrete-switched structure to avoid DC/DC converter. The combination of LTO and LFP batteries in existing studies was selected, so this system comprised LTO and LFP battery subpacks. This study has simplified HBS hardware to cut costs. The power electronics cost of the proposed topology is approximately £400, which is much cheaper than more than £2000 of the conventional HBS employing DC/DC converter. However, simplifying the hardware has to pay more for the control algorithm complexity. Hence, The system model based on cell-level ECM and the topology has been developed to understand the mechanisms of the power allocations between two battery subpacks. According to the system modeling, a high-level rule-based control algorithm with lower-level near-optimal control has been proposed to reach flexible power allocations between two battery subpacks. A rolling discharging/charging approach implemented the module balancing processor to balance the battery modules in each subpack. The principles were demonstrated using a simulated model. The control algorithm developed can successfully allocate power to different battery subpacks. The

LFP and LTO modules were balanced to within 0.01% and 0.1% of each other, respectively.

Nonetheless, no experimental verification of the system operating with discrete switching was documented in Chapter 4. Hence, Chapter 5 designed a module-level experiment to verify the discrete-switched structure. A practical embodiment was a hybrid battery pack combining NMC and lead-acid batteries. The model of the practical embodiment has been built, while a rule-based control strategy has been created by adapting the previously developed control strategy to this pack. Meanwhile, A C code allowing the real-world application, as an embedded code in the controller, has been developed to implement the experiment. Experimental results demonstrate that this structure can successfully allocate power between two types of batteries. Simultaneously, this experiment validates that the discrete-switched structure is controllable, i.e., the power flows can be managed between different battery types in real-world applications.

Moreover, we found that the combination of NMC and Li-S batteries has enormous potential to manage the conflicting requirements between energy and power densities in EV applications. Thus, Chapter 6 proposed a novel HBS using Li-S and NCM batteries using the discrete-switched structure. This article explores hybridizing two promising battery types to overcome the range anxiety and power requirements under limited battery system weight. The battery configuration of the HBS has been optimized, making the HBS lighter and cheaper. Meanwhile, the discrete switching structure has been adopted to cut costs and simplify the hardware compared to conventional HBS using expensive and bulky high-power dc/dc converters. Furthermore, the HBS management system is developed, integrating the state estimators, the system-level controller, and the module balancing processors. The state estimators apply the adaptive extended Kalman filter and forgetting factor recursive least square techniques to estimate each battery module state online to mitigate the impact of the module aging and inconsistencies on power allocations over the system's lifetime. The system-level controller is a nonlinear model predictive control algorithm with integer control variables and a genetic algorithm. The HBS can

reach a cruising range of more than 800 km. Also, the HBS can achieve the maximum power of 208 kW and adapt quickly to considerable changes in power demands.

In summary, this project explored a new low-frequency discrete-switched structure for HBSs from the topology to experimental validation and future potentials. This structure can improve HBS performance in terms of cost and complexity, while proper control strategies allow power allocations in HBSs to be managed. These advantages give HBS greater application potential in the future.

The following chapter will present the completed states of the research objectives listed in Chapter 1, and discuss the studies in this project.

Chapter 8

Achievement and Discussion

8.1 Completion States of Research Objectives

The relationships between the objectives and the chapters of this project are illustrated in Figure 8.1. Completion States of Research Objectives are listed as follows:

Objective 1: investigating various types of traction batteries and state-of-art HBS technologies

Reviews related to this objective were demonstrated in Chapter 2 and the introduction parts of Chapters 4 to 6. Various traction battery chemistries, including Lead-acid, Ni-MH, and Li-ion (LFP, LMO, NCM, NCA, LTO, Li-S) batteries, were investigated. The advantage and disadvantages of each battery chemistry were compared across five technical dimensions. Moreover, the current hybrid battery systems in the research community and industry were investigated. Their power electronics involving DC/DC converters are relatively expensive and complex, as described in Chapter 2.

Objetive 2: developing an HBS structure topology that can decrease costs while

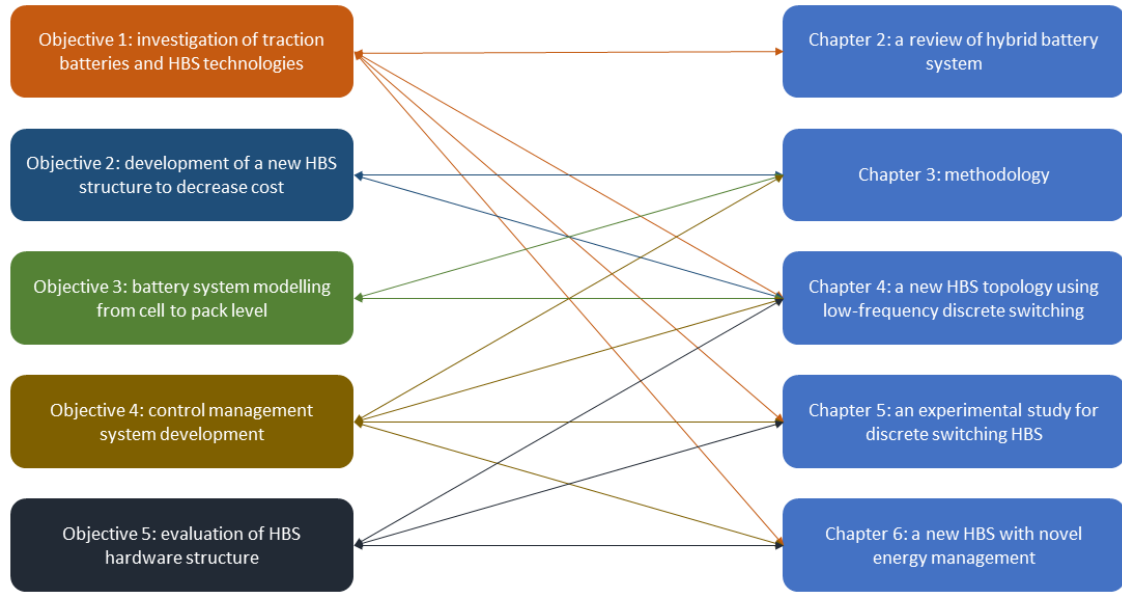


Figure 8.1: A diagram of relationships between the objectives and the chapters

achieving flexible power regulation between multi-chemistry batteries

A new architecture for hybrid battery systems using a discrete-switched structure was developed, which enables the battery pack to allocate power between multi-chemistry batteries flexibly and avoids expensive and bulky DC/DC converters. The capabilities of novel topology were demonstrated in Chapters 4 to 6.

Objective 3: modeling battery from cell to pack level, where the battery datasheet and experimental data parameterize the model

Hybrid battery systems were modeled from a single cell to a whole system. Cell models used equivalent circuit networks; their advantages are analyzed in Chapter 3. Two approaches are applied to obtain the battery's parameterized model: literature reviews and analyzing experimental data. The parameters of NMC, LFP, and LTO batteries were from the literature, while Li-S parameters were from experimental data in our laboratory. Also, the battery module and system were modeled, as shown in Chapters 3 and 4.

Objective 4: developing an appropriate management system matching the novel HBS

hardware structure

The heuristic controls and a model predictive control were developed to manage power flow allocations between different battery chemistries. Chapter 4 presented a heuristic control strategy for the HBS consisting of a rule-based supervisory controller and an objective function. Meanwhile, Chapter 5 presented a model predictive control strategy with a genetic algorithm to overcome the complex integer control variables. These intelligent switching algorithms successfully allocate the power between different battery chemistries and ensure the SOC_s remain broadly balanced. Also, Chapter 5 developed a heuristic control algorithm suitable for a 24-V hybrid battery pack.

Objective 5: evaluating the HBS hardware structure and corresponding management system by simulation and experiment

Simulated and experimental approaches were used to evaluate HBSs using the discrete-switched structure. The results in Chapters 4 and 6 successfully verify the HBS can achieve the power allocations based on various battery states and power demands. Moreover, the management strategy can reach the capabilities of power allocations and SOC balancing. Chapter 5 experimentally validates this structure is controllable, and its current allocations are predictable.

8.2 Discussion

In this project, we have explored the capabilities of the proposed discrete-switched structure in HBSs, including cost competitiveness, the flexibility of power allocations and SOC balancing. The idea of the study processes is a step-by-step research approach; that is, simulation drives the exploration of the new structure and control strategies and a practical embodiment experimentally validates them since building an entire EV battery system is

complex and expensive.

We first used a simulation approach to explore the performance of this architecture and develop its control strategies in Chapter 4. This study presented the new structure and explored its performance and advantages. However, various real-world conditions in automotive applications were not considered. First, this study assumed that the ambient and battery temperatures were constant to control the variables and simplify the study scope, since thermal mechanism and management is a complicated research field for battery systems. Temperature variations could impact system performance, including battery cell parameters relative to SOC and thermal management systems. This point has been highlighted in the BRAD project ¹. The team is exploring the thermal model for the battery system using the discrete-switched structure, and plans to develop a corresponding thermal management system.

Furthermore, the study simulated the power allocations under a typical power demand in EV applications. However, the power demand is based on a 'macro' scale, i.e., sample times of 0.1~1 seconds. In real drive units, motor power is regulated by inverters using a pulse width modulation technique and must operate thousands of times per second. There is a probability that drive units will generate pulse loads, leading to possible short-term current mismatching (i.e. $10^{-3} \sim 10^{-5}$ seconds). A general approach to overcome this problem is to employ a low-pass filter comprised of capacitors and inductors between the electric terminals of the HBS and drive unit. Hence, the effects of pulse loads generated by drive units on the HBS need further study, where the hardware structure and parameters need to be designed to mitigate the impacts.

In Chapter 5, a module-level practical embodiment was designed to verify the feasibility of the architecture in real-world applications. This embodiment is a 'restricted authority' hybrid battery pack, where the discrete-switched structure was not used in each parallel

¹Project description is shown in Appendix B.

string. Although these processes can demonstrate feasibility well, the SOC balancing function was not validated in an experimental environment. Following a step-by-step research approach, the following practical embodiment will be a 'full authority' hybrid battery pack, and explore its SOC balancing function in real-world applications.

Moreover, despite considering the inconsistency between modules, this project did not consider cell-to-cell variations in a single battery module. Although the consistency of commercially available batteries is generally good, it is doubtful whether the aged batteries can still maintain consistency due to the complexity of aging mechanisms. Inconsistency estimation for batteries requires further exploration to address this problem which generally exists in EV battery systems.

After in-depth research, it was found that the advantages of the HBS combining current batteries were insignificant compared to state-of-art NMC batteries. A typical combination in the research community is LFP-LTO HBS, where the LTO battery serves as a quick power supply and the LFP battery functions as the primary energy storage. Nevertheless, the practicality of the LFP-LTO HBS is being doubtful due to the energy density drawback. In Chapter 6, we thus decided to study the HBS using the promising battery combination, i.e., Li-S and NMC batteries. Nevertheless, the availability of the Li-S prototype cells is poor, and no studies are quantifying this, so the features of future commercial Li-S batteries may have some differences. Thus, the Li-S battery performances should be revisited as the technology develops.

Although this project has demonstrated the feasibility of HBSs using the discrete-switched structure well, the structure still has a long way to go from prototypes to actual products in EV applications. The corresponding thermal management system, cell-to-cell variations, the impacts of pulse loads on the micro-scale, and Li-S battery performance need to be further explored in the future.

Chapter 9

Conclusions and Future Work

9.1 Conclusions

Traction batteries in EV applications put forward high requirements for comprehensive performance due to the complexity of the application scenarios. Although EV battery systems are critically sensitive to battery weight and volume, power density, cost, longevity and safety are the leading technical dimension to fulfill the performance requirements. This project first investigated current traction battery types, including lead-acid, Ni-MH, and various Li-ion batteries. By comparing the different battery types, it was found that there are no battery chemistries capable of all salient requirements for EV applications. The research community has proposed HBSs combining two or more battery types to overcome this single-chemistry battery system issue. To date, both research and pre-commercial HBSs solve the regulation of power flow allocations between different battery types by employing costly DC/DC converters in HBSs, leading to much high cost and hardware complexity.

The idea of this project was derived from the fact that related HBS hardware structures

capable of realizing energy management in the research community and industry are complex and expensive. Hence, this project aims to develop an HBS using various batteries with different chemistries, which possess better cost competitiveness and performance than the single-chemistry and conventional hybrid battery systems with DC/DC converters. Simultaneously, another project's target is to explore a feasible battery management approach to allow multiple batteries to be regulated and managed to optimize the overall battery performance.

This project has proposed a new discrete-switched structure for HBSs. In Chapter 4, because the advantages of the hybrid battery system using LTO and LFP batteries have been verified in the literature, we first presented a new topology hybrid battery system combining LTO and LFP batteries to verify the cost-competitive potential compared to the conventional hybrid battery systems with DC/DC converters. The cost analysis for power electronics between the two systems has demonstrated that the new discrete-switched-based hybrid battery systems are much cheaper. The rule-based control algorithm with an objective function has been then developed to regulate power allocations between the two chemistry batteries. Meanwhile, a module-balancing approach has been produced by a rolling discharge and charge to overcome the imbalance issues in each chemistry battery subpack. The simulation results reveal the control algorithm developed can successfully allocate power to different battery subpacks while the two batteries are broadly balanced. To verify the proposed structure is controllable in real-world applications, an experiment has been designed and implemented in Chapter 5. The experimental results prove the power-allocated capability of the discrete-switched structure.

Further studying of characteristics of novel battery chemistries shows that the hybridization of the Li-S and NCM batteries has tremendous potential in the near future. Hence, a next-generation hybrid battery system using the discrete-switched structure has been proposed in Chapter 6. This hybrid battery system combined two promising battery types to overcome range anxiety and power requirements. The battery configuration of this system

has been optimized to make the system lighter and cheaper. A novel management system using a model predictive control technique with a genetic algorithm has been developed to control their power allocations. This hybrid battery system can reach a cruising range of more than 800 km, while the maximum power can achieve 208 kW. This hybrid battery system is verified as a promising candidate for future EV applications.

In summary, the contributions of PhD study are described as follows:

1. A novel HBS topology has been proposed, using the discrete-switched structure to regulate power allocation between two types of batteries. The system switches cells in and out of series strings based on their state of charge relative to other cells in the pack and the power demand.
2. The cost of state-of-art hybrid battery systems and the proposed system has been investigated. Results verify the HBS using the discrete-switched structure has a much lower cost in power electronics.
3. A next-generation HBS for the hybrid Li-S and NMC battery sources using the discrete-switched structure has been proposed. The sizing of the HBS has been optimized under specific design requirements, weight, and cost.
4. A model-predictive control for the next-generation HBS has been developed to manage power allocations between Li-S and NMC battery sources. The controller has applied a genetic algorithm to overcome the complex control problem from the discrete-switched structure.
5. An experiment under the power demands of real applications has validated the capability of the discrete-switched structure.

9.2 Future Work

While this project presents a new structure suitable for hybrid battery systems and explores their capabilities, the following subject areas are suggested as future works:

1. Temperature variations could impact the estimator's performance so that further explorations could include thermal modeling and online parameter identification at different temperatures.
2. This study has not considered cell-to-cell variations in a battery module, i.e., cell inconsistency in a module. Further study could explore an estimation that can estimate the parameters of each cell online.
3. This study has not considered the effects of pulse loads on systems. This situation often occurs on the EV's high-voltage bus because of motors and inverters. Thus, further study could explore the impacts of a high-frequency load on hybrid battery systems and solutions to mitigate the effects.
4. To date, the availability of the Li-S prototype cells is poor, and there are no studies quantifying this, but this should be revisited as the situation develops.

Appendix A: CHIMERA Project

CHIMERA - an intelligent battery management architecture for next-generation electric vehicle batteries using multiple cell chemistries

This work is supported by Innovate UK [grant numbers 48727] [70]. The detail is available at: <https://gtr.ukri.org/projects?ref=48727>

Sponsor

Innovate UK supported this project [grant number 48727].

Project Partners

- Upgrade Technology Engineering Ltd (lead organization)
- Cranfield University
- Aspire Engineering Limited

Project Background

Across all electric vehicle applications - including fully battery powered electric vehicles, plug-in hybrids and fuel cell variants - the battery is critical to overall vehicle cost and performance, especially over the full lifecycle. However, despite Lithium-ion continuing to dominate the EV domain, no single cell chemistry is optimised across all of the battery characteristics targeted by vehicle manufacturers, including:

* Energy density * Power and impulse resilience * Operating temperature range * Cycle life * Susceptibility to thermal runaway * Cost

Electric vehicle batteries based on single chemistries therefore cannot reconcile the conflicting requirements for size, power and operational temperature versus predictability, lifespan and cost. With safety the underlying priority, the resulting design compromises inevitably impact performance, with increasing reliance on cells with high rare earth content (e.g. Cobalt). This presents significant barriers to OEM electrification programmes and end-user adoption.

In response, Upgrade Technology Engineering are developing a novel battery management system with potential to practically integrate multiple cell chemistries within a composite battery module: the Multi-Chemistry Battery (MCB). With each cell chemistry selected to mitigate the others' weaknesses across all key metrics, MCB unlocks a significant UK supply chain opportunity by overcoming challenges of balancing chemistries and power regulation.

Now Upgrade Technology Engineering, with Cranfield and ASPIRE Engineering target the hardware and model-driven embedded software developments to realise a full-scale modular prototype, as the basis to prove hardware switching scalability to multiple chemistries and support UK supply chain engagements.

The project tasks for Cranfield University are to 1) develop a modeling and control framework to describe the switching environment for a multi-chemistry battery system, 2) implement the model and control using MATLAB and Simulink, considering the switched cells' impedance, voltage, and capacitance, and 3) Generate C code for control algorithms.

Appendix B: BRAD Project

Bellerophon Rapid Assembly and Disassembly (BRAD)

This work is supported by Innovate UK [grant numbers 10017550] [71]. The detail is available at: <https://gtr.ukri.org/projects?ref=10017550>

Sponsor

Innovate UK supported this project [grant number 10017550].

Projection Partners

- Upgrade Technology Engineering Ltd (lead organization)
- Cranfield University
- Aspire Engineering Limited
- Eco Charger Ltd

Project Background

The Bellerophon Rapid Assembly and Disassembly (BRAD) project will deliver a quad bike powered by maintainable and reusable batteries, with a concept manufacturing process which reduces manufacture and remanufacture time, providing cost reduction for efficient battery system assembly thus providing an electric powertrain in a market which is dominated by Internal Combustion Engines.

Many quad bikes are petrol with a small percentage using diesel as the fuel. Around 1 million quad bikes were produced in in 2019 and less than 15,000 were electric, all are E-UTV.

The last study showed that in 2010 18 million tonnes of CO₂ was emitted from quad bikes and this figure is expected to have risen since.

The proof-of-concept phase of this project is complete with a UTE battery system designed for addressing the circular economy and reducing Bill of Materials (BoM) costs with a unique process for pack assembly and disassembly to aid remanufacture and second-life potential of spent battery packs. The BRAD project builds on the combined expertise of Upgrade Technology Engineering Ltd, Aspire Engineering Ltd, Eco Charger Ltd and Cranfield University.

Cranfield will build on novel battery management strategies developed in a prior IUK project for UTE (Ref:48727) utilizing algorithms within the BME to solve objective functions capturing dynamic aging, degradation, and thermal characteristics of cells. Improving: 1) battery reliability, 2) Thermal management/safety, 3) lifespan, and 4) State-of-Health determination (for grading of cells in second-life applications). These models underpin virtual validation of thermal management and State-of-Failure (SoF), guarding against sudden catastrophic failure.

References

- [1] P. Bertoldi, F. Diluiso, L. Castellazzi, N. Labanca, and T. Serrenho, “Energy consumption and energy efficiency trends in the EU-28 2000-2015,” *JRC Report*, 2018.
- [2] European Comission. Directorate-General for Mobility and Transport, *White Paper on Transport: Roadmap to a Single European Transport Area: Towards a Competitive and Resource-Efficient Transport System*. Publications Office of the European Union, 2011.
- [3] G. Zhou, X. Ou, and X. Zhang, “Development of electric vehicles use in china: A study from the perspective of life-cycle energy consumption and greenhouse gas emissions,” *Energy Policy*, vol. 59, pp. 875–884, 2013.
- [4] A. M. Bento, K. Gillingham, M. R. Jacobsen, *et al.*, “Flawed analyses of us auto fuel economy standards,” *Science*, vol. 362, no. 6419, pp. 1119–1121, 2018.
- [5] F. Knobloch, S. V. Hanssen, A. Lam, *et al.*, “Net emission reductions from electric cars and heat pumps in 59 world regions over time,” *Nature sustainability*, vol. 3, no. 6, pp. 437–447, 2020.
- [6] IEA, *Electric car registrations and sales share in china, united states, europe and other regions, 2016-2021*, IEA website, accessed February, 2023. [Online]. Available: <https://www.iea.org/data-and-statistics/charts/electric->

car-registrations-and-sales-share-in-china-united-states-europe-and-other-regions-2016-2021.

- [7] S. Dhameja, *Electric vehicle battery systems*. Elsevier, 2001.
- [8] A. Dinger, R. Martin, X. Mosquet, *et al.*, “Batteries for electric cars: Challenges, opportunities, and the outlook to 2020,” *The Boston Consulting Group*, vol. 7, p. 2017, 2010.
- [9] S. Manzetti and F. Mariasiu, “Electric vehicle battery technologies: From present state to future systems,” *Renewable and Sustainable Energy Reviews*, vol. 51, pp. 1004–1012, 2015.
- [10] L. Allen, A. O’Connell, and V. Kiermer, “How can we ensure visibility and diversity in research contributions? how the contributor role taxonomy (credit) is helping the shift from authorship to contributorship,” *Learned Publishing*, vol. 32, no. 1, pp. 71–74, 2019.
- [11] R. Wagner, N. Preschitschek, S. Passerini, J. Leker, and M. Winter, “Current research trends and prospects among the various materials and designs used in lithium-based batteries,” *Journal of Applied Electrochemistry*, vol. 43, pp. 481–496, 2013.
- [12] H. Bode, *Lead-acid batteries*. John Wiley and Sons, Inc., New York, NY, 1977.
- [13] C. D. Rahn and C.-Y. Wang, *Battery systems engineering*. John Wiley & Sons, 2013.
- [14] S. Ziemann, A. Grunwald, L. Schebek, D. Müller, and M. Weil, “The future of mobility and its critical raw materials,” *Metallurgical Research & Technology*, vol. 110, no. 1, pp. 47–54, 2013.
- [15] M. Armand and J.-M. Tarascon, “Building better batteries,” *Nature*, vol. 451, no. 7179, pp. 652–657, 2008.

- [16] B. Scrosati and J. Garche, “Lithium batteries: Status, prospects and future,” *Journal of power sources*, vol. 195, no. 9, pp. 2419–2430, 2010.
- [17] S.-Y. Chung, J. T. Bloking, and Y.-M. Chiang, “Electronically conductive phospho-olivines as lithium storage electrodes,” *Nature materials*, vol. 1, no. 2, pp. 123–128, 2002.
- [18] V. Srinivasan and J. Newman, “Discharge model for the lithium iron-phosphate electrode,” *Journal of the Electrochemical Society*, vol. 151, no. 10, A1517, 2004.
- [19] Y. Ding, Z. P. Cano, A. Yu, J. Lu, and Z. Chen, “Automotive Li-ion batteries: Current status and future perspectives,” *Electrochemical Energy Reviews*, vol. 2, pp. 1–28, 2019.
- [20] M. Jo, M. Noh, P. Oh, Y. Kim, and J. Cho, “A new high power $\text{LiNi}_{0.81}\text{Co}_{0.1}\text{Al}_{0.09}\text{O}_2$ cathode material for lithium-ion batteries,” *Advanced Energy Materials*, vol. 4, no. 13, p. 1301583, 2014.
- [21] K. K. Lee, W. S. Yoon, K. B. Kim, K. Y. Lee, and S. T. Hong, “Characterization of $\text{LiNi}_{0.85}\text{Co}_{0.10}\text{M}_{0.05}\text{O}_2$ (M= Al, Fe) as a cathode material for lithium secondary batteries,” *Journal of power sources*, vol. 97, pp. 308–312, 2001.
- [22] K. Wu, J. Yang, Y. Zhang, C. Wang, and D. Wang, “Investigation on $\text{Li}_4\text{Ti}_5\text{O}_{12}$ batteries developed for hybrid electric vehicle,” *Journal of Applied Electrochemistry*, vol. 42, pp. 989–995, 2012.
- [23] CATL, *Innovative technology*, company website, accessed February, 2023. [Online]. Available: <https://www.catl.com/en/research/technology/>.
- [24] S.-T. Myung, F. Maglia, K.-J. Park, *et al.*, “Nickel-rich layered cathode materials for automotive lithium-ion batteries: Achievements and perspectives,” *ACS Energy Letters*, vol. 2, no. 1, pp. 196–223, 2017.
- [25] A. Fotouhi, D. J. Auger, L. O’Neill, T. Cleaver, and S. Walus, “Lithium-sulfur battery technology readiness and applications—a review,” *Energies*, vol. 10, no. 12, p. 1937, 2017.

- [26] H. Chen, C. Wang, W. Dong, W. Lu, Z. Du, and L. Chen, “Monodispersed sulfur nanoparticles for lithium–sulfur batteries with theoretical performance,” *Nano letters*, vol. 15, no. 1, pp. 798–802, 2015.
- [27] Lyten, *Lyten lithium-sulfur batteries*, company website, accessed February, 2023. [Online]. Available: <https://lyten.com/products/batteries/>.
- [28] S. Dörfler, H. Althues, P. Härtel, T. Abendroth, B. Schumm, and S. Kaskel, “Challenges and key parameters of lithium-sulfur batteries on pouch cell level,” *Joule*, vol. 4, no. 3, pp. 539–554, 2020.
- [29] Y. Xiang, J. Li, J. Lei, *et al.*, “Advanced separators for lithium-ion and lithium–sulfur batteries: A review of recent progress,” *ChemSusChem*, vol. 9, no. 21, pp. 3023–3039, 2016.
- [30] E. Faggioli, P. Rena, V. Danel, X. Andrieu, R. Mallant, and H. Kahlen, “Supercapacitors for the energy management of electric vehicles,” *Journal of Power Sources*, vol. 84, no. 2, pp. 261–269, 1999.
- [31] Z. Song, H. Hofmann, J. Li, X. Han, X. Zhang, and M. Ouyang, “A comparison study of different semi-active hybrid energy storage system topologies for electric vehicles,” *Journal of Power Sources*, vol. 274, pp. 400–411, 2015.
- [32] T. Zimmermann, P. Keil, M. Hofmann, M. F. Horsche, S. Pichlmaier, and A. Jossen, “Review of system topologies for hybrid electrical energy storage systems,” *Journal of Energy Storage*, vol. 8, pp. 78–90, 2016.
- [33] C. E. Holland, J. W. Weidner, R. A. Dougal, and R. E. White, “Experimental characterization of hybrid power systems under pulse current loads,” *Journal of Power Sources*, vol. 109, no. 1, pp. 32–37, 2002.
- [34] X. Zhang, H. Peng, H. Wang, and M. Ouyang, “Hybrid lithium iron phosphate battery and lithium titanate battery systems for electric buses,” *IEEE Transactions on Vehicular Technology*, vol. 67, no. 2, pp. 956–965, 2017.

- [35] B. Hredzak, V. G. Agelidis, and M. Jang, “A model predictive control system for a hybrid battery-ultracapacitor power source,” *IEEE Transactions on Power Electronics*, vol. 29, no. 3, pp. 1469–1479, 2013.
- [36] D. Cericola, P. W. Ruch, R. Kötz, P. Novák, and A. Wokaun, “Simulation of a supercapacitor/Li-ion battery hybrid for pulsed applications,” *Journal of Power Sources*, vol. 195, no. 9, pp. 2731–2736, 2010.
- [37] S. Zhang, R. Xiong, and F. Sun, “Model predictive control for power management in a plug-in hybrid electric vehicle with a hybrid energy storage system,” *Applied energy*, vol. 185, pp. 1654–1662, 2017.
- [38] B. Wang, J. Xu, B. Cao, and B. Ning, “Adaptive mode switch strategy based on simulated annealing optimization of a multi-mode hybrid energy storage system for electric vehicles,” *Applied Energy*, vol. 194, pp. 596–608, 2017.
- [39] R. Xiong, Y. Duan, J. Cao, and Q. Yu, “Battery and ultracapacitor in-the-loop approach to validate a real-time power management method for an all-climate electric vehicle,” *Applied energy*, vol. 217, pp. 153–165, 2018.
- [40] A. Castaings, W. Lhomme, R. Trigui, and A. Bouscayrol, “Comparison of energy management strategies of a battery/supercapacitors system for electric vehicle under real-time constraints,” *Applied Energy*, vol. 163, pp. 190–200, 2016.
- [41] Z. Song, J. Li, X. Han, *et al.*, “Multi-objective optimization of a semi-active battery/supercapacitor energy storage system for electric vehicles,” *Applied Energy*, vol. 135, pp. 212–224, 2014.
- [42] M. Wieczorek and M. Lewandowski, “A mathematical representation of an energy management strategy for hybrid energy storage system in electric vehicle and real time optimization using a genetic algorithm,” *Applied energy*, vol. 192, pp. 222–233, 2017.
- [43] J. Wang, P. Liu, J. Hicks-Garner, *et al.*, “Cycle-life model for graphite-lifepo4 cells,” *Journal of power sources*, vol. 196, no. 8, pp. 3942–3948, 2011.

- [44] Brill Power, *Brill Power: Revolutionizing energy storage*, company website, accessed February, 2023. [Online]. Available: <https://brillpower.com>.
- [45] MEP technologies, *Mep technologies: Custom battery systems*, company website, accessed February, 2023. [Online]. Available: <https://meptec.co.uk/>.
- [46] R. Sharma and H. Gao, "Low cost high efficiency dc-dc converter for fuel cell powered auxiliary power unit of a heavy vehicle," *IEEE transactions on power electronics*, vol. 21, no. 3, pp. 587–591, 2006.
- [47] J. Wang, H. S.-h. Chung, and R. T.-h. Li, "Characterization and experimental assessment of the effects of parasitic elements on the mosfet switching performance," *IEEE Transactions on Power Electronics*, vol. 28, no. 1, pp. 573–590, 2012.
- [48] I. Baccouche, S. Jemmali, B. Manai, A. Nikolian, N. Omar, and N. Essoukri Ben Amara, "Li-ion battery modeling and characterization: An experimental overview on nmc battery," *International Journal of Energy Research*, vol. 46, no. 4, pp. 3843–3859, 2022.
- [49] H. He, R. Xiong, and J. Fan, "Evaluation of lithium-ion battery equivalent circuit models for state of charge estimation by an experimental approach," *energies*, vol. 4, no. 4, pp. 582–598, 2011.
- [50] A. Fotouhi, D. J. Auger, K. Propp, S. Longo, and M. Wild, "A review on electric vehicle battery modelling: From lithium-ion toward lithium–sulphur," *Renewable and Sustainable Energy Reviews*, vol. 56, pp. 1008–1021, 2016.
- [51] S. Miyatake, Y. Susuki, T. Hikiyara, S. Itoh, and K. Tanaka, "Discharge characteristics of multicell lithium-ion battery with nonuniform cells," *Journal of Power Sources*, vol. 241, pp. 736–743, 2013.
- [52] V. Pop, H. J. Bergveld, D. Danilov, P. P. Regtien, and P. H. Notten, "Methods for measuring and modelling a battery's electro-motive force," *Battery Management Systems: Accurate State-of-Charge Indication for Battery-Powered Applications*, pp. 63–94, 2008.

- [53] D. J. Auger, *Electrical power source for simscape*, <https://github.com/daniel-auger/simscape-sselecpowersrc>, GitHub, Accessed: 2022-11-21, May 2015.
- [54] S. M. Lukic, J. Cao, R. C. Bansal, F. Rodriguez, and A. Emadi, “Energy storage systems for automotive applications,” *IEEE Trans. Indus. Electron.*, vol. 55, no. 6, pp. 2258–2267, 2008. [Online]. Available: <https://doi.org/10.1109/TIE.2008.918390>.
- [55] G. Ren, G. Ma, and N. Cong, “Review of electrical energy storage system for vehicular applications,” *Renewable and Sustainable Energy Reviews*, vol. 41, pp. 225–236, 2015.
- [56] G. Mulder, N. Omar, S. Pauwels, *et al.*, “Comparison of commercial battery cells in relation to material properties,” *Electrochim. Acta*, vol. 87, pp. 473–488, 2013. [Online]. Available: <https://doi.org/10.1016/j.electacta.2012.09.042>.
- [57] J. F. Peters, M. Baumann, B. Zimmermann, J. Braun, and M. Weil, “The environmental impact of Li-ion batteries and the role of key parameters: A review,” *Renewable Sustainable Energy Rev.*, vol. 67, pp. 491–506, 2017. [Online]. Available: <https://doi.org/10.1016/j.rser.2016.08.039>.
- [58] Y. Miao, P. Hynan, A. Von Jouanne, and A. Yokochi, “Current Li-ion battery technologies in electric vehicles and opportunities for advancements,” *Energies*, vol. 12, no. 6, p. 1074, 2019. [Online]. Available: <https://doi.org/10.3390/en12061074>.
- [59] A.-I. Stan, M. Swierczynski, D.-I. Stroe, R. Teodorescu, S. J. Andreasen, and K. Moth, “A comparative study of lithium ion to lead acid batteries for use in UPS applications,” in *Proc. 2014 IEEE 36th Int. Telecom. Energy Conf. (INTELEC)*. [Online]. Available: <https://doi.org/10.1109/INTLEC.2014.6972152>.

- [60] Z. Song, H. Hofmann, J. Li, J. Hou, X. Han, and M. Ouyang, “Energy management strategies comparison for electric vehicles with hybrid energy storage system,” *Applied Energy*, vol. 134, pp. 321–331, 2014.
- [61] D. Yan, L. Lu, Z. Li, X. Feng, M. Ouyang, and F. Jiang, “Durability comparison of four different types of high-power batteries in hev and their degradation mechanism analysis,” *Applied Energy*, vol. 179, pp. 1123–1130, 2016.
- [62] N. Devillers, S. Jemei, M.-C. Péra, D. Bienaimé, and F. Gustin, “Review of characterization methods for supercapacitor modelling,” *Journal of Power Sources*, vol. 246, pp. 596–608, 2014.
- [63] C.-S. Moo, K. S. Ng, and Y.-C. Hsieh, “Parallel operation of battery power modules,” *IEEE Transactions on Energy Conversion*, vol. 23, no. 2, pp. 701–707, 2008.
- [64] A. F. Burke, “Batteries and ultracapacitors for electric, hybrid, and fuel cell vehicles,” *Proc. IEEE*, vol. 95, no. 4, pp. 806–820, 2007. [Online]. Available: <https://doi.org/10.1109/JPROC.2007.892490>.
- [65] N. Karim, E. J. Cairns, and P. H. Vroomen, “Electrically rechargeable, dual chemistry, battery system for use in plug-in or hybrid electric vehicles,” 9 774 204, Sep. 2017. [Online]. Available: <https://www.google.com/patents/US9774204>.
- [66] C. J. Hale, “Battery system comprising a control system,” 10 449 868, Oct. 2019. [Online]. Available: <https://www.google.com/patents/US10449868>.
- [67] W. Li, H. Cui, T. Nemeth, *et al.*, “Deep reinforcement learning-based energy management of hybrid battery systems in electric vehicles,” *Journal of Energy Storage*, vol. 36, p. 102 355, 2021.
- [68] J. Ye, W. Zhuang, and G. Yin, “Rule-filter-integrated control of LFP/LTO hybrid energy storage system for vehicular application,” in *2019 IEEE 28th International Symposium on Industrial Electronics (ISIE)*, IEEE, 2019, pp. 1542–1547.

- [69] G. Li, W. Zhuang, G. Yin, Y. Ren, and Y. Ding, “Energy management strategy and size optimization of a LFP/LTO hybrid battery system for electric vehicle,” SAE Technical Paper, Tech. Rep., 2019.
- [70] UK Research and Innovation (2021), *Chimera: An intelligent battery management architecture for next-generation electric vehicle batteries using multiple cell chemistries*, accessed May 26, 2022. [Online]. Available: <https://gtr.ukri.org/projects?ref=48727>.
- [71] BRAD: UK Research and Innovation (2022), *'bellerophon rapid assembly and disassembly*, accessed May 26, 2022. [Online]. Available: <https://gtr.ukri.org/projects?ref=10017550>.
- [72] R. Wegmann, V. Döge, and D. U. Sauer, “Assessing the potential of a hybrid battery system to reduce battery aging in an electric vehicle by studying the cycle life of a graphite NCA high energy and a LTO metal oxide high power battery cell considering realistic test profiles,” *Appl. Energy*, vol. 226, pp. 197–212, 2018. [Online]. Available: <https://doi.org/10.1016/j.apenergy.2018.05.104>.
- [73] A.-I. Stroe, M. Swierczynski, D.-I. Stroe, and R. Teodorescu, “Performance model for high-power lithium titanate oxide batteries based on extended characterization tests,” in *Proc. 2015 IEEE Energy Convers. Cong. Expo. (ECCE)*, pp. 6191–6198. [Online]. Available: <https://doi.org/10.1109/ECCE.2015.7310528>.
- [74] R. Jackey, M. Saginaw, P. Sanghvi, J. Gazzarri, T. Huria, and M. Ceraolo, “Battery model parameter estimation using a layered technique: An example using a lithium iron phosphate cell,” *SAE Technical Paper*, vol. 2, pp. 1–14, 2013.
- [75] Y. Ko and W. Choi, “A new SOC estimation for LFP batteries: Application in a 10 Ah cell (hw 38120 l/s) as a hysteresis case study,” *Electronics*, vol. 10, no. 6, p. 705, 2021.
- [76] D. W. Gao, *Energy storage for sustainable microgrid*. Academic Press, 2015.

- [77] F. A. Silva, “Power electronic converters and systems: Frontiers and applications [book news],” *IEEE Industrial Electronics Magazine*, vol. 10, no. 2, pp. 68–70, 2016.
- [78] A. Jaafar, C. R. Akli, B. Sareni, X. Roboam, and A. Jeunesse, “Sizing and energy management of a hybrid locomotive based on flywheel and accumulators,” *IEEE Transactions on Vehicular Technology*, vol. 58, no. 8, pp. 3947–3958, 2009.
- [79] T. C. Schuetz, *Aerodynamics of road vehicles*. Sae International, 2015.
- [80] Nissan UK, *New Nissan LEAF price and specifications*, accessed July 25, 2021. [Online]. Available: <https://www.nissan.co.uk/vehicles/new-vehicles/leaf/prices-specifications.html#grade-LEAFZE1A-0%7Cspecs>.
- [81] N. Mohan, T. M. Undeland, and W. P. Robbins, *Power electronics: converters, applications, and design*. John wiley & sons, 2003.
- [82] J. Deng, C. Bae, A. Denlinger, and T. Miller, “Electric vehicles batteries: Requirements and challenges,” *Joule*, vol. 4, no. 3, pp. 511–515, 2020.
- [83] H.-P. Lin, D. Chua, M. Salomon, *et al.*, “Low-temperature behavior of Li-ion cells,” *Electrochemical and Solid-State Letters*, vol. 4, no. 6, A71, 2001.
- [84] WAE, *Wae: Battery modules*, company website, accessed February, 2023. [Online]. Available: <https://wae.com/our-solutions/our-products/battery-modules/>.
- [85] Y. Gong, D. J. Auger, A. Fotouhi, and C. J. Hale, “A new topology for electric all-terrain vehicle hybrid battery systems using low-frequency discrete cell switching,” *IEEE Transactions on Transportation Electrification*, 2022.
- [86] C. R. Gould, C. M. Bingham, D. A. Stone, and P. Bentley, “New battery model and state-of-health determination through subspace parameter estimation and state-observer techniques,” *IEEE Transactions on Vehicular Technology*, vol. 58, no. 8, pp. 3905–3916, 2009.

- [87] F. Khanum, E. Loubach, F. Duperly, C. Jenkins, P. J. Kollmeyer, and A. Emadi, "A kalman filter based battery state of charge estimation matlab function," in *2021 IEEE Transportation Electrification Conference & Expo (ITEC)*, IEEE, 2021, pp. 484–489.
- [88] C.-Y. Wang, T. Liu, X.-G. Yang, *et al.*, "Fast charging of energy-dense lithium-ion batteries," *Nature*, pp. 1–6, 2022.
- [89] W. Li, E. M. Erickson, and A. Manthiram, "High-nickel layered oxide cathodes for lithium-based automotive batteries," *Nature Energy*, vol. 5, no. 1, pp. 26–34, 2020.
- [90] R. Schmich, R. Wagner, G. Hörpel, T. Placke, and M. Winter, "Performance and cost of materials for lithium-based rechargeable automotive batteries," *Nature Energy*, vol. 3, no. 4, pp. 267–278, 2018.
- [91] M. S. Houache, C.-H. Yim, Z. Karkar, and Y. Abu-Lebdeh, "On the current and future outlook of battery chemistries for electric vehicles—mini review," *Batteries*, vol. 8, no. 7, p. 70, 2022.
- [92] G. Zhou, H. Chen, and Y. Cui, "Formulating energy density for designing practical lithium–sulfur batteries," *Nature Energy*, vol. 7, no. 4, pp. 312–319, 2022.
- [93] D. Hu, Y. Su, L. Chen, *et al.*, "The mechanism of side reaction induced capacity fading of Ni-rich cathode materials for lithium-ion batteries," *Journal of Energy Chemistry*, vol. 58, pp. 1–8, 2021.
- [94] X. Liu, G.-L. Xu, L. Yin, *et al.*, "Probing the thermal-driven structural and chemical degradation of Ni-rich layered cathodes by Co/Mn exchange," *Journal of the American Chemical Society*, vol. 142, no. 46, pp. 19 745–19 753, 2020.
- [95] H. Zhang and J. Zhang, "An overview of modification strategies to improve $\text{LiNi}_{0.8}\text{Co}_{0.1}\text{Mn}_{0.1}\text{O}_2$ (NCM811) cathode performance for automotive lithium-ion batteries," *eTransportation*, vol. 7, p. 100 105, 2021.

- [96] L. Yu, T. Liu, R. Amine, J. Wen, J. Lu, and K. Amine, “High nickel and no cobalt – the pursuit of next-generation layered oxide cathodes,” *ACS Applied Materials & Interfaces*, 2022.
- [97] G. Ye, M. Zhao, L.-P. Hou, *et al.*, “Evaluation on a 400 wh kg⁻¹ lithium-sulfur pouch cell,” *Journal of Energy Chemistry*, vol. 66, pp. 24–29, 2022.
- [98] C.-X. Bi, M. Zhao, L.-P. Hou, *et al.*, “Anode material options toward 500 wh kg⁻¹ lithium-sulfur batteries,” *Advanced Science*, vol. 9, no. 2, p. 2103910, 2022.
- [99] A. Bhargav, J. He, A. Gupta, and A. Manthiram, “Lithium-sulfur batteries: Attaining the critical metrics,” *Joule*, vol. 4, no. 2, pp. 285–291, 2020.
- [100] J. Guan, J. Sun, X. Shu, *et al.*, “A cost-and energy density-competitive lithium-sulfur battery,” *Energy Storage Materials*, vol. 41, pp. 588–598, 2021.
- [101] X. Huang, J. Xue, M. Xiao, *et al.*, “Comprehensive evaluation of safety performance and failure mechanism analysis for lithium sulfur pouch cells,” *Energy Storage Materials*, vol. 30, pp. 87–97, 2020.
- [102] J. Zhang, C. You, H. Lin, and J. Wang, “Electrochemical kinetic modulators in lithium–sulfur batteries: From defect-rich catalysts to single atomic catalysts,” *Energy & Environmental Materials*, vol. 5, no. 3, pp. 731–750, 2022.
- [103] W. Hua, H. Li, C. Pei, *et al.*, “Selective catalysis remedies polysulfide shuttling in lithium-sulfur batteries,” *Advanced Materials*, vol. 33, no. 38, p. 2101006, 2021.
- [104] Y. V. Mikhaylik and J. R. Akridge, “Polysulfide shuttle study in the li/s battery system,” *Journal of the electrochemical society*, vol. 151, no. 11, A1969, 2004.
- [105] R. Pai, A. Singh, M. H. Tang, and V. Kalra, “Stabilization of gamma sulfur at room temperature to enable the use of carbonate electrolyte in Li-S batteries,” *Communications Chemistry*, vol. 5, no. 1, pp. 1–11, 2022.

- [106] Y. Cao, P. Zuo, S. Lou, *et al.*, “A quasi-solid-state Li-S battery with high energy density, superior stability and safety,” *Journal of Materials Chemistry A*, vol. 7, no. 11, pp. 6533–6542, 2019.
- [107] S. Li, W. Zhang, J. Zheng, M. Lv, H. Song, and L. Du, “Inhibition of polysulfide shuttles in Li-S batteries: Modified separators and solid-state electrolytes,” *Advanced Energy Materials*, vol. 11, no. 2, p. 2000779, 2021.
- [108] Y. Huang, M. Shaibani, T. D. Gamot, *et al.*, “A saccharide-based binder for efficient polysulfide regulations in Li-S batteries,” *Nature communications*, vol. 12, no. 1, pp. 1–15, 2021.
- [109] Q. Zhang, Q. Huang, S.-M. Hao, *et al.*, “Polymers in lithium–sulfur batteries,” *Advanced Science*, vol. 9, no. 2, p. 2103798, 2022.
- [110] I. Baccouche, S. Jemmali, B. Manai, N. Omar, and N. Essoukri Ben Amara, “Improved OCV model of a Li-ion NMC battery for online SOC estimation using the extended kalman filter,” *Energies*, vol. 10, no. 6, p. 764, 2017.
- [111] N. Shateri, Z. Shi, D. J. Auger, and A. Fotouhi, “Lithium-sulfur cell state of charge estimation using a classification technique,” *IEEE Transactions on Vehicular Technology*, vol. 70, no. 1, pp. 212–224, 2020.
- [112] S. Chikkannanavar and G. Kwak, “Advances and developments in batteries and charging technologies,” *Transportation Electrification: Breakthroughs in Electrified Vehicles, Aircraft, Rolling Stock, and Watercraft*, pp. 27–46, 2022.
- [113] N. Rauh, T. Franke, and J. F. Krems, “Understanding the impact of electric vehicle driving experience on range anxiety,” *Human factors*, vol. 57, no. 1, pp. 177–187, 2015.
- [114] M. Faraj and O. Basir, “Range anxiety reduction in battery-powered vehicles,” in *2016 IEEE Transportation Electrification Conference and Expo (ITEC)*, IEEE, 2016, pp. 1–6.

- [115] *Tesla Model 3 electric vehicle database*, <https://ev-database.uk/car/1555/Tesla-Model-3>, Accessed: 2022-11-17.
- [116] *Tesla Model 3*, https://www.tesla.com/en_gb/model3, Accessed: 2022-11-17.
- [117] M. P. Polis, G. G. Yin, W. Chen, Y. Fu, C. C. Mi, *et al.*, “Battery cell identification and SOC estimation using string terminal voltage measurements,” *IEEE transactions on vehicular technology*, vol. 61, no. 7, pp. 2925–2935, 2012.
- [118] X. Hu, S. Li, and H. Peng, “A comparative study of equivalent circuit models for Li-ion batteries,” *Journal of Power Sources*, vol. 198, pp. 359–367, 2012.
- [119] M.-K. Tran, A. DaCosta, A. Mevawalla, S. Panchal, and M. Fowler, “Comparative study of equivalent circuit models performance in four common lithium-ion batteries: LFP, NMC, LMO, NCA,” *Batteries*, vol. 7, no. 3, p. 51, 2021.
- [120] S. M. M. Alavi, A. Mahdi, S. J. Payne, and D. A. Howey, “Structural identifiability of battery equivalent circuit models,” *arXiv preprint arXiv:1505.00153*, 2015.
- [121] D. Xile, Z. Caiping, and J. Jiuchun, “Evaluation of SOC estimation method based on EKF/AEKF under noise interference,” *Energy Procedia*, vol. 152, pp. 520–525, 2018.
- [122] A. Fotouhi, N. Shateri, D. J. Auger, S. Longo, and K. Propp, “A matlab graphical user interface for battery design and simulation,” *From Cell Test Data to Real-World Automotive Simulation*, 2016.
- [123] A. Fotouhi, K. Propp, and D. J. Auger, “Electric vehicle battery model identification and state of charge estimation in real world driving cycles,” in *2015 7th computer science and electronic engineering conference (CEECE)*, IEEE, 2015, pp. 243–248.
- [124] J. E. Nash and J. V. Sutcliffe, “River flow forecasting through conceptual models part i—a discussion of principles,” *Journal of hydrology*, vol. 10, no. 3, pp. 282–290, 1970.