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DIGITAL TWIN-DRIVEN ADAPTIVE CONTROL AND
HARDWARE-IN-THE-LOOP VALIDATION OF DISTRIBUTED
BATTERY SYSTEMS IN SHIPBOARD DC MICROGRIDS

by

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DEDICATION

I dedicate this to my parents Stephen and Kim Peskar, whose encouragement and unwavering support has been the foundation of my journey. Their sacrifices, guidance and belief in me has inspired me to persevere through every challenge in pursuing my goals. This achievement is as much theirs as it is mine.

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ABSTRACT

This dissertation presents a unified framework for the modeling, control and validation of distributed battery energy storage systems in shipboard DC micro-grids. Primarily focusing on the integration of digital twin technology, adaptive control strategies, and intelligent interfacing agents. As modern power systems become more electrified and decentralized, robust scalable and interpretable control of battery systems becomes critical. Battery control is particularly important in safety constrained applications such as the harsh environments experienced on naval and maritime platforms.

The first contribution of this work is the development of a coupled electro-thermal battery emulator capable of replicating both thermal and electrical dynamics of a lithium-ion battery. The emulator is designed for hardware-in-the-loop (HIL) applications, allowing for safe, rapid and repeatable validation of controls and external battery integrated systems. Battery behavior is replicated under realistic operating conditions without exposing physical batteries to degradation or potential failure. This platform bridges the gap between simulation and experimental validation, providing a flexible testbed for distributed energy system application and research.

Further, a distributed adaptive agent-based droop control framework is proposed for load sharing between parallel battery energy storage systems. The strategy implements battery digital twins to predict the health state of a battery specifically the state of charge, remaining useful life and state of health. Allowing the agent to dynamically adjust the battery's contribution to system demand. Unlike conventional resistive droop control, the proposed method enables coordinated yet decentralized behavior improving system robustness, reliability, and longevity. The control strat-

egy is explored by dynamics pulsed loading and an energized supply bus in a power buffer micro-grid operation, demonstrating the droop control's ability to prolong system performance by distributing degradation.

The third contribution introduces an intelligent interfacial agent for engagement with digital twin-enabled systems using a large language model (LLM). This interface enables natural language querying, system interpretation, and structured interaction with digital twin models and control environments. By combining reasoning with physics-based model, this system forms the foundation for next-generation, human-interpretable control architectures for autonomous decision aids in complex energy systems.

Combining these contributions, digital twin-driven control, when combined with adaptive decentralized control and intelligent interfaces, forms a powerful paradigm for distributed battery energy management systems. The results highlight the importance of electro-thermal modeling in control validation, the effectiveness of digital twin informed droop, and the emerging role of artificial intelligence in enabling intuitive interactions with complex systems. This work forms the groundwork for future research in adaptive energy management, autonomous system support, and scalable hardware-in-the-loop validation of cyber-physical energy systems.

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CHAPTER 1

INTRODUCTION



Figure 1.1 Rendering of the future US Navy's Constellation-Class (FFG 62) released by Fincantieri Marinette Marine.

1.1 BACKGROUND AND MOTIVATION

Modern naval platforms are increasingly transitioning toward electrified architectures to support modern high-power systems such as advanced radar, directed energy weapons and integrated electric propulsion. Traditional AC shipboard systems are being replaced or augmented with DC micro-grids, which offers better efficiency, reduced conversion losses and are more flexible to energy storage integration [1].

A major component for shipboard DC micro-grids is lithium-ion battery energy storage systems (BESS). These systems participate in the critical role of load leveling, transient power support, and improving grid reliability and robustness. Batteries

enable shipboard systems to react to large dynamic load while reducing strain and efficiency losses from primary generation sources. However, Lithium-ion batteries are complex systems involving coupled electrical, chemical, and thermal dynamics which can significantly influence their performance, safety, and degradation behavior [2].

Managing these systems effectively requires modeling, monitoring, and adaptable control strategies to account for both dynamic operation and degradation mechanisms. Traditional battery management systems (BMS) rely on embedded estimation algorithms and rule-based controls. This is an effective approach for controlling a singular pack, however when multiple distributed batteries are integrated these controls become increasingly difficult to implement.

Recent advances in digital twin technology demonstrate a promising framework to address these challenges. A digital twin is a virtual representation of a physical system referred to as an asset. digital twins typically integrate physics-based models, operational data, and real-time measurements to closely replicate the state and behavior of the physical asset [3]. Digital twins enable continuous state monitoring, predictive analysis, and adaptive decision-making capabilities through coupling the physical system with computational models.

Digital twins for battery systems incorporate electro-thermal models, degradation models, and operational conditions to provide comprehensive representation of their state and future behavior in each system. When integrated with BMSs, digital twin can support pro-active control decisions which improve power delivery, thermal safety, and health preservation.

However, utilizing battery digital twin control requires several key capabilities. First, real-time models must accurately capture the electro-thermal dynamics present within the battery. Second, control strategies must be capable of coordinating multiple distributed battery units while incorporating health aware metrics such as state of charge (SOC), temperature, and state of health. Finally, digital twins require

intuitive interfaces allowing engineers and operators to easily interact with complex systems.

This dissertation addresses these challenges through the development of a digital-twin driven framework for distributed battery systems in shipboard DC micro-grids.

1.2 RESEARCH PROBLEM

Digital twins have been widely studied in manufacturing and cyber-physical systems, however their application to distributed BESSs remain an active area of research. Integrating battery digital twin poses several challenges before practical controls integration can be achieved.

First, primary research on battery modeling focuses on high-fidelity electrochemical models such as the pseudo-two-dimensional (P2D) models. This model provides detailed insight with high accuracy; however, they are computationally expensive and difficult to fully parameterize. Conversely, equivalent circuit models are computationally efficient, but at the detriment of ignoring thermal and degradation dynamics.

Second, micro-grid control typically relies on static droop controls schemes to distribute power contributions across multiple sources. Droop control is effective as a decentralized control however; static droop ignores battery health indicators such as temperature imbalance and degradation state. As a result, batteries can experience harsh utilization as their dynamics change which reduces overall system lifespan.

Third, digital twin systems for complex systems lack intuitive interfacing mechanisms for user interaction. Operators are forced to interpret volumes of data and simulation outputs to understand the system's behavior and current state. With the emergence of large language models (LLMs), an opportunity to create an intelligent agent to interface with digital twin systems and assist users in interpreting system behavior and control decisions.

These challenges motivate the development of an integrated framework combining

real-time battery modeling, distributed control algorithms, and intelligent interfaces within digital twin architectures.

1.3 RESEARCH OBJECTIVES

1. Develop a real-time electro-thermal battery emulator to replace the electrical and thermal behavior of lithium-ion battery systems for hardware-in-the-loop testing.
2. Design a health aware adaptive agent-based droop control strategy that incorporates the use of a battery health digital twin.
3. Develop a large language model (LLM)-based intelligent agent capable of interfacing with digital twin systems to assist users with monitoring, analysis, and system interaction.

1.4 RESEARCH CONTRIBUTIONS

There are three primary contributions of this dissertation. First, a real-time coupled electro-thermal battery emulator was developed to replicate the electrical and thermal dynamics of a lithium-ion battery under operating conditions. This contribution enables a safe and flexible platform for testing control algorithms and external systems without degrading or exposing a physical battery to dangerous conditions. Secondly, an adaptive agent-based droop control framework is proposed in which distributed batteries adjust their power contributions based on digital twin estimate of their SOC and remaining useful life (RUL). This control approach improves overall system lifespan by spreading degradation to the healthier batteries. And third, a novel large language model-based intelligent agent is developed to interface with digital twin systems. The agent enables intuitive natural language interaction between digital twin models and operators.

1.5 DISSERTATION ORGANIZATION

The remainder of this dissertation is organized as follows. Chapter 2 presents the development of the coupled electrothermal hardware-in-the-loop battery emulator. Chapter 3 introduces a digital twin informed adaptive agent-based droop control framework and demonstration simulation performance for distributed batteries. Chapter 4 presents the development and implementation of the large language model-based intelligent agent for interfacing with digital twin simulations. Chapter 5 concludes the dissertation and discusses open research areas and future directions for digital-twin driven energy systems.

CHAPTER 2

COUPLED ELECTRO-THERMAL BATTERY EMULATOR FOR POWER SYSTEMS TESTING

This chapter is dedicated to the work towards the first research objective. A battery emulator is developed to emulate both electrical and thermal outputs to a real system. This work provides a tool for testing of battery implementation and controls, enabling the ability to induce faults and dynamically adjust battery health for testing without the need to purchasing and damaging larger expensive battery packs. The following is a pre-print journal paper submitted to the Journal of Energy storage[4].

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2.1 ABSTRACT

Understanding the thermal response of lithium-ion batteries is imperative to their safe operation. With investigating cooling methods in mind, an electro-thermo hardware-in-the-loop battery emulator is being developed. The emulator will reproduce both the electrical and thermal outputs of a lithium-ion battery. The coupled electrical model is developed from an electric circuit representation of lithium-ion batteries. To run this model, look up tables have been assembled from experiments to select parameters based off a battery's temperature and state of charge. For the coupled electro-thermo model, an isothermal reduced-order model has been modified to account for liquid cooling and convection. It is important to note that the current

work neglects the side reactions and mixing terms of the equation as they require in-depth knowledge of the battery's specific materials and concentrations; as such, this approach is only valid for low C-rates (1C or less). The model is compared to experimental data of a Samsung 30Q 18650 battery. Results show a good agreement between modeled and experimental results for the battery's electrical and thermal response. Temporal electrical and thermal response for charging and discharging are presented and discussed.

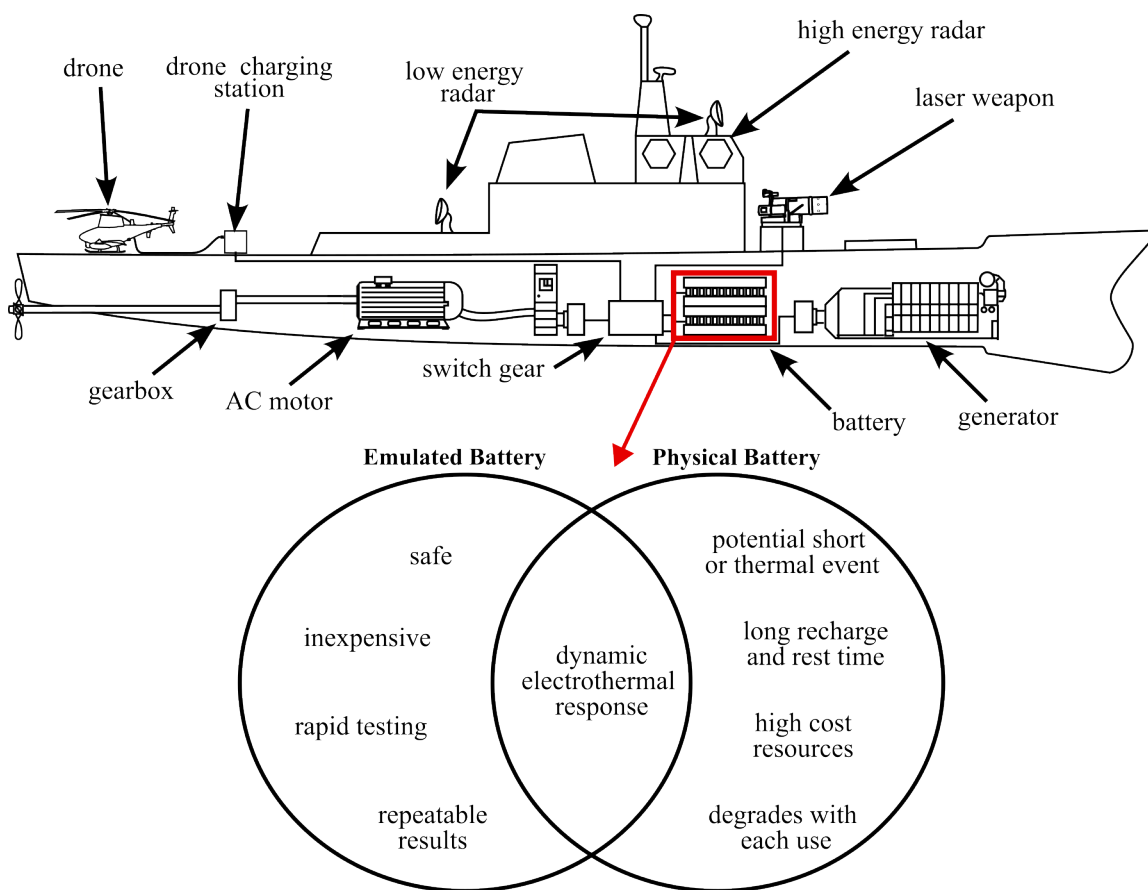


Figure 2.1 Benefits of a hardware in the loop electro-thermal battery emulator versus a physical battery in system level testing and design.

2.2 INTRODUCTION

The electrification of modern transportation platforms, from electric vehicles to aircraft and naval vessels, continues to advance towards higher efficiency and robustness. Paramount to this transition is the integration of lithium-ion batteries which serve as both energy storage and dynamic power buffers. These batteries help store surplus energy during generation peaks and supply power during demand surges, enabling more efficient operation through load leveling and pulsed-power support allowing engines and generators to operate closer to their optimal efficiency [5]. Naval microgrids specifically undergo frequent transitions between load states, making battery energy storage systems (BESS) essential for ensuring stability and performance [6].

Driven by their high energy density, long cycle life, and decreasing cost, the deployment of lithium-ion batteries has surged in both civilian and defense sectors [7]. The term lithium-ion battery encompasses a range of chemistries optimized for different priorities, such as thermal safety, specific energy, or affordability [8]. The primary chemistries that have been adopted for use are lithium-iron phosphate (LFP), nickel manganese cobalt oxide (NMC), and nickel cobalt oxide (NCA). Each chemistry provides certain advantages with trade-offs. LFP cells offer superior thermal stability with high charge and discharge rates. However, they come with lower energy densities. NCA cells provide high energy densities making them attractive for applications with space and weight restrictions; however, they are significantly less thermally stable especially at high charge and discharge rates. NMC chemistry falls in the middle ground of the LFP and NCA chemistries, providing a balance of energy density and thermal stability.

Selecting a suitable battery chemistry for high-power mobile platforms involves navigating a complex design space. System designers should consider weight, volume, thermal management requirements, and energy capacity. For platforms such as electric ships and aircrafts, where mass and space are critical constraints, a higher en-

ergy density chemistry seems like the ideal choice. However, with high energy density comes thermal instability leading to a larger thermal management system often requiring bulky or heavy cooling systems. Adding these extra systems will quickly subvert the efficiency gains of a higher energy density battery. These trade-offs highlight the need for robust tools to support design-phase analysis, enabling rapid evaluation of candidate configurations without destructive testing or costly prototyping. Naval and aerospace platforms present particularly demanding use-cases, often requiring battery systems that can respond to transient high-power loads, such as those from radar arrays, directed energy weapons, or fast propulsion maneuvers [9]. In such cases, electrical and thermal behavior must be understood and accurately modeled to ensure system safety and performance.

To aid in the design and evaluation of these complex systems, battery emulators are increasingly used as flexible, non-destructive tools. Battery emulators replicate the electrical behavior of a battery pack in real-time, allowing engineers to test power systems and control strategies without relying on actual battery hardware. The benefits of a battery emulator in place of a physical battery can be seen in Figure 2.1. Khaleduzzaman et al. [10] discusses three levels to battery emulator; power converter based, integrated emulators, and cell level emulators. Power converter-based emulators are typically higher power and used for larger system level testing through controlling power supply or converters. for example, Koeing et al. [11] demonstrated the use of nonlinear local model networks to capture high fidelity battery dynamics, showing that the high-fidelity voltage dynamics can be emulated through a DC power supply for power hardware-in-the-loop (HIL) applications at 160 kW power levels. The integrated battery emulator level is typically used for modular HIL testing at low to medium power levels. The usual examples of these emulators are deployed on real-time HIL platforms such as TyphoonTM and SpeedgoatTM, where cells can operate across multiple channels or be configured to have one channel output for module

emulation. Varais et al. [12], demonstrated a comparison of model based and image based real-time emulated devices with battery storage. They demonstrated this using a dSPACETM HIL platform to perform the emulation of a lithium-ion battery with a virtual wind turbine. Cell level emulators are used to replicate more accurate dynamics at the cell to enable battery management system (BMS) control techniques. For example, Verani et al. [13], demonstrated a low-cost cell emulator on a PCB that can be connected in series to represent a pack. In doing so, they showed this system can be used to replicate voltage, temperature and current signals to a BMS for controls testing. When deployed in a HIL configuration, emulators enable the testing of system-level interactions [14], including thermal management and fault response [15], without the risks or costs of full-scale physical testing [16].

Despite progress in the development of these emulators, existing emulators are often limited in scope, particularly regarding thermal behavior. Many emulator studies simplify or neglect thermal dynamics, treating temperature effects only as modifiers to electrical parameters rather than as state variables. As thermal behavior is crucial to both safety and performance, especially in high-power applications, this simplification can limit the fidelity and utility of such tools. Progress has been made in developing electro-thermal models to remedy fidelity limitations. For example, Fan et al. [17] demonstrated a high-fidelity battery emulator model that utilizes parameter look up tables to couple the dynamics, enabling the temperature of the cell to modify the electrical parameters. They emulated the battery voltage response successfully through a LabVIEW controlled power supply. However, the temperature was a static input or a predefined profile. Thanheirs et al. [18] went further incorporating a thermal model for real-time temperature calculation as a state variable. Enabling the voltage to be emulated with the variable temperature influence accounted for. In these studies, when thermal behavior is emulated, it is typically done as a software signal from a simulation [19]. This is allowable for most BMS testing; however, when

the scope is increased to include external systems, it is beneficial to physically emulate heat rejection into the shared cooling systems for thermal testing.

In this work, we present the development of an electro-thermal battery emulator designed to address these limitations; building on prior preliminary investigations [20]. The emulator couples a real-time electrical equivalent circuit model (ECM) with a lumped thermal model to capture temperature dynamics at the battery pack level. The system is designed to incorporate varying chemistries with parameters taken at the cell level. For this paper, the LFP chemistry is demonstrated and scaled to match a 44S8P pack resulting in a nominal voltage of 140.8 V with a capacity of 17.44 Ah. Following model development, it is implemented in a hardware platform suitable for HIL testing and validated through two case studies. These studies evaluate the system's ability to emulate both electrical and thermal pack level behavior under realistic dynamic conditions, demonstrating its utility for system design and testing. The contributions of this work are threefold. 1) the formulation of a hardware-in-the-loop battery emulator with coupled electro-thermal emulation, 2) demonstration of methods for the characterization of lithium-ion cells on said hardware; and 3) experimental validation of the developed electro-thermal battery emulator under complex battery pack failure conditions.

2.3 METHODOLOGY

2.3.1 FRAMEWORK

This paper's primary focus is on developing a framework, shown in Figure 2.2, and hardware setup to enable real-time electro-thermal battery emulation. To perform this emulation two main components are needed, a model and hardware to facilitate emulation. The model needs to incorporate both the electrical and thermal domains as well as the ability to scale from single cell data to match the characteristics of varying module and pack sizes. To do this, a generalized approach is shown in

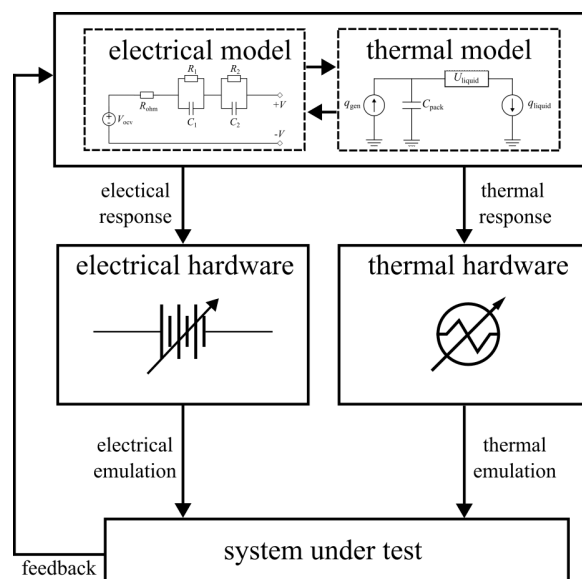


Figure 2.2 high level diagram of the emulator's signal flow from the generated model response to the physical emulation and feedback to the models for the next iteration.

both the needed voltage and temperature response. The electro-thermal model is selected to be computationally efficient enough to be operated on edge-class real-time controller hardware. To emulate the electrical response, a bidirectional power supply is controlled by the real-time controller to reproduce the modeled electrical response of the battery. Further, the thermal response is emulated through a liquid cooling loop. Performed through the control of an in-line heating element, the modeled heat generated from the battery is dissipated into the external cooling system. The necessary hardware to enable true emulation from the models' output is discussed and presented in the sections that follow. With the combination of both electrical and thermal modeling, the coupled characteristics can be physically emulated through the hardware setup.

2.3.2 COUPLED MODEL

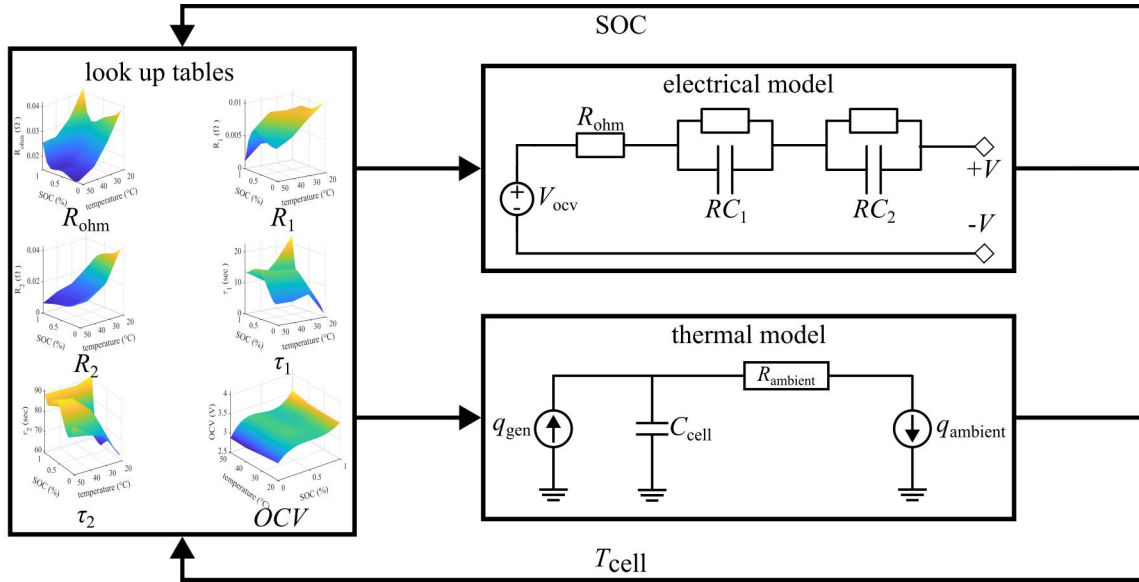


Figure 2.3 The information flow for the coupled models; showing the thermal and electrical state parameters pushed into the models and feedback from the models to update the state parameter for the next iteration.

To replicate the behavior of a lithium-ion battery under dynamic conditions, the strong coupling between the electrical and thermal domains must be accounted for. The electrical performance is heavily influenced by temperature, as the internal resistances and open circuit voltage exhibit temperature dependence [21]. Thermal behavior is directly affected by the electrical loading, as joule heating and other irreversible losses generate heat as a function of current and the internal resistance [22]. Capturing this bidirectional dependence is crucial for accurately replicating the real response of a lithium-ion battery, particularly under dynamic conditions.

To address the interlinked dynamics, a coupled electro-thermal model is developed, composed of two models: an electrical model to represent the voltage behavior and a thermal model to represent the heat generation and transfer. The models are interlinked using shared state variables that update at each time step to ensure feedback across the domains. Specifically, the electrical model computes instantaneous power losses resulting from the current and internal resistance which is passed to the

thermal model for the heat generation and temperature calculation. The resulting temperature is then used to update the temperature sensitive parameters used in the electrical model.

The simulation begins with an initial condition representing the starting state of the battery. For example, the initial state of charge and temperature are set with an initial load of zero amps applied. From this, the model iteratively simulates the battery's electrical and thermal response to an external load profile. At each iteration, the thermal model predicts the next battery temperature based on current heat generation and dissipation, and the electrical model then uses this temperature to update its parameters and compute the resulting voltage and state of charge (SOC). This method of co-simulation enables the electro-thermal feedback loop necessary for a realistic emulation of a battery across a wide range of use cases. A high level view of the information flow is shown in Figure 2.3.

2.3.3 ELECTRICAL MODEL

A variety of modeling approaches exist for simulating lithium-ion behavior, each offering trade-offs between physical fidelity, parameter complexity, and computational cost [23]. Among the most comprehensive are physics-based models, such as the pseudo-two-dimensional (P2D) model which explicitly considers ion and charge transport within electrode particles and electrolytes [24]. While offering deep insight and high accuracy for a battery's electro-chemical state, they are often computationally expensive and require detailed parameters which are difficult to obtain from commercial batteries. This makes the P2D model unsuitable for real-time HIL applications.

An alternative to first principle models is the ECM which represents the battery using lumped electrical elements arranged to capture dynamic voltage behavior found in lithium-ion batteries [25]. ECMs are widely used for their high computational

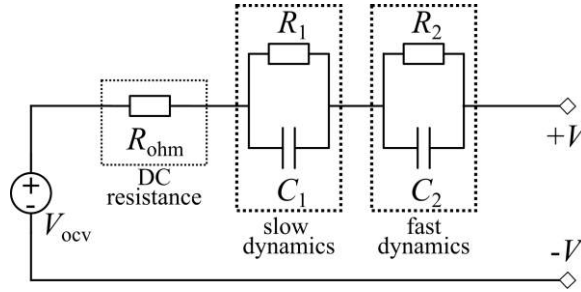


Figure 2.4 Circuit diagram of a second order equivalent circuit representation of a battery used in the electrical model. Both the slow and fast dynamics are represented by a unique RC pair.

efficiency, ease of parameterization, and ability to approximate the steady state and transient electrical response with low complexity. Most importantly, the parameters in ECMs can be empirically derived from cell-level tests and scaled to represent module or pack level behavior.

In this work, the electrical model is composed of a coulomb counting model for the SOC and a 2nd order ECM representation of a battery. To obtain the SOC, the current, $I(t)$, can be integrated over time and normalized to the capacity of the battery. Once added to the initial SOC_0 , the current SOC is obtained at any point in time as

$$SOC = SOC_0 + \frac{1}{Capacity} \int I(t), dt. \quad (2.1)$$

The battery dynamics are modeled using a 2nd order equivalent circuit representation of a lithium-ion battery as seen in Figure 2.4. This was chosen due to low complexity which is needed for limited computational resources of a real-time controller. The model is composed of a voltage source, a series resistor and two RC branches in series. These components represent the batteries open-circuit voltage, DC resistance, and the slow and fast time constant dynamics respectively. There is also a state of charge block that monitors the current across the battery to predict the state of charge based off Coulomb counting. At any one time step, the set pa-

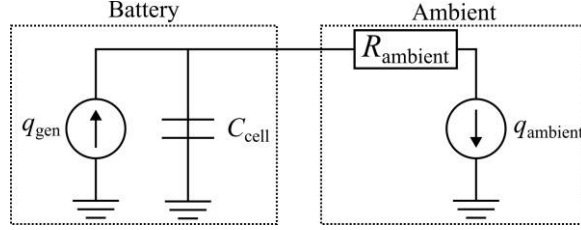


Figure 2.5 Equivalent circuit of the 1D lumped heat transfer from a cylindrical lithium-ion cell to ambient conditions.

Parameters for each of these components are the battery's electrical state. To update these states during battery operations, generalized parameter surfaces are employed. This allows each state value to be continuously updated in real-time based off the battery's history.

The terminal voltage is determined by the difference of the open circuit voltage and the voltage drop across each component; the ohmic resistance, the slow ($V_{R_1C_1}$) and fast ($V_{R_2C_2}$) RC pairs written as

$$V_{\text{terminal}} = OCV(SOC) - I \cdot R_{\text{ohm}} - V_{R_1C_1} - V_{R_2C_2}. \quad (2.2)$$

The voltage drop across each RC pair can be expressed as

$$V_{R_iC_i}(t) = \alpha_i \cdot V_{OCV,t-1} + R_i(SOC, T) \cdot (1 - \alpha_i) \cdot I(t). \quad (2.3)$$

Where α is a variable created to represent the exponential change in the voltage coefficient over the Δt time step, written as

$$\alpha_i = e^{\frac{-\Delta t}{R_i \cdot C_i}}. \quad (2.4)$$

Where $i=1$ is for the slow dynamics and $i=2$ is for the fast dynamics.

2.3.4 THERMAL MODEL

Many approaches have been investigated to model the thermal behavior of a lithium-ion cell. For this application a method that provides reasonable accuracy

and a high level of computational efficiency is needed. Prior research from other groups have shown that lithium-ion cells exhibit a Biot number $\ll 0.1$ [26]. This finding enables the use of lumped models to capture the overall thermal behavior of the cell with high computational efficiency. However, this does come at the cost of depth and accuracy [27]. The lumped models only account for the axial heat transfer of the battery with no local temperature variation. This does not allow the calculations of temperature gradients to develop which are expected to be an important consideration for the degradation of lithium-ion cells [28]. The current focus of this work is for the development of a method to emulate the thermal behaviors seen from batteries through hardware. Due to these reasons a lumped 1D heat transfer model was selected.

The sub thermal model is a reduced order 1D lumped heat transfer model of the battery to ambient conditions. This is shown in figure 2.5 and written out as

$$C_{\text{cell}} \frac{dT_{\text{cell}}}{dt} = \frac{T_{\text{ambient}} - T_{\text{cell}}}{R_{\text{convection}}} + I^2 \cdot R_{\text{ohm}}, \quad (2.5)$$

where q_{gen} is the heat generated by ohmic losses which represents the main thermal contributor. The ohmic losses can be calculated by multiplying the current (I) through the cell by its equivalent series resistance R_{ohm} . C_{cell} is the thermal capacitance of the cell represented by the mass multiplied by the lumped density of the cell. $R_{\text{convection}}$ represents the cumulative thermal resistance to the ambient conditions.

2.3.5 DATA COLLECTION

The coupled electro-thermal model is an empirical model, thus requiring many parameters to be collected. The necessary parameters for the electrical model are the open circuit voltage, R_{ohm} , R_1, C_1, R_2, C_2 , and the cell capacity. To estimate these parameters a hybrid pulsed power load profile [29], seen in Figure 2.6, can be applied to the cell and analyzed. At a known state of charge a 10s discharge pulse at a C-rate of 1 is applied. The voltage response from this discharge is used to estimate

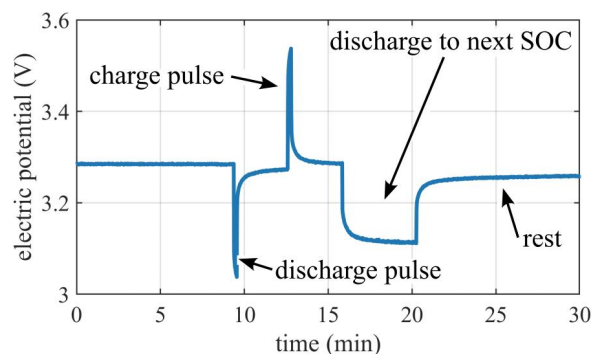


Figure 2.6 HPPC test profile used to characterize the lithium-ion battery.

the electrical parameters of the cell. The initial voltage before the pulse was applied is considered to be the open circuit voltage of the battery at that state of charge. Once the current is applied, the instant drop in voltage can be used to obtain the DC resistance of the cell, R_{ohmic} . The RC pairs, along with better tuning for the R_{ohm} term, can then be fit through nonlinear least squares fitting. This method provides parameter estimation for the cell at a specific SOC. To create a profile that allows for the automation of this test for multiple SOC steps, the discharge pulse is followed by a less aggressive charge pulse to recover the expended SOC. After the discharge and charge pulse the battery can be discharged at a constant C-rate down to the next state of charge point of interest. This profile allows for the estimation of the electrical parameters over many SOC steps to be obtained.

To apply the HPPC profile, an in-house battery test setup, Figure 2.7, was utilized to collect the required electrical data. The in-house setup is composed of a NHR 9200 battery tester, environmental chamber, LabVIEW code, and a thermocouple. The cell to be tested is placed inside the environmental chamber, which maintains a stable ambient temperature for the battery. The LabVIEW code is used to upload and control the load profile to the NHR 9200 and records the data. Electrical data, voltage and current data, is collected directly from the NHR sensors. Temperature data is captured through a National Instruments cDAQ with a thermocouple attached

to the battery with electrical tape.

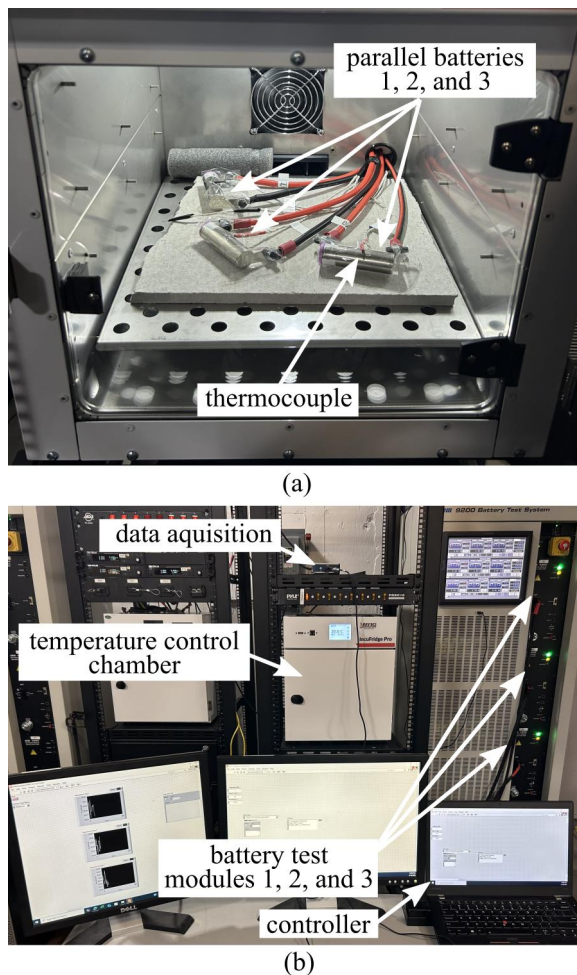


Figure 2.7 In house battery data collection setup up showing: (a) three cells set up for parallel tests in the environmental chamber(Note: the cells shown here are representative only and are not the exact cells used in this work) and (b) the three testing modules, temperature-chamber, data acquisition and LabVIEW control.

Utilizing this testing setup, the HPPC test was performed on a K2 Energy 26650 LFP cell. A discharge pulse was recorded at a step of every 5% from 100-80% and 20-0% SOC. This enables the more exponential regions of the voltage responses to be captured. For the remaining 70-30% SOC, a discharge pulse at every step 10% was recorded. While the ohmic resistance and open circuit voltage can be directly calculated the parallel RC parameters need to be fit through nonlinear least squares.

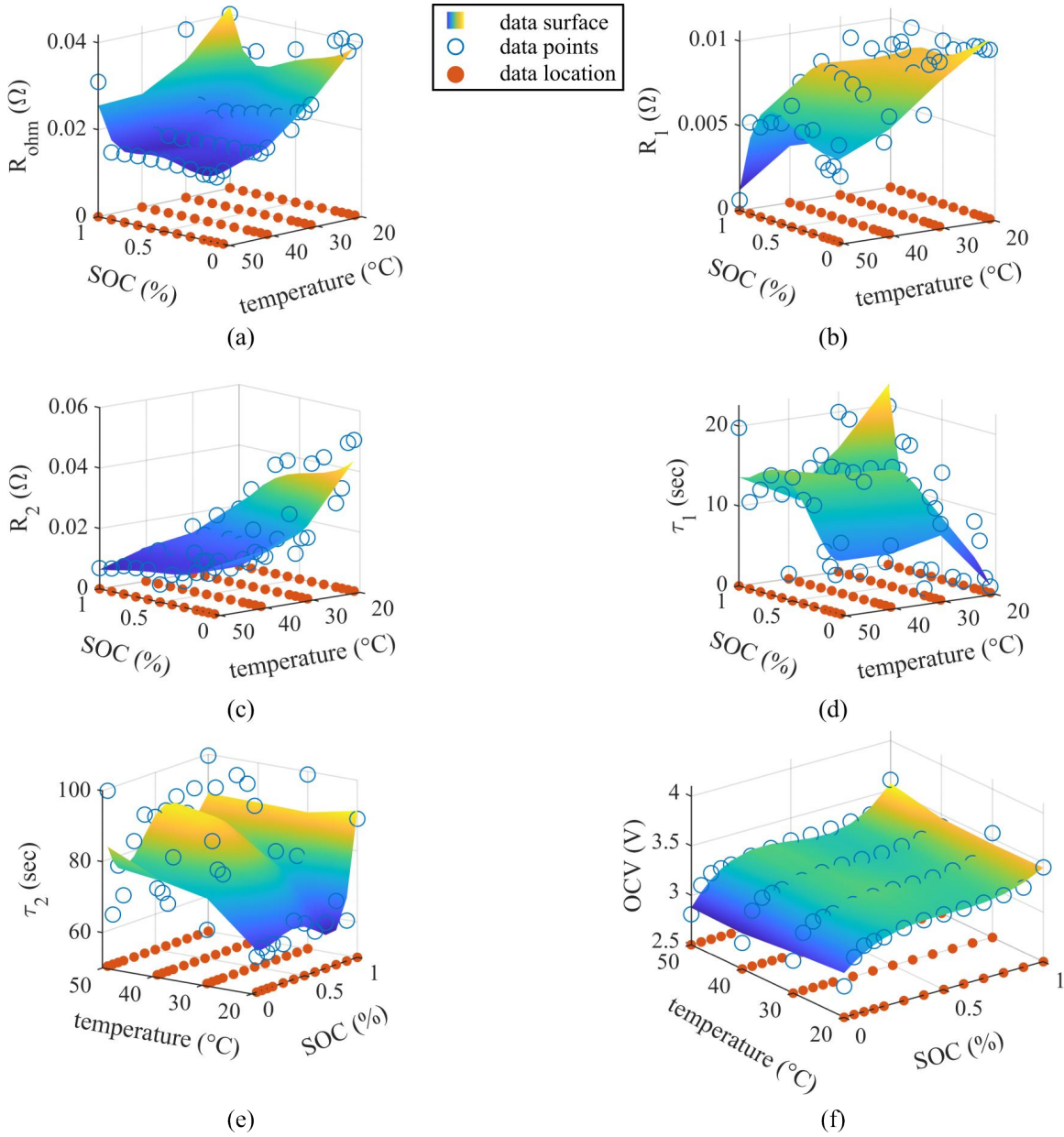


Figure 2.8 Fitted parameters for K2 26650 LFP cell showing: (a) the ohmic resistance R_0 , (b) fast time constant resistance R_1 , (c) slow time constant resistance R_2 , (d) fast time constant τ_1 , (e) slow time constant τ_2 and (f) the open circuit voltage OCV .

The first RC pair is set with a small-time constant range within the milliseconds to acquire the fast time dynamics and the second RC pair was constrained within the seconds magnitude to capture the slower time dynamics. To capture the temperature

related dynamics this HPPC profile was run at 20 °C, 30 °C, 40 °C, and 50 °C. Thus, enabling the empirical model to be valid from 20 °C to 50 °C. This method can lead to an over-fit and specific set of parameters to a single cell. Due to the goal of the emulator needing to represent batteries generally, the parameter space is further generalized by the method of multivariate polynomial response surface approximation. Making use of Pascal's triangle we can expand the polynomial surface to enable a more accurate and general representation of the parameter surface. This method has been demonstrated by Downey et al. [30], to develop generalized surfaces to represent surface strain across multiple data points. Due to the testing performed on a single K2 energy 26650. A lower order polynomial approximation is used to capture the general shape of the battery's parameter spaces. Bellow in Figure 2.8, the generalized electrical parameters across both the SOC and temperature range can be observed with the RMSE error listed in Table 2.1. Larger scale testing of multiple cells will lead to higher order approximations and thus a more accurate parameter space for the model.

Table 2.1 The RMSE values for each generalized parameter surface to the found parameters at each testing location across state of charge and temperature.

Parameter	RMSE
$R_{ohm}(m\Omega)$	2.5 m Ω
$R_1(m\Omega)$	1.1 m Ω
$R_2(m\Omega)$	4.0 m Ω
$\tau_1(s)$	4.1 s
$\tau_2(s)$	8.9 s
OCV (mV)	50.5 mV

As for the thermal model, the necessary parameters are mass, density, and thermal resistance to the ambient conditions. These parameters can be directly fitted to constant current discharge tests under controlled ambient conditions. To do this 1C-rate constant current discharges on the K2 Energy 26650 LFP cell were performed and recorded, Figure 2.9. Using the previously found ohmic resistances, the thermal

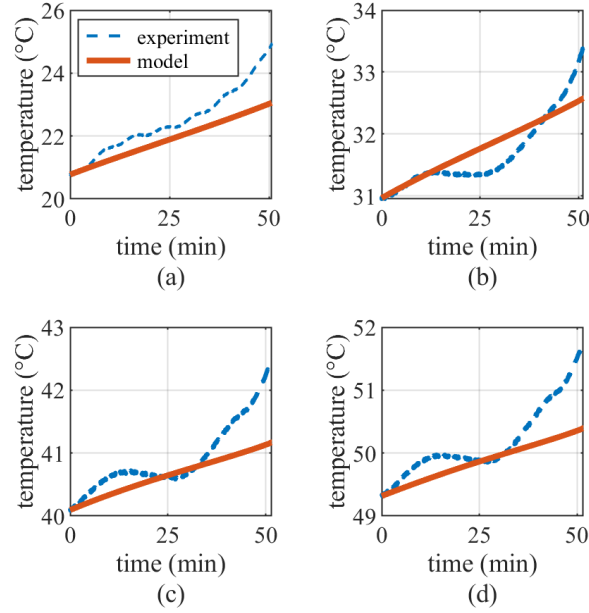


Figure 2.9 Modeled temperature response to a 1C discharge at (a) 20 °C, (b) 30 °C, (c) 40 °C, and (d) 50 °C.

heat generated can be found by multiplying the R_{ohmic} by the current. Using this, the unknown parameters were fitted using nonlinear least squares within reasonable limits. The model was able to achieve RMSE values of 0.143, 0.051, 0.065 and 0.063 °C at 20 °C, 30 °C, 40 °C, and 50 °C respectively.

2.3.6 SCALABILITY OF THE MODELS (C-RATE)

The input parameters for the 2nd order equivalent circuit model are affected not only by the temperature and state of charge, but also by the C-rate that the battery is experiencing. To account for this relationship the state parameters were assigned a uniform scaling variable, β , to find the change with respect to C-rate. Due to the focus of this paper being primarily on the hardware setup, a uniform scaling variable applied to all of the resistances was deemed sufficient. Note that the τ parameter is the products of the resistances and capacitance of the RC pair. Thus, scaling just the resistance is also scaling the τ values. The equation for this scaling variable was

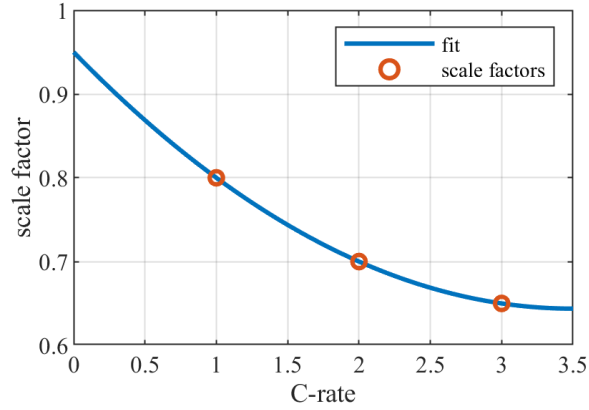


Figure 2.10 Fitted scaling variable relationship found from three discharge tests performed at C-rate of 1, 2 and 3.

an empirical fit to match discharge tests performed on the K2 26650 cell. The fitting was performed against experimental data recorded at 1, 2, and 3C discharges. Below in Figure 2.10, the individual β values that best fit each experiment are shown. Since they are shown to not be linear a 2nd order polynomial was fit to further define the relation.

With the relationship found the parameters can be adjusted to allow the coupled model to more accurately reproduce the electrical behavior of the cell. The equations for adjusting the parameters are written as

$$P_i = P_{i,0} \cdot \beta \quad (2.6)$$

where

$$\beta = (0.025 \cdot \text{C-rate}^2 - 0.1750 \cdot \text{C-rate} + 0.950) \text{ and} \quad (2.7)$$

$$P_i = [R_0, R_1, R_2].$$

Since these changes affect the terminal voltage calculation, this goes further to update the thermal output to match the new behavior of the cell with respect to C-rate. The RMSE values for the discharge tests are presented in the results section.

2.3.7 SCALABILITY OF THE MODELS (CELLS TO PACK)

To be more practical to real world applications, the coupled model needs the ability to represent batteries at the pack level. To do this, simple modifications can be made to both the electrical and thermal models. First, there can be two approaches to scale the electrical model's behavior. The input parameters can be individually scaled to match that of a pack level, or the current inputs and voltage outputs can be scaled corresponding to the desired packs size and arrangement. The latter option is preferable due to the minimum number of changes to the model. This further helps limit the computational burden when employed on hardware and allows for variable battery sizing. To do this, the desired battery pack series and parallel arrangement need to be known. With this, the input current to the model can be scaled down by the number of cells in parallel,

$$I_{\text{cell, input}} = \frac{I_{\text{pack, input}}}{n_{\text{cells in parallel}}}, \quad (2.8)$$

solving for the current that a cell would experience. For the model output, voltage can be scaled up by the number of cells in series, expressed as

$$V_{\text{pack, terminal}} = V_{\text{cell, terminal}} \cdot n_{\text{cells in series}}. \quad (2.9)$$

Thus scaling the voltage from cell level to the correct pack level output.

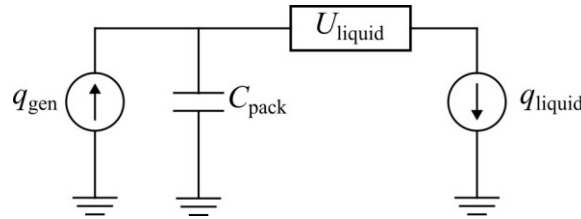


Figure 2.11 Heat transfer model for the level representation of the battery.

For the heat transfer model, a reduced order 1D lumped model is employed again as seen in Figure 2.11. To account for the heat generation g_{gen} of the total pack.

The heat generated from a single cell is multiplied by the total amount of cells in the pack,

$$q_{\text{gen,pack}} = n_{\text{total cells}} \cdot q_{\text{gen,cell}}. \quad (2.10)$$

The thermal capacitance of the cell is also scaled to match that of the pack. This is achieved by scaling the mass to the cumulative mass of the desired pack, written as

$$C_{\text{pack}} = n_{\text{total cells}} \cdot m_{\text{cell}} \cdot c_{p,\text{cell}}. \quad (2.11)$$

At the pack level, the heat transfer driving force is primarily the convection into the coolant. To calculate the temperature differential for the driving force, the log mean temperature (LMTD) of the coolant is utilized as

$$\text{LMTD} = \frac{T_c - T_h}{\log\left(\frac{T_c}{T_h}\right)}. \quad (2.12)$$

The LMTD, enables a more averaged heat transfer calculation that accounts for the temperature gradient between the inlet and outlet of the coolant flow. T_c represents the temperature difference between the inlet and battery, while T_h represents the temperature difference between the battery and outlet. In the presence of a non-uniform coolant temperature throughout the cooling plate, this provides a better representation of the heat flow to coolant. This can be implemented at the pack level as

$$C_{\text{pack}} \cdot \frac{dT_{\text{pack}}}{dt} = -U \cdot A_{\text{conv}} \cdot \text{LMTD} + q_{\text{gen}}. \quad (2.13)$$

where a single parameter U describes the overall heat transfer coefficient from the battery to the liquid, A_{conv} is the convective surface area, and LMTD is the effective differential of the inlet and outlet.

2.3.8 EMULATOR HARDWARE

With the generalized coupled model fully developed, the model can now be deployed onto hardware. The hardware needs to have a real-time controller with a means of

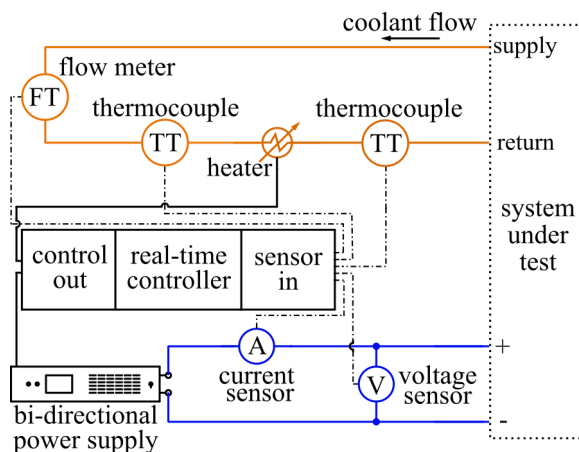


Figure 2.12 Diagram of the emulator hardware; Showing the electrical emulation loop in blue, thermal emulation loop in orange, controller hardware in black, where the connections to external systems are dashed.

replicating the electrical and the thermal response of the battery. This is done with a cRIO 9054 real-time controller, ITECH 6006C Bi-Directional power supply for the electrical response, and a BK 9103 power supply for the thermal response. A hardware diagram is shown in Figure 2.12 and physically configured in Figure 2.13. The coupled model execution and data acquisition is performed by the real-time controller. Both executing the model and sampling the thermal and electrical sensors at a rate of 100 Hz.

For emulation of the electrical response a bi-directional power supply is needed, as seen in colored blue in Figure 2.12. The importance of a bi-directional power supply is its ability to not only provide power but also to sink it. This facilitates the emulation of both charging and discharging behaviors. The selected bidirectional power supply for this study is the ITECH 6006C-500-40 which provides an output range of 6 kW limited to 500 V and ± 40 A with a transient voltage response time of ≤ 2 ms. This enables the emulation for a maximum pack configuration of 156S for the maximum voltage, or 15P for the maximum of 40 A being a 1C discharge for K2 energy cells. This power supply also provides the benefit of analog control which provides access

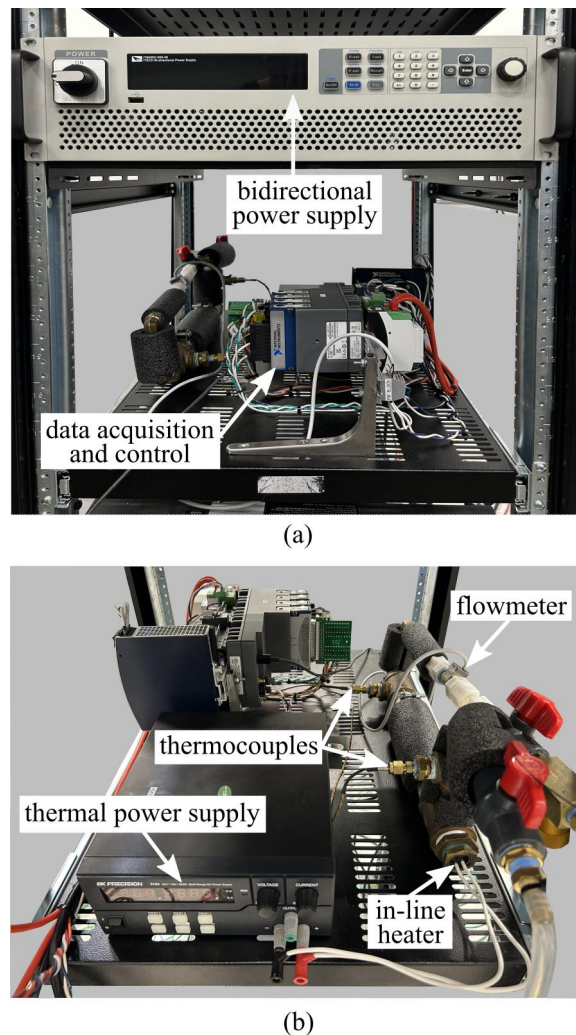


Figure 2.13 Physical hardware layout where (a) is the front facing view and (b) is the rear.

for a continuous and easy to implement control method from the cRIO. For electrical feedback, a current sensor is in line with the output connection, and a voltage sensor is used to monitor the output voltage. At the first time step of operation the cRIO will tell the bi-directional power supply to set its output to the open circuit voltage of the battery. Once set the load will then begin to draw a current based off the voltage. Once the current starts to flow the current sensor will record and inform the controller of the amount of current the load is pulling. This is in effect the load across the emulated battery. The controller will then make use of this information

in the model and calculate the new voltage output of the emulated battery. Once done the controller will send that command to the power supply thus emulating the electrical characteristics of a battery through hardware.

For the thermal emulation, only liquid cooling can be performed. The emulator has an internal cooling loop with an inline heater controlled by a power supply as seen colored orange in Figure 2.12. There are also thermocouples placed before and after the heater as well as a flow meter. To interface with external cooling systems there is an inlet and outlet port. For the testing of this system an external pump, tank, and radiator were added. How all these parts come together during operation is as follows, On the initial time step of operation the real-time controller will take temperature readings and the flow rate of the coolant as well as the initial temperature of the emulated battery as set by the model. Using this information as well as the heat generated from the electrical model, the thermal model will then determine the surface temperature of the battery. Making use of a proportional–integral–derivative (PID) controller, the real-time controller will then send control signals to the power supply that controls the heater. The PID adjusts the control signal to the heater to match the calculated temperature of the battery. This flow of events continues for as long as the emulator is being operated, thus emulating the thermal responses of a liquid cooled lithium-ion battery. Since this design is made to replicate the dynamics of the battery, tuning the PID controller is a priority. There is a time delay due to the transient nature of the thermal system. To account for the delay between commanding a wattage at the heater and an observable temperature increase at the outlet, a Smith predictor structure [31] was created. In the Smith predictor structure, two transfer functions that represent the thermal system; one with and one without a time delay are developed. Both transfer functions are used as feedback to the PID enabling the controller, with Simulink's PID tuner app, to be tuned to operate the system with as little delay as possible.

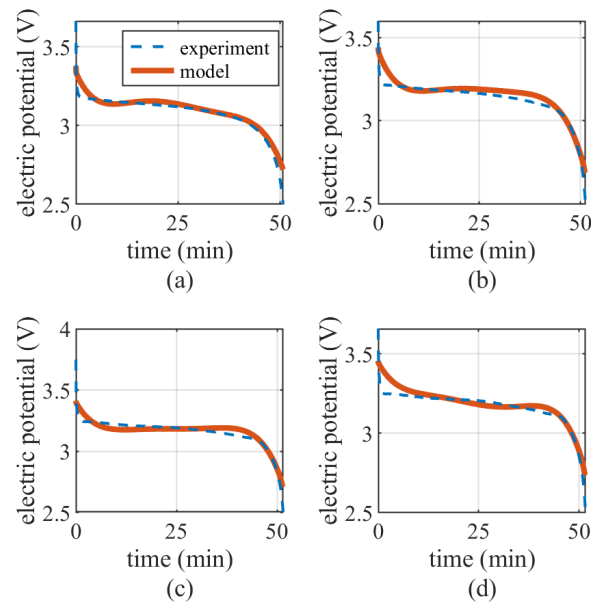


Figure 2.14 1C discharge at (a) 20°C, (b) 30°C, (c) 40°C, and (d) 50°C.

2.4 RESULTS

Validating the accuracy of the single cell electro-thermal model is a critical step to establish confidence in its predictive capability and suitability for real-time emulation. To gauge the model performance, a set of 1C discharge tests was conducted on the model using the K2 Energy 26650 LFP parameters across a range of temperatures. These tests were designed to evaluate the model's ability to capture the temperature dependent electrical dynamics found during constant current operation at varying ambient conditions.

Figure 2.14 presents the electrical model's response compared to the experimental discharge voltage curve across the temperature range of 20°C to 50°C. As expected from electrochemical theory, the discharge voltage increases with temperature and improved electrochemical kinetics. The model successfully replicates this trend, showing strong agreement with the measured data across the temperature range. Achieving RMSE values of 21, 22, 22 and 25 mV at 20°C, 30°C, 40°C, and 50°C respectively. The voltage RMSE values are provided along with the temperature RMSE values, in

Table 2.2 Summary of the voltage and temperature RMSE values for the the single cell coupled model against 1C discharge experiments performed at 20 °C, 30 °C, 40 °C, and 50 °C.

	Voltage RMSE	Temperature RMSE
20°C	21 mV	0.143°C
30°C	22 mV	0.051°C
40°C	22 mV	0.065°C
50°C	25 mV	0.063°C

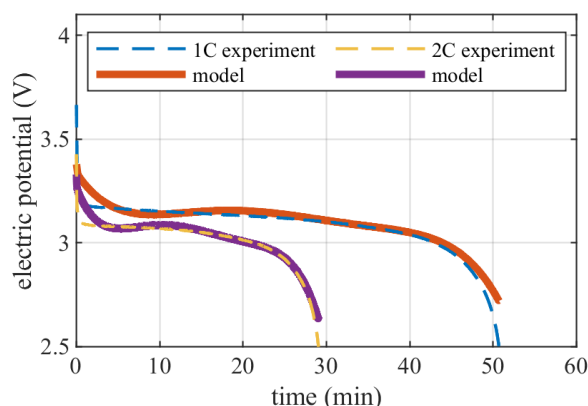


Figure 2.15 Modeled and experimental voltage response at different C-rates.

Table 2.2, from the data collection section for a full view of the model performance.

This fidelity is achieved using the previously mentioned SOC and temperature generalized parameter surfaces. Enabling the model to dynamically adjust key parameters such as the internal resistances, OCV, and SOC base off the temperature of the battery. By exploiting the single bivariate polynomial for each parameter, the model can provide accurate results without significant computational complexity. The results of this model provide confidence in the single-cell model's accuracy in both the thermal and electrical domain, providing a reliable foundation for scaling up to a pack level response.

To further validate the model C-rate scaling is important for the electro-thermal emulator as discussed in the previous section. To validate the model's ability to capture the C-rate dependent dynamics, two constant current discharges were per-

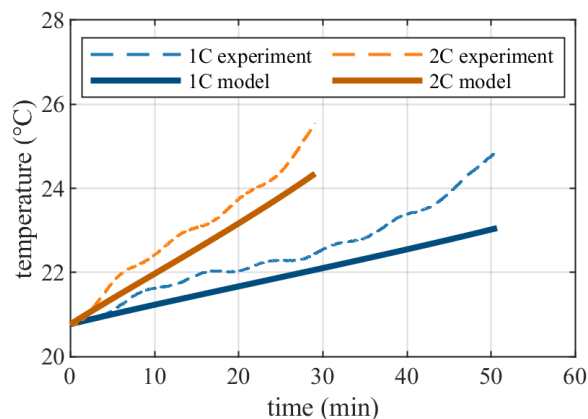


Figure 2.16 Modeled and experimental thermal response at different C-rates.

Table 2.3 The voltage and temperature RMSE value reported for the single cell model against experimental discharge data at a C-rate of 1 and 2.

C-rate	Voltage RMSE	Temperature RMSE
1	20 mV	0.142°C
2	17 mV	0.113°C

formed at a constant ambient temperature. Seen in Figures 2.15 and 2.16, both the capacity and drop in voltage is affected by this. With the scaling term discussed in the methodology section, the model can accurately reproduce the change in voltage dynamics with RMSE value of 20 and 17 mV at C-rates of 1 and 2. This is significant as this result means the electro-thermal emulator can reproduce discharge rates up to 2C. Since the temperature response is also affected by the C-rate. This too was validated from the same tests. The model is also able to reproduce the change in temperature response from the scaled ohmic resistance. With RMSE values of 0.142 and 0.113 °C at a C-rate of 1 and 2. Both the voltage and temperature RMSE values are organized in Table 2.3.

2.4.1 PACK LEVEL CASE STUDIES

With the single cell model validated, the model was then deployed on the hard-

ware. There are two outputs that need to be validated on the hardware, the voltage response and heat transfer to coolant. To get pack level outputs a battery pack configuration of 44S8P was set in the electro-thermal emulator. Composed of the K2 Energy cell, a pack this size results in a nominal voltage of 140.8 V with a capacity of 17.44Ah. To validate the hardware's ability to reproduce the electrical and thermal responses of the model two case studies were developed. These studies investigate the hardware's ability to emulate the modeled response of the battery under a time varying load and a use case for emulation during a fault. To gauge usefulness, the emulator's performance in the case studies is analyzed by three key metrics. First is the RMSE to gauge the amplitude fitness of the emulated output to the model. The second metric to be utilized is the Pearson correlation with a time shift. The Pearson correlation can be used to compare how similar two vectors are judged by the magnitude of the correlation coefficient value (r). A higher value means the more similar the two vectors are. For time series data, one of the vectors can be evaluated over a time shift range with each time shift generating a new correlation value. This metric will provide the effective time delay (τ) between the emulated (x_i) versus the modeled (y_i) outputs by finding the time shift with the highest correlation, written as

$$r = \max_{\tau} \left\{ \frac{\sum_{i=1}^N (x_i(t) - \bar{x})(y_i(t + \tau) - \bar{y})}{\sqrt{\sum_{i=1}^N (x_i(t) - \bar{x})^2 \sum_{i=1}^N (y_i(t + \tau) - \bar{y})^2}} \right\}. \quad (2.14)$$

With the delay determined from the Pearson correlation the third metric can be applied, time response assurance criterion (TRAC). TRAC is used to gauge the similarity in terms of shape for the time adjusted signal and the modeled output [32]. The TRAC equation,

$$\text{TRAC} = \frac{\left[\sum_{i=1}^N x_i, y_{i+\tau} \right]^2}{\left(\sum_{i=1}^N x_i^2 \right) \left(\sum_{i=1}^N y_i^2 \right)}, \quad (2.15)$$

is a time-domain correlation metric that quantifies the similarity between two dynamic responses. The TRAC metric can range from 0 to 1, where 1 is a perfect signal to

Table 2.4 A summary of the errors for the experimental emulated voltage and thermal outputs of the emulator compared to the modeled outputs for Cases 1 and 2.

	Parameter	RMSE	TRAC	τ (s)
Case 1	V	46.7 mV	0.9963	1
	Q	0.359 W	0.8850	0
Case 2	V _{healthy}	14.1 mV	0.9998	0
	Q _{healthy}	0.155 W	0.9979	0
	V _{damaged}	17.9 mV	0.9998	0
	Q _{damaged}	0.167 W	0.9936	0

signal match in terms of shape and phase. Using these three metrics we can define the amplitude error (RMSE), shape (TRAC), and delay(τ) to adequately compare the emulated and model signals for each case study. A summary table of these metrics for the case studies is provided in Table 2.4.

2.4.2 CASE STUDY 1: DYNAMIC LOAD (DRIVE CYCLE)

The first case study investigates the emulated battery under the loading of a time varying load profile. The chosen load profile is the Urban Dynamometer Driving Schedule (UDDS) load profile, seen in Figure 2.17. This profile is a general profile given by the Environmental Protection Agency (EPA) that represents the load seen by a battery during urban driving conditions. The purpose of this case is to investigate the emulator's response time and accuracy in physically emulating the modeled pack level response of the pack under highly dynamic conditions.

Figure 2.18, Shows the emulation results during this case study. The electrical model response shows a rapidly changing voltage in response to the varying UDDS load profile. The emulator's response, shown by the solid line, follows the modeled response accurately. There is little lag in the physical voltage response (a) compared to the modeled voltage response and was able to achieve an RMSE value of 46.7 mV, TRAC score of 0.9963 and an effective delay of 1 s. The thermal emulation results are

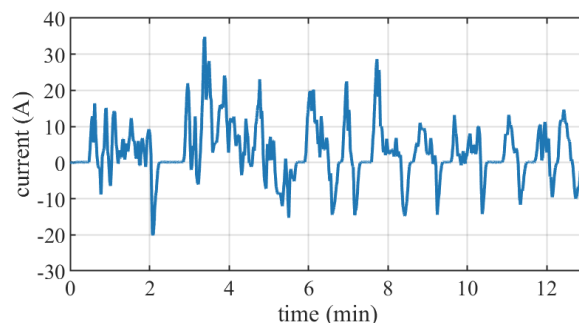


Figure 2.17 The EPA's Urban Dynamometer Driving Schedule load profile.

shown in, (c), the heat transferred to coolant graph. At the start of the emulation the modeled thermal response instantly predicts a heat transfer rate of 6 W into the coolant, causing the PID controlled thermal emulation to quickly ramp up and overshoot the model. This is believed to be caused by improperly set initial conditions on the emulated battery compared to the real inlet and outlet temperatures seen in the physical liquid cooling loop. This leads to the thermal emulation to achieve a RMSE value of 0.359 W and TRAC score of 0.8850 with no effective delay. Regardless, this is still an informative response as it shows how quickly the emulator can adjust its heat transfer rate into the coolant and the resulting overshoot of that action by the PID. As time progresses from the initial overshoot, the emulated heat transfer rate begins to converge but is continually disturbed by the time varying thermal response to the UDDS profile. This case gives key insight to the current emulator's limitations in replicating the thermal response of a pack under a time varying load profile.

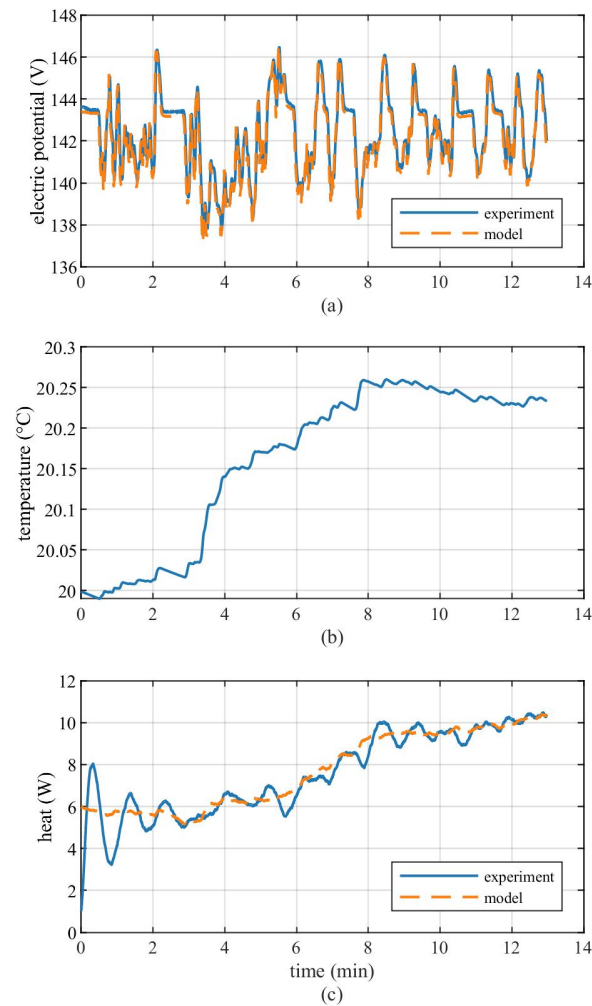


Figure 2.18 Emulator and modeled responses to UDDS load profile. Specifically showing: (a) voltage, (b) pack temperature, and (c) the heat transfer rate to the coolant.

2.4.3 CASE STUDY 2: LOSS OF A PARALLEL STRING

Case two involves the loss of two of the parallel modules as seen in Figure 2.19. The expected result is to see a drop in both state of health and SOC, as $1/4^{\text{th}}$ of the battery has been disconnected. The resulting voltage should follow a similar shape but reach the knee-off region more quickly. The current profile is expected to remain the same since the pack will still supply the same total load. However, with two modules down, the remaining modules will bear a larger load, resulting in an expected increase in

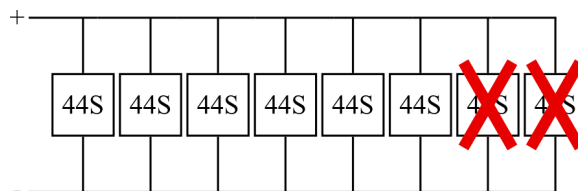


Figure 2.19 The full emulated pack, showing the two modules disconnected during the second Case study.

temperature.

Figure 2.20 shows the modeled and emulated voltage and temperature response of both a healthy pack and a damaged pack that loses two modules at 21 min. As the modules are disconnected, an instant drop in voltage is seen and starts to immediately deviate from that of the healthy pack. This deviation is due to the increased current in each remaining module. It can also be seen that the damaged pack reaches full discharge sooner than the healthy pack due to $1/4^{\text{th}}$ of its capacity being lost. Looking at the solid lines, the emulator was able to reproduce both the healthy and damaged voltage curves, (a), accurately throughout the test. There was no effective delay in the emulated voltage response to the disconnecting of the two modules resulting in the instant drop and deviation. The resulting RMSE and TRAC scores of the emulated to the modeled voltage is 14.1 mV and 0.9998 with no delay for the healthy pack. The damaged pack achieved and RMSE of 17.9 mV and a TRAC metric of 0.9998.

Similarly, the temperature response, (b), diverges immediately, with the damaged pack showing higher temperatures as the remaining modules handle the increased load. This temperature increase leads to a higher heat transfer rate to the coolant. For most of the tests, both the healthy and damaged pack's heat transfer rates were accurately emulated through the emulator's Smith predictor based PID controlled heater. However, around 40 W an oscillation begins to develop with an increasing amplitude in the damaged test. This shows the PID is becoming unstable during the emulation of higher heat transfer ranges. This leads to higher RMSE values

for the thermal emulation of 0.155 and 0.167 W for the healthy and damaged pack respectively. The TRAC scores were 0.9979 and 0.9936 for the healthy and damaged packs, both with no effective delay. The cause of the developing oscillations at rates just above 40 W indicates nonlinear behavior rooted in a changing convective heat transfer coefficient within the heater-coolant contact area. If the Smith predictor's transfer function feedback does not account for nonlinear behavior, then the PID tuning is no longer valid at that range. However, this heat transfer rate is nearing the extreme end of validity for the electro-thermal model and methods to account for the non-linearity was not pursued. In future cases, the PID control with the Smith predictor compensation needs to be extended to account for the non-linearity for emulation of larger packs and cooling rates. However, this case does demonstrate that the emulator can accurately replicate a battery pack's electrical and thermal response given the oscillations in the thermal control.

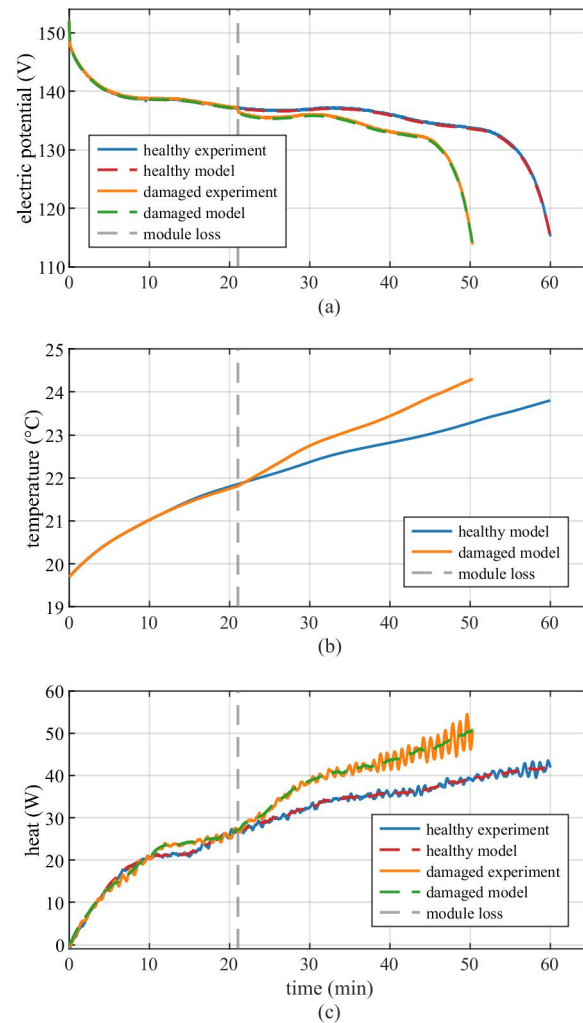


Figure 2.20 Showing the Emulator and modeled (a) voltage, (b) pack temperature, and (c) heat transfer to the coolant response to a fault event in which two parallel modules are lost.

2.5 DISCUSSION

Emulator accuracy is limited by the fidelity of the coupled electro-thermal models used in this investigation. In this work a 2nd order equivalent circuit model was used for the electrical dynamics and a lumped 1D heat transfer model was used for the thermal dynamics. Both models were selected for their simplicity and computational efficiency, however they may fail to capture more complex cell dynamics. Also, this

study used only data from a single cell to parameterize the entire battery pack. This approach ignores all scenarios where one cell might have a different resistance than another (i.e. cell-to-cell variability); which can lead to accelerated degradation of the full-size pack [33]. Testing of multiple cells is required to account for uncertainty and further refine and the generalized parameter spaces.

The thermal modeling approach taken in this paper leveraged a 1D lumped model, which again does not account for cell-to-cell variation or hot-spots that may lead to accelerated degradation. The modeling approaches taken in this work meets the minimum requirement for testing battery packs. However, when localized cell degradation is of interest, the thermal model's fidelity needs to be increased as thermal gradients have been shown to be a contributor to cell degradation [34]. Leveraging a higher fidelity thermal modeling approach that considers axial, radial and cell to cell heat transfer is left to future work.

The current hardware used to produce the model's desired electrical and thermal domains also limits the outputs of the electro-thermal emulator. In this work the electrical response is reproduced by controlling a bi-directional power supply (ITECH 6006C) which is limited to a 6 kW output with 40 A and 500 V limits. The emulated 2.45 kWh battery discussed in the results section was limited to a 2C discharge before hitting the extreme end of the power supply's limitation. For packs reaching automotive-scale sizes, a larger bi-directional power supply (or more power supplies connected together) can increase the system's usable output. Thus, increasing the size of the battery pack that can be emulated electrically. The thermal emulation was performed through the Smith predictor based PID controller operating the in-line heater powered by a power supply (BK 9104). For emulation of a larger pack the Smith predictor structure needs to be extended to account for the non-linear control ranges in the heating system. Depending on pack size the heater and power supply needs to be scaled to accurately reflect that heat; considering that modern

batteries today have thermal efficiencies of 98% under normal conditions [35]. It is recommended to oversize the heater and power supply to allow for more aggressive control and account for higher C-rates. The current power supply is able to represent a 16 kWh battery pack under normal (1C) loading.

2.6 CONCLUSION

Naval, aerospace and automotive industries are all moving toward electrified systems with battery integration. The design phase testing of these systems is limited, requiring large cost and time commitments, as batteries are inherently slow due to long charge and discharge cycles while degrading with each use. To minimize these commitments, battery emulators have been developed to enable rapid testing of the systems without the constraints of a physical battery. However, current battery emulators only emulate the electrical behavior and do not consider the thermal behavior. In multi-domain testing, the thermal response also needs to be emulated. The development reported in this paper enables liquid-cooled system hardware under development to be tested for both electrical and thermal operations.

This work introduces and demonstrates an electro-thermal HIL system that allows the electrical and thermal domains of battery packs to be emulated in place of physical ones. To do this a coupled electro-thermal model was developed using a 2nd order ECM for the electrical response and a reduced order lumped heat transfer and generation model for the thermal response. The model parameters are characterized from a K2 Energy 26650 LFP cell. A 44S8P pack is modeled by scaling the inputs and outputs of the model. The coupled electro-thermal model is implemented into a HIL setup enabling; electrical emulation through a bi-directional power supply, and thermal emulation through a heater in a liquid cooling loop. Time varying and fault responses of the emulator are tested by two case studies. In the time varying case, both the electrical and thermal emulated outputs kept pace with the rapidly changing

drive cycle load profile. For the fault case, two modules were disconnected during a 1C discharge. In the case of the faulty battery, the emulated response replicated the expected instantaneous drop in voltage and increase in heat generation. Analysis of the studies showed the emulator can accurately replicate the modeled response to both cases. Across both case studies, the maximum RMSE was 46.7 mV electrically and 0.359 W thermally with the lowest TRAC score being 0.8850. However, some thermal control instability was present at the higher heat transfer rates.

The implications of this approach provide major benefits during a system's design phase; particularly related to cost, safety, and time. To test a BMS or external functionality of a system with a real battery requires a significant investment in time related to recharging batteries after each test. Whereas with the electro-thermal battery emulator the testing time will only be limited to the test itself. After any testing profile the electro-thermal battery emulator can be immediately re-initialized back to any SOC or temperature needed. This enables savings in time investment to design a system that requires battery integration. Safety is also a major concern for large lithium-ion battery packs; particularly for edge case testing of stressful scenarios or investigations into faults. If a real battery is being pushed too hard, it can cause venting of harmful gases and even thermal runaway resulting in explosion in the worst of cases. For a testing environment this is a major concern for the safety of anyone or equipment near the battery. As for investigations into a system's response during scenarios where the battery itself experiences a fault, replicating a fault within a battery safely is next to impossible, and even if done, it still requires faulting the battery. Large battery packs are expensive and destroying one for a single test will lead to increased cost during the testing phase. For these scenarios the electro-thermal battery emulator would be a key tool. It can accurately replicate faults for tests without the need to be replaced. Further, the electro-thermal emulator enables is the testing of different packs.

When considering iterative systems design, the electro-thermal battery emulator enables an easy pipeline to emulate batteries of differing chemistries. This allows the effects of different dynamics to easily be investigated for use within a system. For example, an LFP chemistry is being investigated for implementation into a system. Due to LFP's low energy density, the required pack may occupy too large of a volume to be a viable option. In this case, the electro-thermal emulator can be used to easily switch to an NMC chemistry to test a smaller battery pack but with a higher energy density. This will fulfill the energy requirement within the allotted space and weight, However NMC chemistries are more thermally unstable than an LFP. The electro-thermal battery emulator can be further used to investigate if the current system can provide enough cooling through thermal emulation. If the cooling is insufficient, the emulator can be used to quickly increase the size of the pack, generating less heat from the individual cells to find a middle ground. Investigations about battery size and chemistry can be easily tested and answered with the use of the electro-thermal battery emulator.

Future work may include the use of machine learning models to capture the more complex dynamics of a lithium-ion battery and improve generalization. These models can be computationally efficient once trained. However, training requires a larger data set. To minimize the large data set requirement, physics-informed machine learning models can also be investigated. By including known dynamics and constraints, both the data set requirement and training time could be minimized. Leading to a potentially more flexible, easy to train, and higher fidelity model for the electro-thermal battery emulator.

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gratefully acknowledged. Any opinions, findings, conclusions, or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the United States Navy. This work has been Approved for public release with unlimited distribution on 01/29/2026 under the DCN# 2026-1-9-1845.

CHAPTER 3

ADAPTIVE AGENT-BASED CONTROL FOR LITHIUM-ION BATTERY MANAGEMENT IN NAVAL MICRO-GRIDS

3.1 INTRODUCTION

Modern naval micro-grid infrastructure is facing higher powered loads with large transient swings. It is crucial to maintain bus stability while being able to meet critical loads such as radars and direct energy weapons [36]. To handle these high-powered loads the on-board generators would be forced to ramp at unsustainable rates, damaging the machinery and under serving quick-acting pulsed loads [37]. To aid the generators during these damaging events energy storage systems (ESS) are being implemented. ESSs provide the capability to handle the large amplitude pulses that are necessary to operate these critical loads without ramping the generators. A range of ESSs are used to perform this role; capacitors are great at fast power delivery but hold limited energy, while flywheels provide similar power but are expensive and large. Battery energy storage systems (BESS), offer higher energy densities and reasonable power delivery. Making them well suited for buffering grid level fluctuations; however, when pushed to deliver high-rate power, they experience accelerated degradation and can become thermally unstable [38]. This motivated the development of a hybrid energy storage systems (HESS) that pair the rapid power delivery of capacitors with the energy density of batteries to meet high-powered pulsed loads [39].

Hybrid battery-capacitor storage systems are uniquely used in scenarios where higher pulsed load are required to be isolated from a main grid. High powered pulsed

loads not only cause damaging voltage swings at the bus level but they can also inject harmonics [40] into the bus. Most sensitive electronic on the bus that use low level control voltage can absorb these harmonics which leads to damaging the most critical systems on board. A method to prevent such damage is to isolate the intense load from the grid and supply it power from hybrid energy storage system like the battery-capacitor system. In doing so, the capacitor can provide the large amount of power needed to operate systems like rail guns and direct energy weapons while the slower acting battery can act as a recharge mechanism. Due to the higher energy capacity and fair power level, the capacitor can be recharged at a fast rate after depleting its charge for the load. When the battery is not charging the capacitor, it can be recharged from the main bus at a favorable power level [41]. In this way, the high-powered load can be satisfied while little to no harmful transients being pushed to the main shipboard grid. Thus, protecting sensitive electronics and allowing the generator to ramp at safe rates.

Battery energy storage system control in DC microgrids has been widely studied, with droop control emerging as the preferred method for distributed BESS coordination due to its decentralized nature and ability to achieve load sharing without requiring high-bandwidth communication. In conventional droop control, each BESS unit adjusts its output voltage proportionally to its current with a fixed virtual droop resistance R_d , enabling autonomous power sharing across the bus. While effective for basic load sharing, fixed droop control does not account for differences in battery state, meaning batteries with varying SOC levels contribute equally regardless of their available capacity. This limitation has motivated the development of SOC-based adaptive droop control, where R_d is dynamically modified as a function of each unit's SOC to achieve balanced SOC distribution across the distributed BESS. Several works have demonstrated SOC-adaptive droop in DC microgrids, showing improved SOC balancing and extended operational range compared to fixed droop implementa-

tions. This approach has also been extended to shipboard DC microgrids, where SOC balancing is particularly important given the isolated nature of naval power systems and the absence of a utility grid connection.

Despite these advances, SOC-based adaptive droop control only involves the immediate availability of charge and does not account for the long-term health of the battery. Battery degradation in lithium-ion cells is driven by a combination of factors including average SOC, depth of discharge, temperature, and charge rate, each of which accelerates capacity fade at different rates. In high C-rate applications, repeated fast charging is particularly damaging, contributing to lithium plating, SEI layer growth, and accelerated capacity fade. While SOH estimation methods for lithium-ion batteries are well established, ranging from empirical capacity fading models to equivalent circuit-based estimators, their integration into real-time BESS control loops remains limited. A small body of work has begun incorporating SOH as a weighting factor in energy management and droop control, typically de-rating the contribution of degraded units. However, these approaches treat SOH as a slow-varying parameter used for static re-weighting rather than as a dynamic input that actively shapes droop behavior in response to ongoing degradation. This gap is particularly consequential in naval DC microgrids where BESS units are subjected to repeated higher C-rate charging as part of a hybrid energy storage architecture supporting high powered dynamic pulsed loads such as directed energy weapons. In this scenario, the battery must repeatedly recharge a capacitor bank at higher rates following each pulse discharge event, creating a chronic stressful charge profile that conventional SOC-aware droop control is not equipped to mitigate. The work presented in this chapter addresses this gap by proposing a distributed health-aware hierarchical droop control strategy in which R_d is dynamically modified as a function of both SOC and SOH, where SOH is estimated online using an empirical capacity fade model. By incorporating battery health state directly into the droop parameter,

the proposed controller actively moderates charge rate stress on degraded units, re-distributing load toward healthier batteries and preserving remaining capacity across the distributed BESS. Thus, improving the longevity of the system overall.

The following sections of this chapter develops an adaptive agent-based control framework that incorporates the health states of a battery to improve system longevity and reliability. The proposed framework utilizes a hierarchical droop control method which is dynamically adjusted based off battery health. To determine battery health in real-time a digital twin is used to estimate and provide updates to the agent-based controller. This framework is tested through simulations to investigate the benefits of incorporating battery health states into the decentralized control of distributed ESS.

3.2 METHODOLOGY

3.2.1 ADAPTIVE AGENT-BASED CONTROL FRAMEWORK

The adaptive agent-based framework implements a dedicated agent to each ESS. The ESS comprises a battery, converter, and contactors to satisfy bus demand while maintaining safe operating conditions. Each ESS is controlled across three layers: the physical layer, sensory layer, and the agent layer as seen in 3.1. The physical layer involves the battery and converter hardware. The sensory layer houses the digital twin which receives sensor data from the hardware and sends calculated health states (SOC, RUL, T) to the agent. The Agent layer utilizes the agent to monitor and control the ESS. When the health states are calculated from the digital twin, the agent receives them and proceeds to adjust the battery output by dynamically changing the droop resistance (R_d) in the converter control with the goal of extending RUL. The agent's logic is determined by monitoring constraints and load on the auxiliary bus. In doing so the agent adheres to three operational modes: charge, discharge, and idle. First the agent adheres to safety by entering "idle mode" which disconnects the

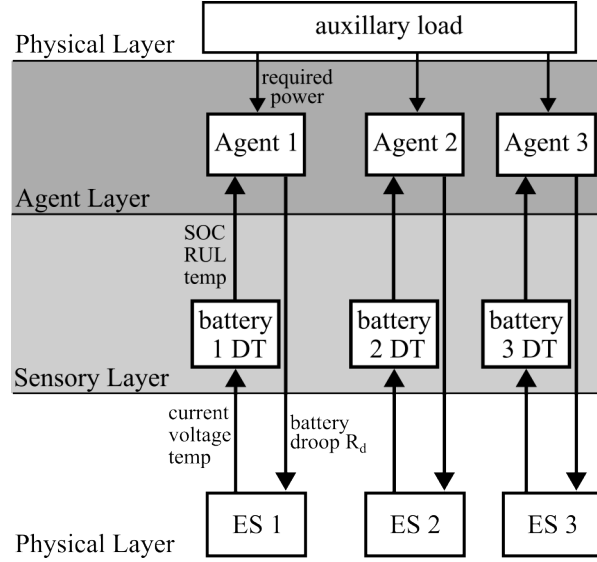


Figure 3.1 The three-layer architecture of the adaptive agent framework when the auxillary load is active. The Physical Layer includes ES units (ES3 is the emulator), the Sensory Layer uses digital twins (DT) to monitor state (SOC, RUL) in coordination with the Agent Layer to issue droop values (R_d) for each battery.

ESS when constraints are violated. The agent monitors both temperature and SOC constraints. Ensuring the battery stays under a predefined maximum temperature (T_{max}) which is known to accelerate degradation [42]. If the battery is under the thermal constraint the SOC and load activity will determine the selected operational mode. 1) if $SOC \leq 10\%$ charge mode is selected; 2) if $SOC \geq 90\%$ and there is load present on the auxillary bus, discharge; 3) if there has been no load activity for the last 30 seconds, charge; 4) if there is load activity and SOC is within the SOC limits, then droop resistance are calculated and sent to the converter. Once the converter receives the updated droop resistance its output voltage is set by

$$V_{set,i} = V_{bus} - R_{d,i} I_i \quad (3.1)$$

where $V_{set,i}$ is the converter output voltage, V_{bus} is the auxillary bus voltage, I_i is the ESs current contribution, and $R_{d,i}$ is the resistive droop coefficient. Using hierarchical droop, distributed agents manipulate $R_{d,i}$ at three levels. *Primary* control distributes

load across all available ES units using a nominal droop resistance $R_{d,0} \approx 0.33$.

This was chosen to explore load sharing, assuming there are not constraints on bus voltage sag for this investigation.

Operating at the extremes of the SOC range accelerates degradation and heat generation in a lithium-ion battery [43], [44]. Therefore, to encourage convergence toward mid-range SOC, *secondary* control influences the nominal droop resistance using

$$R_{d,\text{SOC}} = R_{d,\text{base}} \cdot (1 + \alpha(\text{SOC} - 0.5)^2) \cdot (1 + \beta \cdot \text{sign}(0.5 - \text{SOC})) \quad (3.2)$$

when discharging, where α and β are constants that determine the rate that SOC will converge. When charging, the agent controls SOC convergence using

$$R_{d,\text{SOC}} = R_{d,\text{base}} \cdot \text{SOC} \quad (3.3)$$

to charge at a greater current when the battery is at a lower SOC; however, this system is not designed to absorb surplus energy on the grid, so the contactors will open, rather than charge, when $\text{SOC} > 0.5$.

In implementation, $R_{d,i}$ must be bounded not only to avoid overly aggressive load sharing, but also to ensure the associated converter controls remain stable. In droop-controlled converters, excessively small droop resistance can create a flat I – V characteristic, increasing sensitivity to measurement noise and inner-loop delays, while excessively large droop resistance can lead to sluggish response and poor bus-voltage regulation. Accordingly, the selected droop values are constrained to a stability-preserving range,

$$R_{d,\min} \leq R_{d,i} \leq R_{d,\max}, \quad (3.4)$$

where $R_{d,\min}$ is chosen to maintain adequate damping and phase margin of the combined inner current loop and outer voltage loop, and $R_{d,\max}$ is selected to limit steady-

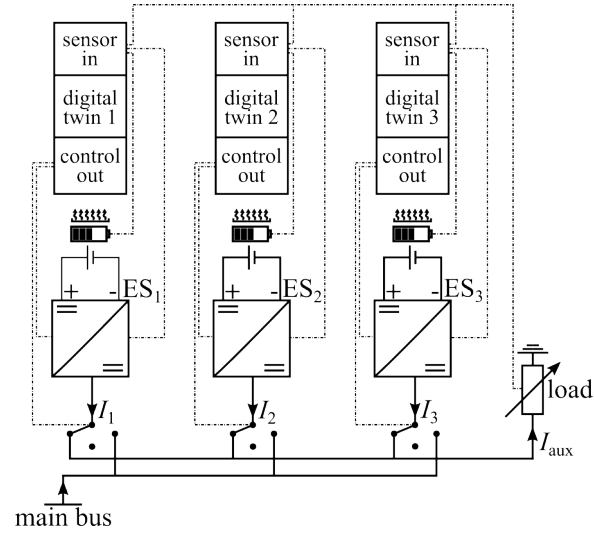


Figure 3.2 Schematic of the experimental setup. A microgrid with three ESS (ES₁, ES₂, ES₃) is shown. Each ESS is governed by a digital twin running on a real-time controller to observe the system state, change voltage set points, and switch between charging, discharging, and standby.

state bus-voltage deviation under the maximum expected current. To prolong system life and decrease maintenance costs, the distributed energy storage units should reach end of life approximately the same time t . The agent accomplishes this via the *tertiary* control using

$$R_{d,RUL} = \frac{R_{d,SOC}}{RUL^2} \quad (3.5)$$

where $RUL \in [0, 1]$ is the remaining useful life (RUL).

RUL is defined from the capacity fade ratio C_i/C_0 , where C_i is the current capacity and C_0 is the original capacity. The unit is considered end-of-life at 80% remaining capacity, so

$$RUL = 1 - \frac{1 - \frac{C_i}{C_0}}{0.2} \quad (3.6)$$

3.2.2 DIGITAL TWIN IMPLEMENTATION

Shown in Fig. 3.2, is the system architecture used to investigate the proposed framework. The testbed consists of three ESS connects to a shared DC microgrid and tasked to supply load to an auxiliary pulsed load. Each ESS contains a battery, DC-DC converter, and contactors, and is supervised by a digital twin implementing an associated adaptive agent. Each agent transmits a droop coefficient $R_{d,i}$ to its corresponding ESS converter and receives real-time voltage, temperature, and load demand feedback. When the load is inactive, the agent determines whether the battery switches to the main bus to charge, or switches to idle too cool.

To inform the adaptive agents, the digital twins must predict each battery SOC, RUL, and temperature, given the load profile. SOC estimation is done by coulomb counting as

$$SOC(i) = SOC_{i-1} - \frac{1}{C_i * 3600} \int (I(t)dt). \quad (3.7)$$

where C_i is the battery capacity in Ah, and I is the current at time step (t).

Proposed by Lam and Bauer, the event based capacity fade model dependent on temperature, state of charge, and depth of discharge for LiFePO₄ batteries is used [45]. By windowing data into the digital twin into 1800 s second frames, the capacity fade ξ_m during a window m , that discharges capacity Ah_m , is given as

$$\begin{aligned} & \xi(T_{avg}, SOC_{avg}, SOC_{dev}, Ah)_m \\ &= \left(\left(k_{s1} SOC_{dev,m} \cdot e^{(k_{s2} \cdot SOC_{avg,m})} \right. \right. \\ & \quad \left. \left. + k_{s3} e^{(k_{s4} \cdot SOC_{dev,m})} \right) e^{\left(-\frac{E_a}{R} \left(\frac{1}{T_{avg,m}} - \frac{1}{T_{ref}} \right) \right)} \right) Ah_m \end{aligned} \quad (3.8)$$

where SOC_{avg} is the average SOC, and SOC_{dev} is the normalized deviation in SOC during window m given by

$$SOC_{dev} = \sqrt{\frac{3}{Ah_m} \int (SOC(i) - SOC_{avg})^2 dAh} \quad (3.9)$$

where Ah_m is the capacity discharged, or charged, within window m .

Lam and Bauer found the battery temperature to have an Arrhenius effect on degradation where E_a is the activation energy determined from testing, R is the gas constant, T_{avg} is the average temperature for window i , and T_{ref} is the reference temperature, both in Kelvin. Parameters denoted by $k_{s,i}$ are constants determined through curve fitting.

To update RUL properly in droop control, the active battery capacity C_i is first updated in the adaptive agent to equal C_m , the active capacity is determined by

$$C_m = C_{m-1} - \xi_m \quad (3.10)$$

where C_{m-1} is the battery capacity from the previous window.

Thermal behavior is captured by a lumped capacitance model describing the transient temperature $T(t)$ as in (3.11), where C_{lumped} and R_{lumped} are the effective thermal mass and resistance to ambient or coolant as

$$T(t) = T(t-1) + \left[-\frac{1}{C_{lumped}R_{lumped}}T(t-1) + \frac{1}{C_{lumped}R_{lumped}}T_{\infty} + \frac{Q_{gen}}{C_{lumped}} \right] \Delta t. \quad (3.11)$$

The generated heat Q_{gen} , shown in (3.12), combines ohmic and polarization losses with an entropic term that may be neglected at moderate C-rates, resulting in

$$Q_{gen} = I(t)[V_{OCV}(SOC, T) - V_{term}(t)] + I(t)\frac{dV_{OCV}}{dT}. \quad (3.12)$$

Moving from single-cell to pack level follows linear scaling, where current is divided by parallel cells and voltage multiplied by series cells.

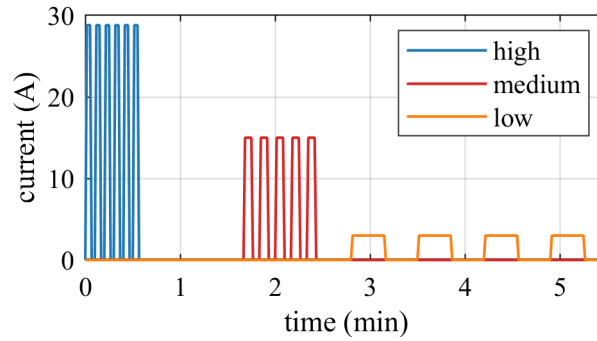


Figure 3.3 The pulsed load sequence on the auxillary bus, recharging capacitors that power six 2 s, 28.8 A pulses, five 4 s, 15 A pulses, and four 20 s, 3 A pulses.

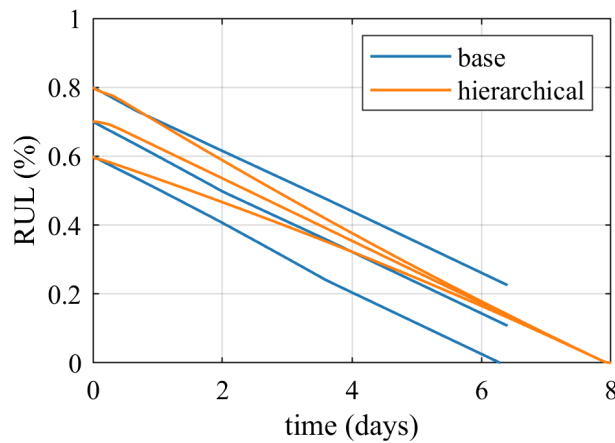


Figure 3.4 The simulated RUL of each ESS with hierarchical and primary droop control. Primary droop evenly distributes the load, while hierarchical is both SOC and RUL aware.

3.3 RESULTS

To test the adaptive agent framework, the batteries switch between a DC bus to charge from the main ship microgrid, and the auxillary load bus, shown in figure 3.2, to support the pulsed load. The selected dynamic load sequence is composed of a high rate 34.56 kJ, medium rate 30 kJ, and low rate 24 kJ pulses seen in figure 3.3. The auxillary load sequence is repeated until one ESS reaches end of life, or $RUL = 0$.

In simulation, the agents with hierarchical control are tested when ESS1, ESS2, and ESS3 begin at 80%, 70%, and 60% RUL, and 80%, 60%, and 40% SOC, respec-

tively. Under primary droop with equal load sharing, the system lifetime is 6.4 days, as shown in Fig. 3.4. When compared to primary control, the adaptive agents, utilizing all three levels of hierarchical droop extended lifetime to 7.9 days, corresponding to a 23% longer system lifetime. To reduce simulation time, the capacity-degradation term was multiplied by 1000 at each step. Therefore, the reported lifetime values should be interpreted as relative comparison metrics rather than physical service-life predictions. If actually employed, the system would last ≈ 8000 days and over 1000 times as many cycles. Furthermore, the initial difference between the lowest and highest RUL is only 20%. When the system is run with a greater difference in RUL, the increase in lifetime expectation due to hierarchical droop becomes greater.

figure 3.5 displays the current sharing and SOC of each battery under hierarchical droop control. Early in the test, SOC converges in 7.2 hrs limited by the maximum battery discharge rate of 28.8 A per battery, before the load share begins to prioritize RUL. Furthermore, across battery lifetime, the requested auxiliary load is met for 100% of the test. Comparing RUL governed by hierarchical control in figure 3.4 to the load share in figure 3.5, the load distribution trajectory changes proportional to the RUL distribution between each ES unit to increase system lifespan.

3.4 CONCLUSION

Ensuring reliable power support in naval microgrids depends on coordinating distributed battery resources while respecting electrical behavior and thermal limitations. By pairing an adaptive, agent-driven decentralized control approach with a digital twin informed hierarchical droop, this work illustrates a method to reduce system maintenance and ensure mission success. In simulation, adaptive agents employing hierarchical droop prolonged system operational lifetime by 23% when compared to even load distribution. Furthermore, the adaptive agent control scheme achieved SOC convergence in 7.2 hrs, while meeting all pulsed loads demanded of the auxiliary

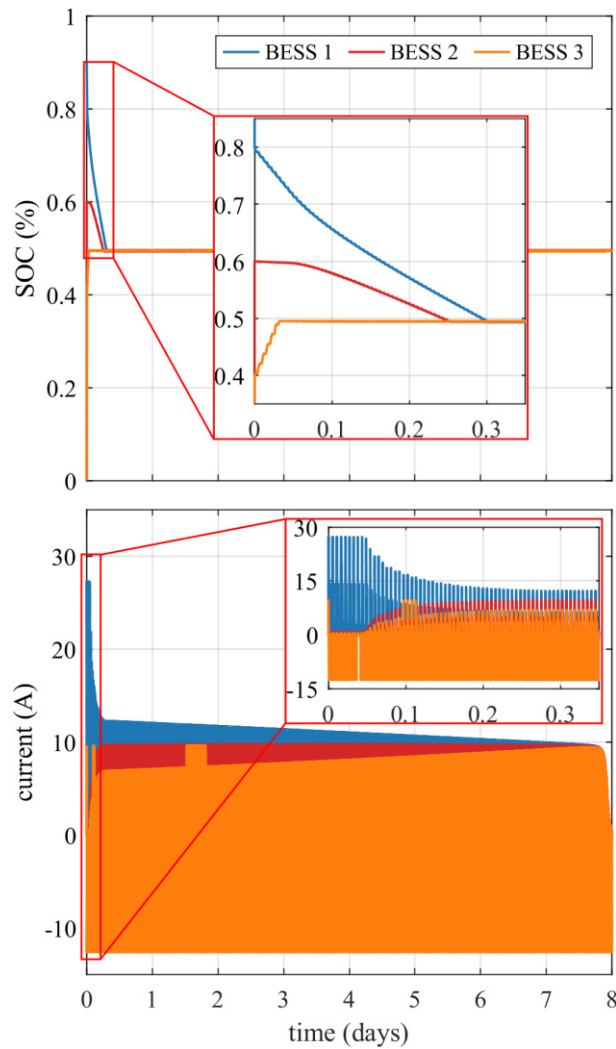


Figure 3.5 The load share and state of charge for each ES unit with hierarchical droop control.

bus. The presented framework introduces a control approach that extends the life of a multi-battery DC microgrid and demonstrates how DT-informed agents can adapt to improve mission reliability and maintenance. With higher fidelity battery digital twins this can be further improved by providing more accurate estimations of health improving the droop control adjustments.

CHAPTER 4

EDGE-BASED CONVERSATIONAL INTELLIGENT AGENT FOR A MULTI-DOMAIN DIGITAL TWIN IMAGE FRAMEWORK IN POWER ELECTRONICS

4.1 ABSTRACT

Research on digital twins for power electronics has driven the creation of a vast range of digital twin images in terms of domains and fidelities. This large library necessitates a method to select and use these digital twin images to answer specific questions. In prior works, the authors proposed a framework for asking questions to a digital twin that incorporates natural language processing (NLP) based inference algorithm which can select a combination of digital twin images to best answer the intentional meaning of a query. This NLP algorithm works to parse keywords in a user's query allowing a query-image mapping algorithm to map the keywords to relevant digital twin image and its dependencies. This required keywords to be mapped through a structured database that uses static hard coded entries to gauge the intent of the query. This is an easy to implement approach for applications that require only a limited number of digital twin images; however, it is limited in both scale and generality.

This work proposes the implementation of a large language model (LLM) based intelligent agent to be used to increase the scale and interpretability of the query. Conversational AI has become an increasingly powerful asset deployed in applications across many industries. The main benefit of these conversational AIs is their ability to

interpret general meaning and provide responses to a broad set of queries. Harnessing this capability can greatly increase the scale of the previously proposed framework and more specifically its adaptability and generality. This work demonstrates the integration of an Intelligent agent composed of a base LLM model along with a tool call framework to plug into the digital twin image portfolios addressed in the prior work. Results demonstrate and compare the key benefits such as efficiency and adaptability while discussing the challenges of intelligent agent integration.

4.2 INTRODUCTION

In recent years digital twin (DT) technology has become an innovative technology for monitoring, simulation, and optimization of physical assets in power electronics[46]. Digital twin integration into complex systems have become increasingly viable with the increase in computational resources [47]. However, many digital twin models have been developed to represent many different aspects of the same physical asset. These different representation can be referred to as digital twin images. In power electronics, images can be used to calculate the state of an asset in different domains, time steps, or fidelities. Images provide the advantage of reducing computation requirements by allowing just the necessary digital twin model to operate to answer a user's query. However, with the expanding number of images a new problem is created that needs to be solved for digital twin implementation into a complex system. A library can be compiled of many different images but knowing which ones to activate can be a challenge.

In prior work, a query and response DT framework for a multi-domain, multi-function digital image folio was applied to a DC-DC converter system [48]. User queries were mapped to digital twin images by employing a natural language processing (NLP) module in conjunction with a hard coded database of keywords and DT image mappings. This allowed user intent and digital image dependencies to be efficiently

resolved, enabling accurate image activation. The NLP approach is effective for small systems involving a fixed image set but limited in terms of scalability and generality. Manual database updates are required for each new image, the NLP fails on queries that don't involve keywords, and there is no reasoning capability for informal queries or partial descriptions.

Large language models (LLM) have demonstrated strong abilities in contextual multi-step reasoning, tool use, and semantic interpretation of natural language. LLMs combined with tool calling interfaces can work through complex tasks, recover from errors, and adapt to intermediate results [49]. An LLM agent can be implemented to generalize the connections between a user's query and a digital twin interface without requiring a manual keyword and connection database, thus improving on the scalability issues present in the NLP approach.

This paper proposes an LLM-based intelligent agent to replace the NLP and query mapping algorithm in the prior work. Deployed locally using an open-weight model, the agent accepts natural language queries, classifies intent, queries a structured DT knowledge base, resolve dependency chains, and activates the necessary DT images without hard coded mappings. The primary contributions of this work are; (1) Replacing the static NLP keyword -mapping algorithm with an LLM based intelligent agent, improving scalability and generality, (2) Engineered prompt with a three tiered classification scheme constraining agent behavior, and (3) Autonomous multi-level dependency resolution through iterative tool use, demonstrated across five test cases on a boost converter digital image folio.

4.3 METHODOLOGY

4.3.1 PHYSICAL SYSTEM AND DIGITAL TWIN MODELS

The physical system investigated in this work is a battery interfacing with a load bus through a DC-DC boost converter. The only measurable sensors are the converter

output current (`load_side_current_converter`) and the converter temperature measured at the device package. All other states including internal electrical signals and component temperatures must be determined using digital twins.

Two high fidelity DT models were defined for this system. The high fidelity electrical digital twin (`elh_dt`) uses a switching model representation of the converter. Using the `load_side_current_converter` as an input, accurate estimates of the switching and conduction power losses(`power_losses_converter`), and the input current (`input_side_current_converter`) are calculated at finite time steps. The high fidelity thermal model (`th_dt`), uses a cauer thermal network to accurately model the heat transfer from the junctions to the heat-sink. The thermal DT takes the converter power losses as an input and outputs the junction, case, and heatsink temperature. Crucially, `th_dt` is dependent on `elh_dt`, requiring the calculated power losses as its input.

4.3.2 AGENT ARCHITECTURE

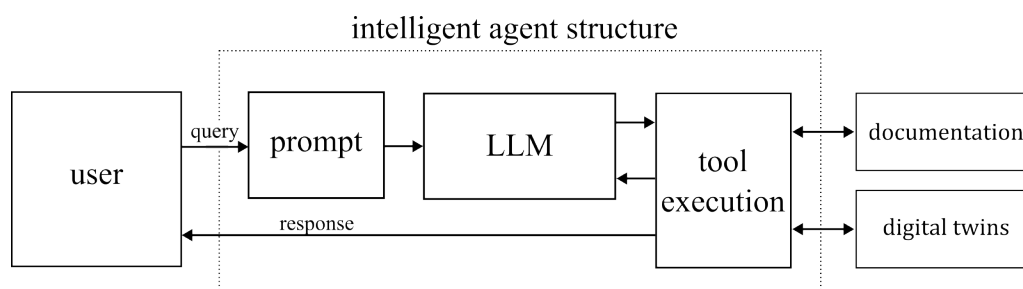


Figure 4.1 Diagram of the information flow of the intelligent agent. Starting from user query to the prompt, polling the LLM, parsing and executing tool calls, to the final response.

The agent is built around an LLM hosted locally with LM Studio [50] which utilizes OpenAI-compatible API endpoints. The chosen LLM was the llama-3-groq-70b-tool-use model [51] operated with a zero temperature to provide deterministic

behavior. The agent operates in a structured agentic loop where at each step the LLM receives the full conversation history, including previous tool calls and results, and then selects its next action from a predefined tool set. This loop continues until the agent selects the finish tool signaling task completion.

The agent is governed by a system prompt that provides its role, available physical signals, and a dependency resolution protocol. The four steps within the protocol are: (1) identify the DT that produces the requested signal, (2) inspect the required inputs of the DT, (3) trace for upstream DTs that can supply those inputs, and (4) activate all DT models in the correct order. This structured reasoning process is only provided and enforced through prompt engineering, with no hard-coded dependency logic.

4.3.3 TOOL INTERFACE

There are six tool available to the agent using the structured OpenAI function- calling schema. Each of the available tools are summarized in Table 4.1 by their name, purpose, inputs, and outputs. The `search_DT_info` tool performs a keyword-base matching against structured DT documentation returning the DT document entry with the most matches. The `find_DT_by_input` and `find_DT_by_output` tools allow for a specific search of the DTs, allowing the agent to trace dependencies more efficiently. The activation status of the DTs can be inspected or adjusted by the agent utilizing `get_DT_state` and `set_DT_state` tools.

4.4 RESULTS

Five test cases were designed to evaluate the agent's response across three categories of intent. These categories were defined in the system prompt as status queries (type 1), explicit activation or deactivation requests (type 2), and output-driven requests (type 3). An ambiguous query was also included to investigate how the agent would

Table 4.1 Tools available to the intelligent agent

Tool	Description	Inputs	Outputs
get_DT_state	Returns the current activation status of a DT	DT name	Status string
set_DT_state	Activates or deactivates a DT	DT name, setting	Confirmed status
search_DT_info	Keyword search of DT documentation	Query string	Matching DT documents
find_DT_by_output	Finds DTs producing a specific output	Signal name	Matching DT documents
find_DT_input	Finds DTs by specific inputs	Signal name	Matching DT documents
finish	Terminates loop and returns final response	Agent response text	User facing message

respond to failure. The llama-3-groq-70B-tool-use model at zero temperature was used for all test cases.

4.4.1 TEST CASE 1 EXPLICIT ACTIVATION WITH DEPENDENCY

In this test case the following query was provided to the agent: "Activate the high-fidelity thermal model.". This query was intentionally a high-level request by not providing the specific names of the model (th_dt), the associated input or output signals, and no mention of dependencies. The agent's tool-call loop is summarized in Table 4.2.

The agent first attempted to query the state of the " high fidelity thermal model" and received an error due to no model having that exact name. The agent recovered on the next step by searching the DT documentation to find the thermal model's name is th_dt and it requires power losses of the converter as an input. The agent then traced the dependency chain by searching for which model takes the only sensor available sensor value (load_side_current_converter). From this the agent learns that elh_dt takes the sensor value as an input and sees that it outputs power_losses_converter.

Further, the agent searches for which model takes power_losses_converter as an input and confirms it is the required input to the thermal model. With the dependency chain found from the sensor input to the required input for the request thermal model, the agent begins activating each model. First the agent checks on the status of the elh_dt model and learns that it is deactivated. The agent then proceeds to activate it and then checks and activated the requested thermal model (th_dt). Upon completion of the agent's task it calls the finish tool and reports back to the user that both models were activated. This task was successfully performed in 8 tool-call rounds without requiring more clarification from the user.

Table 4.2 Agent tool-call trace for test case 1.

Step	Tool Called	Arguments	Results/ Observation
1	get_DT_state	DT: "high fidelity thermal model"	Error: Unknown DT name not in registry
2	search_DT_info	query: "high fidelity thermal model"	Found th_dt and elh_dt
3	find_DT_by_input	input_name: "load_side_current_converter"	confirmed elh_dt's input is available (sensor)
4	find_DT_by_input	input_name : "power_losses_converter"	Confirmed th_dt requires power_losses_converter
5	get_DT_state	DT:"elh_dt"	elh_dt status: de-activated
6	set_DT_state	DT:"elh_dt", Setting:"activate"	elh_dt status: activated
7	get_DT_state	DT:"th_dt"	elh_dt status: de-activated
8	set_DT_state	DT:"th_dt", Setting:"activate"	th_dt status: activated
9	finish	final_response: summary_string	Agent informs user of model activation

4.4.2 TEST CASE 2 - STATUS QUERY (TYPE 1)

In this test case the agent was provided with the query: "What is the status of the high fidelity electrical digital twin?". The agent correctly classified this query as a type 1 intent. It first attempted get_DT_state with the name "high fidelity electrical" and received an unknown digital twin error. From this search_DT_info was called

and the agent resolved the correct name to `elh_dt`. Next, `get_DT_state` was called for `elh_dt` and the status was returned as deactivated. The agent then returned that the `elh_dt` was deactivated to the user using the finish tool. This task was completed with three tool call turns and responded to the user with the status and offered further help without performing any unnecessary actions. This demonstrates the agent correctly classifies the type 1 intent and notably displays restraint.

4.4.3 TEST CASE 3 - EXPLICIT DEACTIVATION (TYPE 2)

This test provided the agent with the query: "Deactivate the thermal model". Similar to the previous test cases the agent resolved the name to the correct `th_dt` name by using `search_DT_info`. The agent then used the `get_DT_state` tool and found `th_dt` was deactivated already but still called the `set_DT_state` tool to ensure that `th_dt` was deactivated. The agent then called finish to inform the user that the model was already deactivated. The demonstrated behavior in which the agent always checks the status of a model first is desirable in a real deployment where status consistency must be guaranteed. This task was completed in four tool call turns.

4.4.4 TEST CASE 4 - OUTPUT-DRIVEN ACTIVATION (TYPE3)

Test case 4 provided the agent with the query: "I need the power losses of the converter.". The agent correctly identified this as a type 3 output. Instead of starting with a general information search, the agent went directly to the `find_DT_by_output` tool. Searching specifically for "power losses", provided the agent with the `elh_dt` as the need model for that output. The status of the `elh_dt` model was then checked and activated. After activating the DT image, the agent performed a `search_DT_info` which gathered more context on the electrical digital twin. From this the agent called finish and returned to the user that the model was activated and listed its inputs and outputs. This task was completed in five tool call turns and notably did not activate

the th_dt model or search for erroneous information. This shows the agent correctly limited activation to only the required model to satisfy the user.

4.4.5 TEST CASE 5 - UNSUPPORTED OUTPUT QUERY (GRACEFUL FAILURE)

Test case 5 provided the query: "What is the voltage output?". This query was provided because there are no DT images that were defined to predict the output voltage. The agent attempted to use find_DT_by_output and the search_DT_info for voltage output, which both returned with empty results. Then it pivoted to search_dt_by_input for load_side_current_converter, identified elh_dt as contextually related and proceeded to activate it before reporting that no DT produced the output voltage. While activating the elh_dt was not needed, the agent reported back to the user that the model was activated but doesn't directly provide the requested signal. This response demonstrates the absence of an explicit unsupported-query response, instead defaulting to activating the closest contextually related model rather than just reporting back to the user. This identifies an instruction gap in the prompt for future refinement.

4.4.6 DISCUSSION

Across all test cases the agent demonstrated strong natural language understanding by correctly resolving informal and partial model name through semantic searches in every case. The three-tier classification protocol in the prompt proved effective at constraining the agent's behavior. Type 1 status queries consistently resulted in search only tool calls, while type 2 and type 3 intents lead to appropriate activation sequences. Table 4.3 summarizes key metrics for all test cases.

Important behaviors emerged across the test cases. First, the agent demonstrates consistent error recovery. In every case where an informal name was provided, an error was returned but the agent self-corrected with the search tools rather than

Table 4.3 key metrics across the test cases.

Test Case	Query	Intent	Tool Calls	Correct
1	Activate high fidelity thermal model	Type 2	8	Yes
2	What is the status of high fidelity electrical DT?	Type 1	3	Yes
3	Deactivate the thermal model	Type 2	4	Yes
4	I need the power losses of the converter	Type 3	5	Yes
5	What is the voltage output?	Type 3 (unsupported)	6	Partial

immediately stopping. Second, dependency resolution was correctly performed in test case 1, with the agent resolving a two-level signal chain and activating the models in the correct order. This was performed without any hard coded logic. Third, the agent consistently checks for a model's state before activating or deactivating it. In test case 3, the model state was verified before acting which is a desirable behavior for safe deployment in a real system where safety is crucial.

The partial failure present in test case 5, displays a limitation of pure prompt-based classification in smaller models. When all search strategies are exhausted the model defaults toward action rather than refusing. This is consistent with the aggressive tool-use bias introduced by the Groq fine-tuning applied to the llama 3.1 70B model. This suggest that explicit unsupported-query handling requires its own tool call or a stronger refusal instruction and should be included in future iterations.

4.4.7 COMPARISON WITH PRIOR NLP APPROACH

The prior NLP-framework utilized a static lookup table to map keywords and context strings to digital twin images. This approach was effective for a well-defined set of images, it exhibited clear limitations that the LLM agent addresses directly. Table 4.4 summarizes query difference between both approaches.

A direct CPU utilization comparison between the two approaches is not present

Table 4.4 key metrics across the test cases.

Aspect	NLP System	LLM Intelligent Agent (this work)
Query mapping	Static keyword look up table	Semantic LLM reasoning
Dependency resolution	Hard-coded lookup table	Autonomous tool-calls
Informal model names	fails, not in keyword DB	Resolved with semantic search
Additional images	Requires manual DB update	Natural language description only
Unsupported queries	Defaults to lowest fidelity	Search exhaustively, reports absence
Hardware target	NI PXIe-8880	Local PC workstation (70B model)

in this work. The prior NLP algorithm was deployed on NI PXIe-8880 real-time controller, while the LLM agent operates on a local workstation hosting a 70B parameter model. The computational demand of an LLM inference pipeline is significantly greater than the NLP algorithm. A meaningful efficiency comparison requires optimization and deployment of the LLM agent on equivalent or constrained edge hardware. This is identified as a key direction for future work, where lightweight quantized models [52] and speculative decoding strategies [53] are candidate approaches for reducing the computational requirements.

4.5 CONCLUSION

This chapter presents an LLM-based intelligent agent framework for interfacing with a digital twin-enabled system in power electronics. The agent utilizes structured tool-calling to interpret natural language queries, searches a DT knowledge base, and resolves multi-level dependencies without user or hard-coded guidance. Demonstrated on a boost converter DT image ecosystem, the agent correctly identified and activated both high fidelity digital twins in the appropriate order by resolving a two-level dependency chain.

The key strength of this approach is scalability. New DT models can easily be added to the knowledge base with basic natural language entries without modifying

the agent's logic. The intelligent agent also provides accessibility by enabling users to operate it without detailed knowledge of the models or signal dependencies in a complex system. The use of locally hosted LLMs also ensures data privacy and operational independence from cloud services.

LLM based agents demonstrates a clear benefit for complex digital twin systems. Providing the groundwork to a supervisory agent that not only provides general information and insight from models but can monitor and adjust controls on its own. With an expansion in tool calling capability and databases the intelligent agent can greatly improve operator burden and efficiency as the system is always monitored.

CHAPTER 5

CONCLUSION

5.1 CONTRIBUTIONS

This dissertation demonstrated a comprehensive framework for the modeling, control and validation of hardware-in-the-loop systems for distributed batteries in a shipboard micro-grid. Focusing on digital twin integration into systems, the key challenges addressed was electro-thermal dynamic emulation, decentralized control of BESS, and intelligent system-level interface with digital twin enabled systems.

The primary contribution of this research is threefold:

5.1.1 ELECTRO-THERMAL BATTERY EMULATOR FOR CONTROL AND POWER SYSTEMS TESTING

An electro-thermal hardware-in-the-loop battery emulator was developed to replicate the coupled dynamic behavior of lithium-ion batteries under realistic operating conditions. This work incorporates; 1) Coupled electrical and thermal model of a lithium-ion battery developed from single cell test data and scaled to the pack level, 2) Real-time hardware-in-the-loop integration of both electrical and thermal emulation, and 3) Thermal emulation method for the heat generated from pack level batteries. This battery emulator platform enables safe, repeatable, and cost-effective testing for controls and battery integrated power systems. This is done without the associated risks of battery degradation or failure and serves as a critical bridge between simulation and physical deployments.

5.1.2 ADAPTIVE AGENT BASED DROOP CONTROL FOR DISTRIBUTED BATTERIES IN NAVAL MICRO-GRIDS

A distributed control framework that integrates a battery SOH digital twin with adaptive droop control was introduced for distributed energy storage systems within a naval micro-grid. This approach leverages; 1) Tertiary level control with SOH and SOC influence on droop resistances, 2) Digital twin integration of SOH and SOC models for monitoring battery state, and 3) Agent based monitoring and control of distributed BESS. The control approach enables battery to dynamically share a common load based while maintaining safety constraints and improving system robustness. Unlike traditional resistive droop, this framework takes advantage of battery state awareness through digital twins, enabling intelligent distribution of power and degradation across the batteries.

5.1.3 INTER-FACIAL INTELLIGENT AGENT FOR DIGITAL TWIN ENABLED SYSTEMS

A novel intelligent interface was developed using a large language model to enable interactions with complex digital twin systems. This system demonstrates; 1) Natural language interaction with complex digital twin systems, 2) Querying and interpretation of digital twin states, and 3) A foundation for agentic decision making and control. With the integration of LLM-based reasoning and digital twin models, this work demonstrates a new approach to human-machine interaction in energy storage systems, where operators can query digital twins in an intuitive and context-aware manner.

5.1.4 KEY FINDINGS

Important insights that emerged from each area of this research. Hardware-in-the-loop validation increases confidence in control strategies and enables rapid testing capabilities. When utilizing a HIL battery emulator to investigate system integra-

tion, both electrical and thermal dynamics are essential. These dynamics are heavily coupled and need to be considered especially in a safety constrained system. Digital twins provide actionable state estimations. When coupled with a distributed battery control framework, they can be utilized to improve system longevity and robustness. Digital twin systems can become complex quickly, LLM based agents can act as a scalable natural language bridge between complex systems and a human operator.

5.1.5 LIMITATIONS

This dissertation provides a strong foundation for implementing, testing, and operating digital twins but comes with several limitations. The electro-thermal battery relies on data driven lumped and reduced-order models, which limits its valid operational range and accuracy. The distributed adaptive agent-based control is built with known pulse loads which influence its charging scheme and tuned parameters. This implementation may be sensitive under highly dynamic or extreme conditions. The intelligent agent framework is limited in autonomous actions. It relies completely on predefined structures for interactions with digital twins and documentation databases.

5.2 FUTURE RESEARCH DIRECTIONS

This work leads to several promising directions for continued investigation into advanced digital twin development, Optimization of the distributed agent-based control, and intelligent agent autonomy. For innovative controls, more advanced digital twins will be required. Some focus areas should be higher fidelity degradation and aging models that can be developed from easy to obtain cell data sets. A digital twin model to represent the cell-to-cell variance and dynamics within the pack will also be crucial for physical implementation. Further, real-time model updating needs to be investigated as physical assets need to be accurately modeled throughout their full lifetime.

Some open research directions for the distributed agent-based control of batteries is investigating optimization. Lapunov stability analysis should be carried out to guarantee stability along with an optimization-based control approaches specifically for load sharing and longevity. Further, explorations into a wider range of scenarios for non-convergent or oscillator SOC behavior for improved life cycle performance is needed to validate the framework.

As for the open areas in the intelligent agent, a major focus should be placed on expanding tools and actions. Expanding the LLM-based agent's tool to enable real-time sensory input can enable supervisory level of control. Autonomous decision making can be carried out to achieve system wide objectives without constant operator's attention. Combining the intelligent agent's logic with an internal optimizer and control solver will also aid in the agent's implementation. Further, expanding the tool calling schema to include executing digital twin simulations, generating reports, and modifying controls will amplify the usefulness of the LLM based agent for consistent operators in complex

5.3 FINAL REMARKS

This dissertation demonstrates that integrating digital twins, adaptive controls, and intelligent interfaces prove to be trans-formative approach to managing distributed energy storage systems. By combining physics-based modeling, adaptive controls, and artificial intelligence, this work provides the foundation for next generation energy management. Creating a more efficient and robust system that is interpretable and interactive. The combination of these technologies enables a shift from static system designs into self-aware, and adaptive energy systems capable of meeting increasingly complex demands in operational environments.

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