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DEEP NEURAL NETWORK-BASED MODELING OF ELECTRO-THERMAL LITHIUM-ION BATTERIES RESPONSES LEVERAGING HYBRID PULSE POWER CHARACTERIZATION

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ABSTRACT

Predicting the electro-thermal response of lithium-ion batteries is critical for energy storage system integration. However, due to their rate dependent behavior battery testing is expensive and time intensive. There is a need to develop reliable predictive models that can emulate the electro-thermal behavior of a battery. Traditional physics-based models, while effective, are computationally intensive and require detailed knowledge of electro-chemical properties to parameterize, making them difficult to implement for hardware-in-the-loop battery system testing. To address theses limitations, this paper presents a data-driven electro-thermal battery modeling approach using deep neural networks trained on hybrid pulse power characterization data. The proposed model aims to predict both electrical and thermal responses of lithium-ion batteries under various dynamic load conditions, offering a scalable and efficient alternative to physics-based electro-thermal battery modeling. Applying an iterative approach to step through a load profile, a deep neural network ensemble predicts the change in temperature, voltage, and state of charge given previous conditions was able to calculate future behavior for a 1C constant current discharge with 0.07 V, 2.35%, and 0.25°C average absolute error, for voltage, state of charge, and temperature respectively.

Keywords: Deep neural networks, battery modeling, data-driven approach, hybrid pulse power characterization, online learning, electro-thermal prediction, activation functions, machine learning, energy storage, battery safety

1. INTRODUCTION

Operational and maintenance costs are critical concerns for the maritime industry. Ships often face high maintenance cost due to power fluctuations that degrade engine performance and increase wear.To address these inefficiencies, the integration of energy storage systems has been investigated as a means to smooth load fluctuations and enable engines to operate closer to their optimal efficiency [1]. These benefits have driven growing interest in the continued electrification of shipboard power systems. Due to the nature of the maritime industry, electrification requires the application of efficient and robust mobile energy storage systems. To validate these systems at the design stage, battery emulators are often used [2]. Interest in electro-thermal battery emulation systems [3] is growing, as they enable more efficient electro-thermal testing and deployment of energy storage systems. This work develops data-driven models that could be leveraged by electro-thermal battery emulators in the future.

Owing to their high energy density, long cycle life, and falling cost, the deployment of lithium-ion batteries has surged [4]. However, significant challenges arise surrounding battery misuse, including overheating, deep discharging, and thermal runaway [5]. These issues pose a major risk to lithium-ion battery's implementation on maritime platforms. To improve robustness, accurate electro-thermal modeling and prediction of battery behavior are imperative before degradation or safety hazards occur [6]. Physics-based models, such as the equivalent circuit model or the single particle model, require extensive computation and are difficult to implement due to the nonlinear behavior of batteries [7].

The subsequent rise in data-driven methods has highlighted neural networks for capturing the nonlinear dynamics subject to a wide array of variables [8]. While the electrical and thermal domains within a battery are highly interdependent, existing research employing neural networks for battery prognostics has seen success in both domains, regarding state of charge (SOC) [9] and temperature estimation under varying conditions [10]. Furthermore, neural networks significantly reduce the cost of computation, a major limitation in the application of physics-based models [11], enabling real-time monitoring of the dynamics that complex physics-based models could not previously support.

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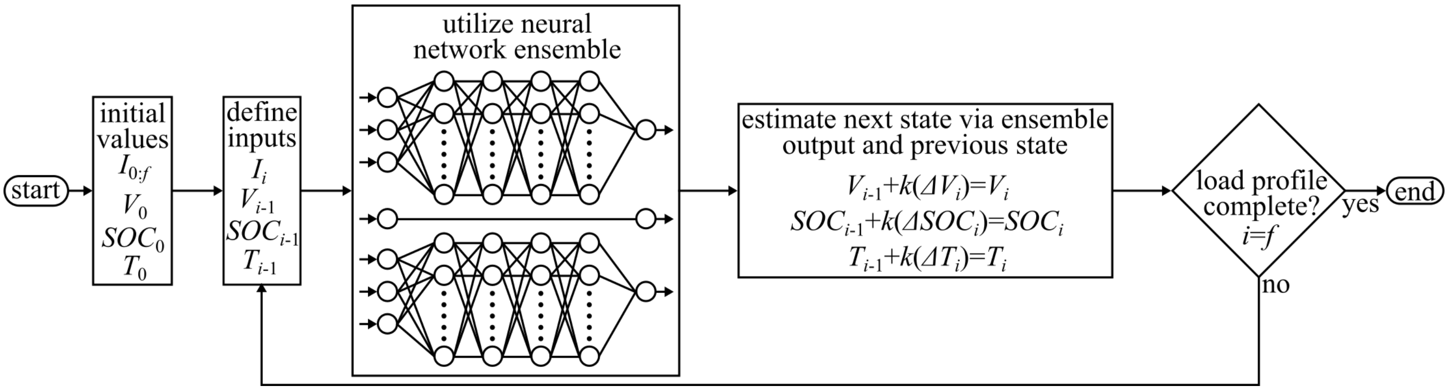

FIGURE 1: A block diagram to visualize the flow of information through each iteration of a current load profile to predict the electro-thermal response.

This work introduces a framework for developing and employing deep neural network ensemble (DNNE) to predict the electro-thermal response of a lithium-ion battery via hybrid pulse power characterization (HPPC). To expand, the proposed electro-thermal model will employ a group of neural networks to estimate the change in voltage, state of charge, and temperature as a response to a current to calculate the battery state under the considered load profile. The contributions of this paper are twofold. First, it illustrates the development of a deep multi-layer perceptron ensemble for predicting battery behavior in multiple domains, demonstrating a data-driven method to minimize cost of computation for complex nonlinear relationships. Second, it builds the groundwork for a robust data collection method utilizing HPPC to allow a wide range of model applicability.

2. METHODOLOGY

This section introduces the proposed DNNE and supporting testing and training methodologies.

2.1 Deep Neural Network Ensemble

The deployment of the DNNE to predict battery state throughout a load profile is outlined in figure 1. Requiring the initial voltage, state of charge, temperature, and scheduled applied current, the model determines the expected change in each variable to predict the next state. Having been trained on data of ten second windows, the predicted change in state is over the next ten seconds of operation, requiring a scaling factor (k), proportional to the step change in time (Δt), as seen in equation 1. Iterating through, after the initial values are used to predict the first state under load, the input to the model is replaced by the most recent predicted state for each step

$$k = \frac{\Delta t}{10}. \tag{1}$$

From development to implementation, the process to utilize a DNNE to predict the battery state for a load profile via HPPC training is represented in figure 2. While data collection is time intensive up front, HPPC under varied conditions provides a strong foundation for learning. To minimize tuning efforts, all three submodels were trained using the Adam Optimizer [12].

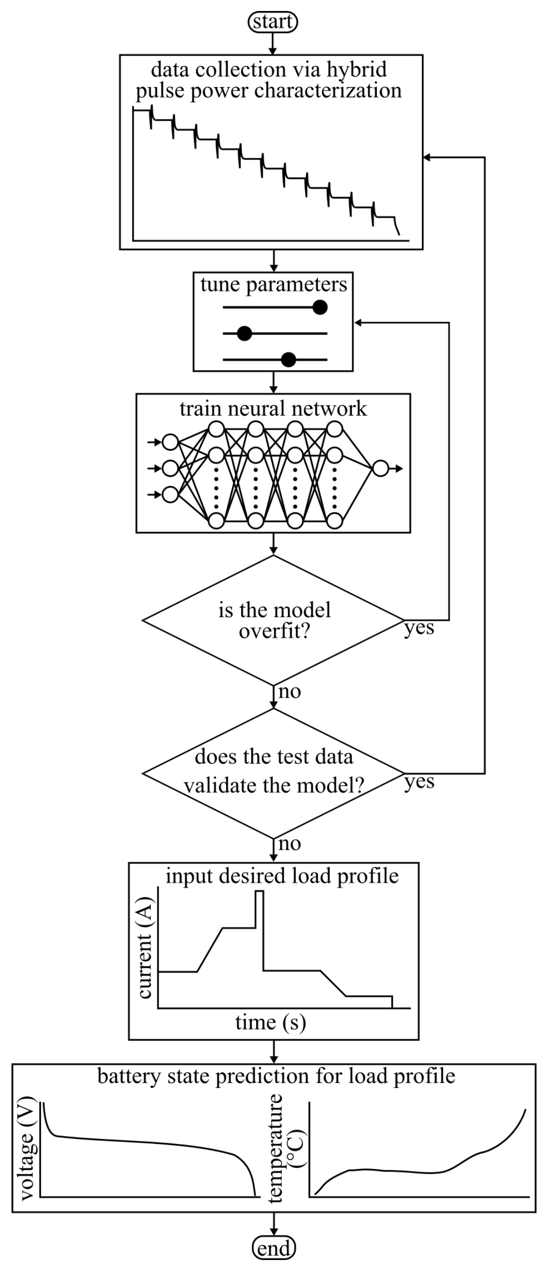

FIGURE 2: The logical flow to develop and employ the neural network for battery state prediction for a given load profile.

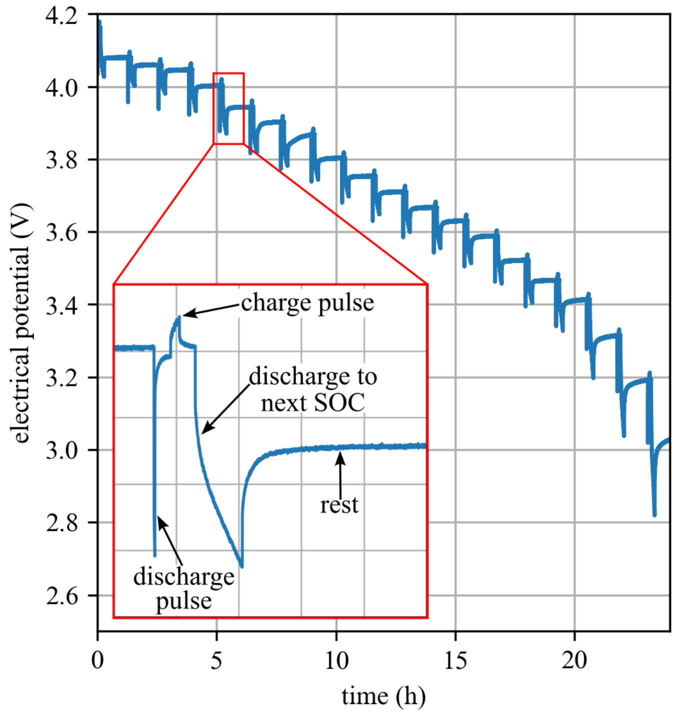

FIGURE 3: The voltage throughout an HPPC protocol every 5% state of charge with a closer look at the 80% pulse.

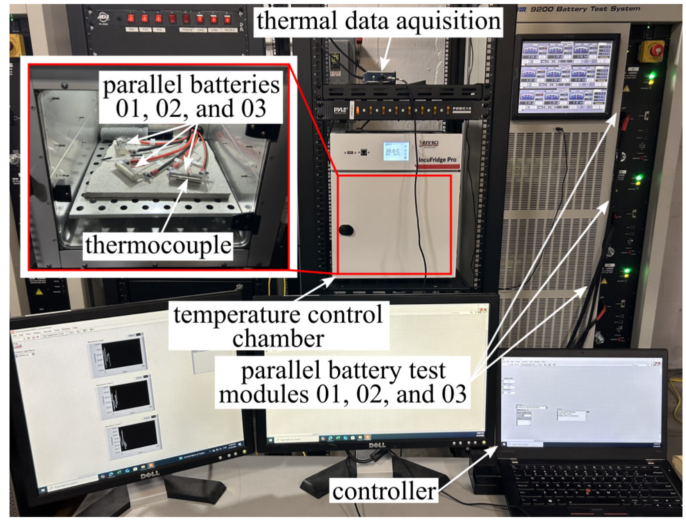

FIGURE 4: The experimental setup used to collect HPPC data from three temperature controlled cells simultaneously.

TABLE 1: The amount of HPPC tests run under each condition to collect training data.

	discharge pulse rate		
T_{amb}	C/2	1C	2C
20°C	3	3	3
30°C	3	3	3
40°C	3	3	3

To learn and predict complex nonlinear battery characteristics, rather than a single multiple output neural network, an ensemble of parallel networks was chosen. Separating each model mitigates overfitting to HPPC training [13], and increases resilience to noise as well as unexpected input outliers [14]. Comprised of three submodels, one for each output, the DNNE requires four inputs: current (I_i), previous voltage (V_{i-1}), previous SOC (SOC_{i-1}), and previous temperature (T_{i-1}), to predict the change in voltage (ΔV_i), change in state of charge (ΔSOC_i), and change in temperature (ΔT_i), for each step. Including four hidden layers, each containing twenty nodes, the input layer of voltage step submodel receives the current, previous voltage, and previous SOC. Similarly, the submodel to predict the change in temperature is a deep neural network; however, it contains three hidden layers, including 10, 10, and 9 neurons each. The temperature submodel has an input layer requiring the current, previous SOC, and previous temperature. Both deep neural networks make use of the rectified linear unit as the activation function to introduce nonlinear relationships between the data, while mitigating the vanishing gradient problem [15]. Alternatively, the network used to predict the change in state of charge only receives current information. Due to the linear nature of SOC, no hidden layers were used but is left in the form of a neural network for consistency.

The batch size and learning rate are key in avoiding overgeneralization and overfitting [16], so the models should be tuned against constant current test conditions as HPPC training often highlights dynamic behavior. Once the model is validated, the DNNE can be employed to instantly predict the battery state over long term load applications.

2.2 Hybrid Pulse Power Characterization

In this work, HPPC is used to extract the response from an 18650 3.6V 3000 mAh lithium nickel manganese cobalt (NMC) cell (Samsung 30Q). HPPC is a protocol frequently used to build physics-based models for its ability to highlight the dynamic characteristics a battery exhibits under load [17]. Shown in figure 3, the HPPC protocol conducts a discharge and charge pulse at every 5% SOC. Prior to each HPPC test the cells were charged under a constant current 0.5C, followed by a constant voltage until the current was less than 0.05C; therefore, it can be assumed that each protocol was started from 100% SOC. From the discharge pulse, rate constants can be determined for a physics-based equivalent circuit model. Developing a data-driven model, this discharge schedule allows the DNNE to learn the dynamic behavior without requiring extensive computation of electro-chemical equations.

Monitoring the battery response to HPPC protocol was conducted using the experimental setup displayed in figure 4. To observe the thermal response, each cell had a thermocouple placed on the outer center of the cell case using an NI-9210 thermocouple single conditioner at 1 S/s. Electrical data acquisition and control is conducted through the NHR-9200 battery tester also at 1 S/s. A sampling rate of 1 Hz was chosen to minimize the effect noise might have during model training, which was further decreased to 0.1 Hz during data processing. As outlined in table 1, HPPC data was collected from three different cells at three pulse rates of 0.5C, 1C, and 2C, and at three ambient temperatures of

20°C, 30°C, and 40°C, using an IncuFridge Pro temperature control chamber. Variable rate and temperature data was necessary for each neural network to autonomously learn the complex relationships between the electrical and thermal parameters in order to build a robust model capable of generalizing to different load conditions as

$$SOC(i) = SOC_{i-1} - \frac{1}{Q_{\text{nom}}} \int (I(t)dt). \tag{2}$$

2.3 Training the Deep Neural Network Ensemble

Raw data contains current, voltage, and temperature data for each battery, so significant data processing is necessary before the neural network can be trained. State of charge at each step ($SOC(i)$) was calculated via coulomb counting, described by equation 2, where the current ($I(t)$) was integrated over each step, then normalized by the nominal capacity (Q_{nom}). To determine the change in SOC, the normalized capacity is then subtracted from the previous state of charge (SOC_{i-1}). Because each neural network requires target outputs for training, the change in voltage, state of charge, and temperature for each step was then appended. Each model was developed using the MLPRegressor function from the scikit-learn python library, requiring the data be scrubbed for errors in acquisition such as missing, or infinite values due to toolkit sensitivities. As the DNNE is not time oriented, all of the data is appended to one file, and used for either training or validation; however, data collected at 1 Hz proved too noisy for learning. Windowing the data into 10 s frames prevented errors due to noise, yet was fast enough to retain the dynamic behavior of the battery. For each 10 s frame, the average current, initial voltage, initial SOC, and initial temperature were input to the model, and it was trained to output the difference in voltage, SOC, and temperature. Moreover, frames that contained an average current of greater than -0.9 A were not used in training, due to voltage relaxation after a discharge producing a positive change in voltage despite a negative average current.

3. RESULTS

The model showed good agreement between the DNNE and a Samsung 30Q 18650 lithium nickel manganese cobalt cell under a 1C constant current discharge as reported in figure 5. Under a 1C discharge, the average absolute error in voltage, state of charge, and temperature prediction was 0.07 V, 2.35%, and 0.25°C, respectively. The error in voltage and temperature can be attributed to two primary factors. First, imperfect tuning methods could lead to avoidable errors in prediction, therefore future work is required to optimize hyperparameters for deep neural networks. Second, noise in measurement requiring data windowing makes it difficult for the model to learn less significant relationships between variables, which could lead to over-generalization.

It should be noted that, while overestimating its contribution, the model appears to account for the entropic heating of the battery, evident by the accelerated temperature increase at extremely low SOC. By training via an HPPC protocol, designed to highlight the more dynamic behavior, the neural networks successfully captured the nonlinear response exhibited by the battery. Furthermore, the model succeeds in both domains, also capturing nonlinearity in the electrical potential, observing both the initial and final voltage drops.

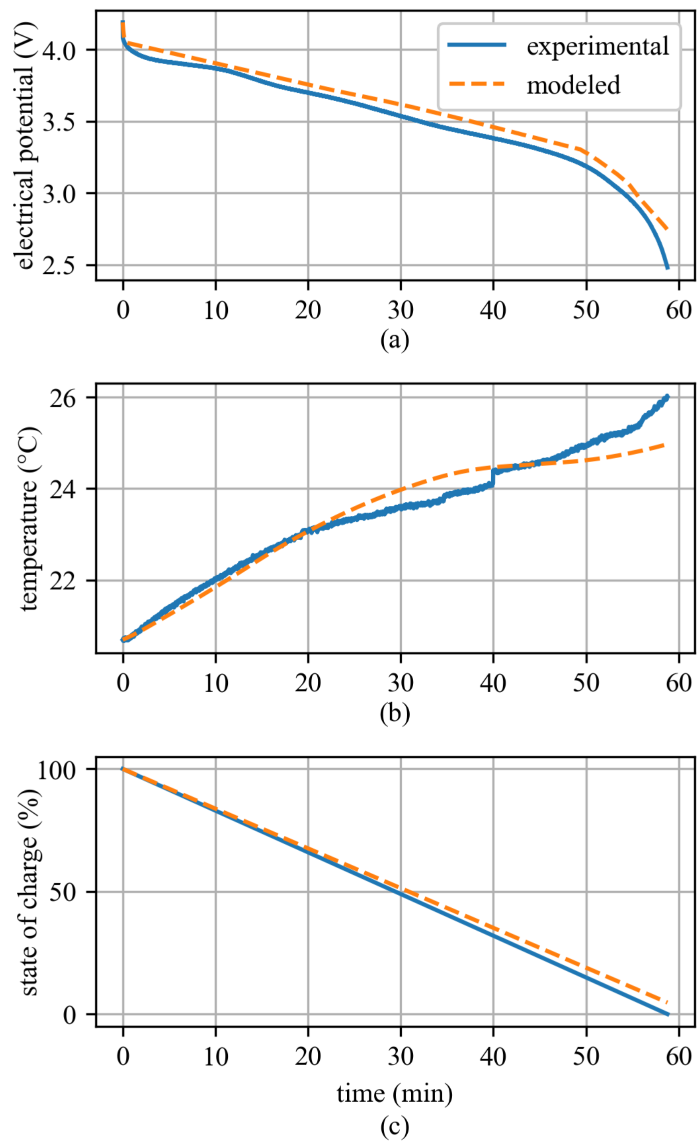

FIGURE 5: The a) voltage, b) temperature, and c) state of charge for a load profile as calculated by the model and tested experimentally.

While able to operate with limited data, the DNNE is currently unaware to factors that cannot be seen from its input parameters. In the experimental data, SOC is calculated via coulomb counting using the current, and the neural network, acting as a linear regressor, calculates state of charge via the same method. However, it was assumed when determining the state of charge for the training data, that each cell had a perfect 3000 mAh capacity, when this is unlikely. Differences in the cell history or production could cause mismatches regarding the assumed nominal capacity, which the DNNE does not currently account for. In future model development, it is vital for accurate state of charge estimation that cells with documented history, or well measured initial capacity are used to account for differences in usable capacity.

4. CONCLUSION

This work presented a data-driven framework for modeling the electro-thermal response of lithium-ion batteries using a deep neural network ensemble (DNNE) trained on hybrid pulse power characterization (HPPC) data. The model predicted voltage, temperature, and state of charge under dynamic load conditions, achieving average absolute errors of 0.07 V, 0.25°C, and 2.35%, respectively. By deploying separate neural networks for each output domain and using windowed training data, the approach effectively captured nonlinear battery dynamics while reducing computational cost compared to physics-based models. This framework demonstrated a scalable and efficient alternative to traditional modeling techniques and established a foundation for future work in online learning and hybrid physics-informed architectures.

Future work will focus on implementing an online learning framework to enable continuous model adaptation as new operational data becomes available. Additional efforts will include refining the neural network architecture and expanding the training dataset to incorporate high C-rate discharge conditions, thereby improving model generalizability. Hybrid modeling approaches that integrate physics-based constraints with data-driven learning will also be explored to further enhance predictive accuracy. These developments aim to extend the applicability of deep learning in battery modeling and support more robust and scalable energy storage system optimization.

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