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A Comparative Study between Physics, Electrical and Data Driven Lithium-Ion Battery Voltage Modeling Approaches

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Abstract

This paper benchmarks three different lithium-ion (Li-ion) battery voltage modelling approaches, a physics-based approach using an Extended Single Particle Model (ESPM), an equivalent circuit model, and a recurrent neural network. The ESPM is the selected physics-based approach because it offers similar complexity and computational load to the other two benchmarked models. In the ESPM, the anode and cathode are simplified to single particles, and the partial differential equations are simplified to ordinary differential equations via model order reduction. Hence, the required state variables are reduced, and the simulation speed is improved. The second approach is a third-order equivalent circuit model (ECM), and the third approach uses a model based on a Long Short-Term Memory Recurrent Neural Network (LSTM-RNN)). A Li-ion pouch cell with 47 Ah nominal capacity is used to parameterize all the models. The models are tested and compared using four standard drive cycles at six ambient temperatures ranging from -20^{0}C to 40 ^{0}C. The proposed models are benchmarked using various qualitative and quantitative means including, accuracy, engineering effort to parametrize and create the model, and the ability of each model to represent the nonlinear behavior of the battery. The comparison between the three models shows that the ECM and the LSTM models have better accuracy than the ESPM. However, the ESPM requires a reduced set of calibration data, is highly capable of incorporating the complex nonlinear behavior of the battery, and the parameters have physical meaning.

1. Introduction

With the global transition to clean energies, lithium-ion batteries have been widely used in electric vehicles and energy storage devices [1]. The advantages of lithium-ion batteries are high-energy, high-power densities, long life, low self-discharge, and less energy loss in charge and discharge. On the other hand, the batteries are still delicate and must be kept within safe environmental and operating conditions. Lithium-ion cells with high Ni contents (such as NCM811, NCMA) are more prone to thermal reactivity and exothermic decomposition [2]. The working temperature of these batteries needs to be kept in a safe range, such as +10°C to +35°C. Meanwhile, to maintain long life and high efficiency, health of the batteries needs to be closely monitored. These requirements show the importance of the battery management systems (BMS) which ensure the safety and reliability of battery packs [3]. Inside the BMS, battery models are used for SOC and SOH estimation and are a key piece to ensure the proper functioning of the system. Many different types of models and algorithms have been investigated in prior research, including equivalent circuit models [4-6], electrochemical models [8, 10-13], and artificial intelligence data-driven approaches [14, 17].

TABLE 4 Comparison between ECM, LSTM, and ESPM models.

	ECM	LSTM	ESPM
Parametrization Tests Required at Each Temperature	HPPC	Eight drive cycles and charges	GITT, HPPC, Capacity Tests
Number of Parameters	About 800	About 800	About 120
Computational Effort of Model Parametrization	Low *(Fitting)*	High *(Training)*	High (fitting)
Engineering Effort to Create and Parametrize Model	High *(Custom software tools)*	Medium *(Standard software tools)*	High (custom software tools)
Ability of Model to Incorporate Complex Nonlinear, Time Dependent Behavior	Medium *(Function of model form and HPPC data)*	High *(Model captures behavior in training data)*	Medium (weak at low temperatures)
Physical Meaning of Model Parameters	Yes *(Parameters capture OCV, R)*	No *(Parameters are abstract)*	Yes

A qualitative and quantitative comparison of the results for each method is given in Table 4. This table shows the ECM has the benefit of having low computation effort to fit the model parameters to the parametrization test, and that the model parameters have some physical meaning, and that it is reasonably good at capturing the nonlinear characteristics of the battery. The LSTM in comparison has the benefits of requiring less engineering effort to create the model and being able to better fit the behavioral characteristics of the battery, while it has the downside of the model parameters not having any physical meaning. The ESPM models requires less data to parameterize than the LSTM but more calibration efforts, since three sets of dedicated tests are needed. In the case of electrochemical models, more complex equations need to be introduced if accurate results are needed in extreme conditions, such as at high C-rate or in the low temperature areas. On the other hand, it is worth noting that the ESPM model utilizes considerably fewer parameters than the other two models.

5. Conclusions

In this work three approaches to modelling lithium-ion batteries were presented and compared. The first was a third-order ECM including nonlinear resistance, the second was recurrent neural network machine learning approach with an LSTM. The third one was the ESPM model. Quadratic programming was used to fit the ECM to HPPC test data. The learnable model parameters for the LSTM were determined by training it with data from eight mixed drive cycles performed at six different temperatures. The ESPM model was parameterized using the GITT, capacity and HPPC tests. The three proposed models were then tested at each temperature with four standard automotive drive cycles. The models performed similarly for the four cycles at positive temperatures. The difference in the models' performances started to increase at low temperatures, among which ESPM, in this study, shows worse performance than the other two. It is worth mentioning that, however, ESPM does have the potential benefits that the other two do not have, which is that the physics-based nature of this model lends itself to the integration of first-principle models describing degradation mechanisms (for instance, SEI layer growth and lithium plating).

Future work will focus on expanding the study to include aging models (both physics-based and data-driven) and comparing the ability of the three modeling approaches to predict capacity fade.

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Nomenclature

a_s - solid/electrolyte interfacial area per unit volume or active surface area per electrode unit volume for electron transfer reactions [1/cm]

A - area [m^2]

c_p - specific heat capacity [J/kg°C]