Dynamic current profiles estimations using the hybrid model for lithium ion batteries

Anshul Nagar*, Jonghoon Kim*
Energy Storage Conversion Lab., Chungnam National University*

ABSTRACT

Lithium-ion battery technology, a fundamental component of contemporary energy systems, has undergone extensive investigation, especially in the area of mathematical modeling. Yet, the sector still faces challenges in achieving a delicate equilibrium between model precision and computational efficiency. To tackle these issues, the paper suggests integrating the Doyle Fuller Newman (DFN) model with the Feed-forward Neural Network (FNN) model for predicting the voltage of lithium-ion batteries under a dynamic current profile. The core concept behind merging the models lies in leveraging the physics-based model to provide insights into the battery's internal states, which are directly connected to its instantaneous conditions. A hybrid model is evaluated for its ability to forecast the battery voltage under various dynamic conditions. This method enhances accuracy while also drastically simplifying the model's complexity. The predicted voltage outcomes have been shown to exhibit remarkable precision.

1. Introduction

Lithium-ion batteries (LiBs) are pivotal in powering the energy storage revolution, fueling everything from electric vehicles (EVs) and smartphones to laptops, thanks to their compact, lightweight design and robust charge-discharge capabilities. As the push for electrification grows, so does the demand for batteries that combine high performance and longevity with cost-effectiveness and safety. Addressing this demand necessitates the development of sophisticated Battery Management Systems (BMS), which serve as the battery pack's "brain," optimizing its operation for enhanced performance, extended lifespan, and safety compliance.

Our research introduces a novel hybrid modeling strategy that merges the detailed electrochemical insights of physics-based models (PBMs), specifically the Doyle Fuller Newman (DFN) model, with the dynamic predictive power of neural networks from machine learning. This combination exploits the DFN model's in-depth exploration of LiB electrochemical processes and neural networks' ability to uncover patterns within complex datasets, offering a comprehensive and computationally efficient analysis of battery behavior.

This hybrid model aims to overcome the limitations of standalone modeling techniques, providing a versatile tool that melds the thoroughness of PBMs with the predictive efficiency of machine learning. This is particularly beneficial for sectors like EVs and portable electronics, where high-performance, reliable batteries are crucial. Our approach promises more accurate and flexible battery performance predictions, enabling smarter BMS strategies. [1]

In this paper, we have used the pybamm module, which is based on Python. Python Battery Mathematical Modelling (Pybamm) solves continuum models for batteries using both numerical methods and asymptotic analysis. the Doyle Fuller Newman (DFN) electrochemical model to extract critical parameters that reflect the internal workings of lithium-ion batteries. [2] These parameters are then utilized to train a neural network, enabling the precise estimation of battery voltage across dynamic current profiles such as the Drive Schedule Test (DST), Urban Dynamometer Driving Schedule (UDDS), and US06. This innovative approach combines the depth of electrochemical modeling with the adaptability of machine learning, offering enhanced predictive capabilities for battery voltage in response to varied driving conditions.

2. Methodology

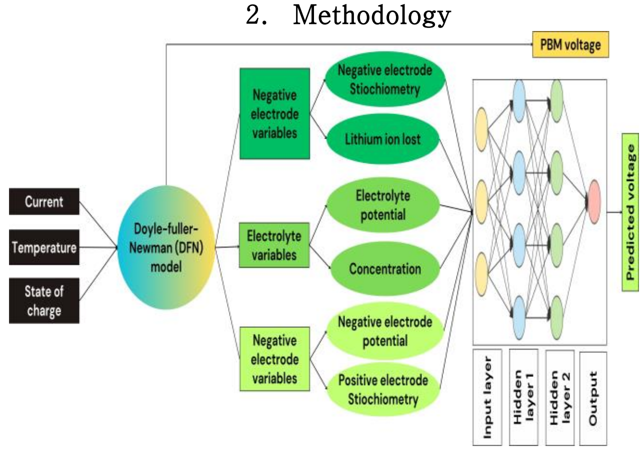

Fig.1 The architecture of the proposed hybrid model

Our methodology integrates a physics-based model (PBM) with machine learning to refine battery dynamics predictions. We enhance its forecasting accuracy based on experimental data by adjusting the PBM's parameters (e.g., diffusion coefficients, rate constants). Despite the complexity of models like DFN and the challenge of parameter identification, this combined approach offers a promising and interpretable strategy for precise battery behavior prediction, as shown in Fig 1 above.

3. Results

The DFN model produced the variables that provide the internal state of the battery model. The variables such as electrode stoichiometry provide information about the battery state of

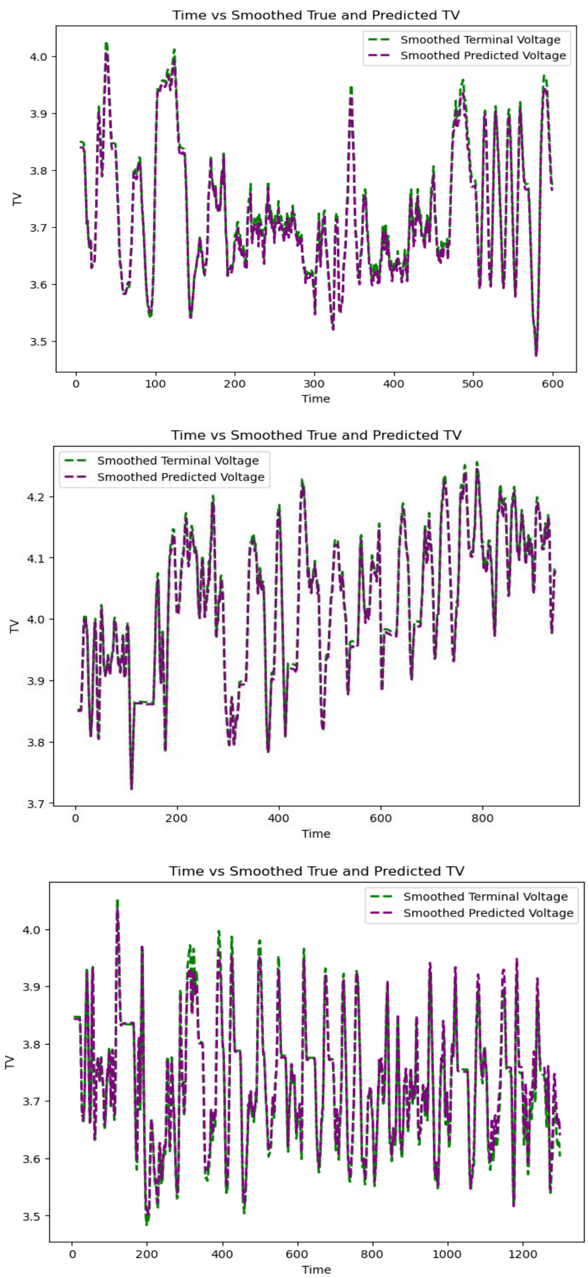

Fig.2 Model Validation: Terminal and predicted voltage for DST, FUDS, and US06 show accuracy across driving conditions

charge at both electrodes, and the concentration of lithium ions at the electrode and in the electrolyte, and give the idea about the diffusion of lithium ions from one electrode to another electrode. The loss of lithium ions gives information on solid electrolyte interphase (SEI) formation, which consumes lithium ions. These variables are selected using the hit-and-trial method by calculating each variable contribution in predicting the voltage. The most impactful variables give full information about the internal state of the battery. Therefore, the variables are considered to train the Neural Network model, which predicts the battery's terminal voltage as shown in Fig2.

To validate the model, simulations are done at different Dynamic current profiles such as DST, FUDDS and US06. The results show very good accuracy. From these graphs, the predicted voltage trace follows the true voltage very closely across different dynamic profiles, indicating that the model is capturing the dynamics of the system with high fidelity. Despite the varying conditions, which introduce different power demands and thus different voltage responses, the model appears robust and accurately reflects the battery behavior.

4. Conclusion

In conclusion, the innovative hybrid model presented in this paper successfully bridges the gap between the detail-oriented Doyle Fuller Newman (DFN) model and the adaptive prowess of the Feed-forward Neural Network (FNN). This approach has proven to be a significant advancement in predicting the voltage of lithium-ion batteries under dynamic current conditions. The DFN model's rigorous characterization of the battery's internal states, combined with the neural network's capability for pattern recognition, culminates in a predictive tool that is both accurate and computationally efficient. Validation against various dynamic current profiles, such as DST, FUDDS, and US06, confirms the model's reliability and robustness.

This research was supported by the Korea Energy Technology Evaluation Institute (No. 20210501010020) with the support of Hyundai Motor (development of the SOC estimation BMS algorithm for LFP batteries) and the government (Ministry of Trade, Industry and Energy) in 2021 and the Korea Evaluation Institute of Industrial Technology (No. 200116167, Development of Battery Safety Diagnosis System (BDS) SoC that predicts the internal state, explosion risk, remaining useful life, and replacement timing of electric vehicle batteries).

5. References

[1] H. Tu, S. Moura and H. Fang, "Integrating Electrochemical Modeling with Machine Learning for Lithium-Ion Batteries," 2021 American Control Conference (ACC), 2021, pp 44014407

[2] Sulzer, Valentin & Marquis, Scott & Timms, Robert Robinson, Martin & Chapman, S. (2020). Python Battery Mathematical Modelling (Pybamm). 10.1149/osf.io/67ckj.