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Estimation of Surface Temperature Distributions Across an Array of Lithium-Ion Battery Cells Using a Long Short-Term Memory Neural Network

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Abstract

As electric vehicles are becoming increasingly popular and necessary for the future mobility needs of civilization, further effort is continually made to improve the efficiency, cost, and safety of the lithium-ion battery packs that power these vehicles. To facilitate these goals, this paper introduces a data driven model to predict a distribution of surface temperatures for a lithium-ion battery pack: a long short-term memory (LSTM) neural network. The LSTM model is trained and validated with lithium-ion cells electrically connected to form a battery pack. Voltage, current, state of charge (SOC), and cell surface temperature from two arrays are used as inputs from a wide range of high and low temperature drive cycles. Additionally, ambient temperature is added as an input to the LSTM model. In summary the LSTM model can accurately characterize and predict a distribution of lithium-ion cell surface temperatures arranged in a battery pack under extreme conditions to an accuracy of 1.53°C. Furthermore, making use of an external sensor to measure the ambient temperature of the battery pack further increases the accuracy of the LSTM model. With this data driven model, fewer testing data is required to validate a battery pack during development, less sensors are needed in production to monitor the health of the battery pack, and data can be generated for a wide variety of applications which may or may not be possible in a lab environment.

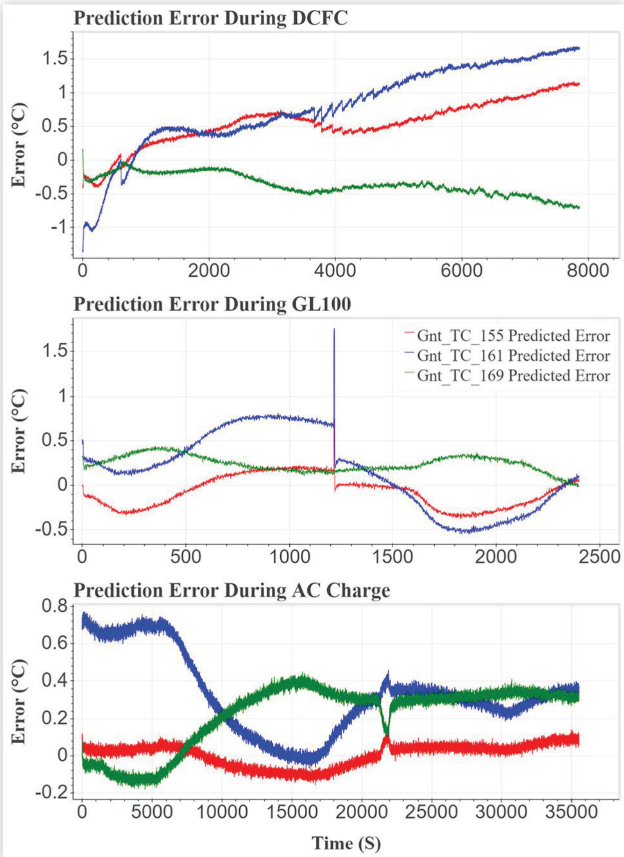
Introduction

As electric vehicles become increasingly relied upon to solve the future mobility needs of society, further research and development of this technology is required [1-4]. One of the major components of electric vehicles consist of lithium-ion batteries, and as improvement to energy density and storage is developed, it is also critical to improve technologies for monitoring and controlling these devices when used in vehicle applications. Common technologies to do this include the battery management system (BMS) which consists of a battery energy control module (BECM) along with sensor measurements and software [5]. These measurements are continually monitored by the BECM during use of the vehicle and software is implemented to increase life of the battery, extend useful range, and ensure safe operation by operating the battery within safe boundaries and intervening during detected faults [6]. Furthermore, cost is another factor governing electric vehicles as this continues to be a major barrier of entry for consumers [7]. If cost of production for electric vehicles can be minimized, then it follows that wider adoption will take hold.

As mentioned, cost, safety, and performance are critical of furthering the use and adoption of electric vehicles. One facet of criteria includes accurate temperature modeling and characterization of the battery pack [5, 8, 9]. During development, engineering analysis is performed to locate optimal temperature sensors for the pack. From these measurements, temperature is monitored to ensure safe operation. As an example, if a battery cell is punctured, resulting in thermal runaway, the BECM will intervene by cutting power to the pack and alerting the consumer. Also, during cold conditions, battery pack performance is limited to preserve the life and longevity of the battery pack. A key component to this is an accurate thermal characterization of the battery pack which relies on careful placement of the measurement sensors. If an accurate model can be developed to 1) locate optimal sensor placement within the pack, 2) estimate battery temperatures that are not feasible for measurement sensors due to packaging constraints, and 3) reduce the total number of sensors needed to monitor the battery pack in online applications, then it follows that safety and performance can be improved and cost of production reduced.

Li-ion battery temperature is one of few measurables that influence battery characteristics and performance. Since both electrochemical and mass transfer processes in the lithium-ion battery are thermally activated, an accurate estimation of the battery temperature leads to an accurate battery behavior prediction which is crucial in the lithium-ion BMS to enhance both safety and performance [6]. There are two common

FIGURE 9 Temperature error prediction vs time for each test data set: DCFC, GL100, and AC Charge.



when making temperature predictions. Physically, temperature derivatives cannot be this large in practice and therefore it is recommended to apply a low pass filter on the predicted data to remove any noise or irregularities. One may also add longer lookback windows to smooth the data or attempt to smooth the current and voltage input signals; however, both methods can have adverse consequences as was shown in Figure 5.

Another important observation is under all test conditions, TC 161 results in the largest error, followed secondly by TC 155. One reason for this is the nature of the training data and setup of the LSTM model. Recall that two cell surface temperature inputs are used to predict three cell surface temperatures on a separate battery array. Both temperature inputs are located at the end of the array, towards the center of the battery pack. However, TC 161 is located in the middle of the battery array and TC 155 is located on an end cell towards the outer edge of the battery pack. TC 169 is located on an end cell towards the middle of the battery pack which most closely resembles the inputs to the model. This implies a location dependence when predicting cell surface temperatures. Further support for this implication can be found in the physics of heat transfer to the battery cells. The boundary conditions of the end cells are different from the middle cells in that the middle cell experiences conduction on both sides as opposed to a single surface. Therefore, it would be beneficial to include multiple cell locations as opposed to a single location in inputs of future LSTM models.

A final remark to emphasize is the LSTM model constructed in this paper was evaluated with worst-case conditions. Namely, a minimum of two temperature measurements would be expected for a production battery pack. Furthermore, array 1 is physically located the farthest from array 7 and is a different size than the other arrays. Limiting the temperature inputs to a quantity of two along with a dissimilar array show the robustness of the model. In practice, more temperature inputs could be used to achieve higher accuracy. Also, the amount of data used to train, validate, and test the model was limited. Generating pack level data is costly, and therefore it is not realistic to expect unlimited data for production intent models. It is evident from the results presented previously the LSTM model is robust against a wide range of operating conditions, inputs, and irregularities that are required when operating in a production environment.

Summary

A LSTM based method for estimating battery pack temperature distributions is proposed in this paper. In the investigation, it is demonstrated that the LSTM based method is capable of estimating the battery pack temperatures that are spatially different from the measured battery pack temperatures. Under all test conditions evaluated, the max observed error was 1.53°C and most all MSEs were less than 1°C. For the future work, a study on the measurement data locations will be conducted to enhance the training data quality and performance of the LSTM model. In addition, the LSTM was trained and validated using only the data from the experiments. We plan to use data from physics-based models to further improve the accuracy. More specifically, we plan to develop a physics informed neural network with the intent to better characterize the heat transfer relationship between the battery cells and improve the accuracy of temperature predictions.

References

1. Pritchard, E., Mackey, L., Zhu, D., Gregory, D. et al., "Modular Electric Generator Rapid Development DC Microgrid," in *presented at 2017 IEEE Second International Conference on DC Microgrids (ICDCM)*, Germany, June 27-29, 2017, doi:10.1109/ICDCM.2017.8001030.
2. Sonnenberg, M., Pritchard, E., and Zhu, D., "Microgrid Development Using Model-Based Design," in *presented at 2018 IEEE Green Technologies Conference (GreenTech)*, USA, April 4-6, 2018, doi:10.1109/GreenTech.2018.00019.
3. Zhu, D. and Pritchard, E., "NCSU Year Three Final Technical Report," SAE Technical Paper 2014-01-2907, 2014, doi:10.4271/2014-01-2907.
4. Zhu, D., Pritchard, E., Dadam, S.R., Kumar, V. et al., "Optimization of Rule-Based Energy Management Strategies for Hybrid Vehicles Using Dynamic Programming," *Combustion Engines* 184, no. 1 (2021): 3-10, doi:10.19206/CE-131967.

5. Naguib, M., Kollmeyer, P., Vidal, C., and Emadi, A., "Accurate Surface Temperature Estimation of Lithium-Ion Batteries Using Feedforward and Recurrent Artificial Neural Networks," in *presented at 2021 IEEE Transportation Electrification Conference & Expo (ITEC)*, USA, June 21-25, 2021, doi:10.1109/ITEC51675.2021.9490043.
6. Zhu, D., Chikkannanavar, S., and Tao, J., "SOC Estimation Error Analysis for Li Ion Batteries," in *presented at 2021 IEEE Transportation Electrification Conference & Expo (ITEC)*, USA, June 21-25, 2021, doi:10.1109/ITEC51675.2021.9490137.
7. Li, S., Tong, L., Xing, J., and Zhou, Y., "The Market for Electric Vehicles: Indirect Network Effects and Policy Design," *Journal of the Association of Environmental and Resource Economists* 4, no. 1 (2017): 89-133.
8. Xia, G., Cao, L., and Bi, G., "A Review on Battery Thermal Management in Electric Vehicle Application," *Journal of Power Sources* 367: 90-105, doi:10.1016/j.jpowsour.2017.09.046.
9. Ojo, O., Lin, X., Lang, H., and Kim, Y., "A Recurrent Neural Networks Approach for Estimating the Core Temperature in Lithium-Ion Batteries," in *presented at 2020 Canadian Society for Mechanical Engineering (CSME) Congress*, Canada, June 21-24.
10. Gu, W.B. and Wang, C.Y., "Thermal and Electrochemical Coupled Modeling of a Lithium-Ion Cell," *Proceedings of the ECS* 99 (2000): 748-762.
11. Prada, E., Di Domenico, D., Creff, Y., Bernard, J. et al., "Simplified Electrochemical and Thermal Model of LiFePO4-Graphite Li-Ion batteries for Fast Charge Applications," *Journal of The Electrochemical Society* 159, no. 9 (2012): A1508.
12. Zhu, D., Campbell, J.J., and Cho, G., "Battery Voltage Prediction Using Neural Networks," in *presented at 2021 IEEE Transportation Electrification Conference & Expo (ITEC)*, USA, June 21-25, 2021, doi:10.1109/ITEC51675.2021.9490081.
13. Cho, G., Zhu, D., and Campbell, J.J., "A Comparative Study of Recurrent Neural Network Architectures for Battery Voltage Prediction," SAE Technical Paper 2021-01-1252, 2021, doi:10.4271/2021-01-1252.
14. Zhu, D., Cho, G., and Campbell, J.J., "Neural Networks Battery Applications: A Review," in *presented at 2021 IEEE International Conference on Electro Information Technology (EIT)*, USA, May 14-15, 2021, doi:10.1109/EIT51626.2021.9491835.
15. Kingma, D.P., and Ba, J., "Adam: A Method for Stochastic Optimization," in *presented at the 3rd International Conference on Learning Representations (ICLR)*, USA, May 7-9, 2015.
16. Chollet, F., *Deep Learning with Python, First Edition*, (Simon and Schuster, 2017), ISBN:ISBN: 9781617294433.

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Definitions/Abbreviations

ANN - artificial neural network
BECM - battery energy control module
BMS - battery management system
DCFC - direct current fast charge
FNN - feed-forward neural network
LSTM - long short-term memory
MSE - mean squared error
RNN - recurrent neural network
SOC - state of charge
SOH - state of health
TC - thermocouple