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SoH Predition Model for Lithium-ion Batteries Based on Transformer

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Extended Abstract

A lithium-ion battery is widely used in portable electronic devices because of its high energy density and low self-discharge degree even when not in use[1]. External environmental conditions and degradation determine battery life, which is subject to the risk of explosion due to battery aging. To ensure the stability and performance of lithium-ion batteries, many researchers proposed a battery state of health (SoH) prediction model. Modelling methods based on electrochemical models[2], expandable kalman filters[3], particle filters[4], and so on were studied. And recently, many studies have been conducted on predicting remaining life through long short-term memory (LSTM), which has an advantage in estimating a time series and learns by estimating a lithium-ion battery's dynamic state[5].

However, in the case of LSTM, it is difficult to receive sequential inputs and process them in parallel, resulting in a high computation volume. To solve this problem, a Transformer model[6] capable of predicting long-term prediction using multi-head self-attention has gotten a lot of attention. Transformer models can solve long-term dependency problems that cyclic neural network-based prediction models find difficult on time specific data. It also has a significant advantage over CNN in situations where temporal characteristics cannot be considered because it extracts characteristics that include time information held by the time series data[7].

We compared the predictive performance of existing CNN-LSTM model and transformer-based deep learning model in this paper. The transformer has a structure that combines several encoder and decoder. This study's encoder included a multi-head attention layer, an add & normalization, and a convolution layer.

The aging experiment data of 18650 lithium-ion battery #5 (B0005), #6 (B0006) and #7 (B0007) battery cells provided by NASA Ames PCoE were used in the learning. The deep learning model's performance was evaluated using data from the #18 (B0018) battery cell. On the basis of the discharge data, the training data was pre-processed. As correct and prediction values, SoH values calculated based on environmental conditions and capacity values were used. The model's performance was assessed using the RMSE and R-square value.

Based on the RMSE value, the CNN-LSTM model received a score of about 0.03 and the transformer model received a score of about 0.016. The CNN-LSTM model had a high accuracy of about 87 percent for R-square values, while the transformer model had a high accuracy of about 96 percent. The accuracy of the transformer model, in particular, tends to increase over time.

This study could help to improve the transformer model for predicting battery SoH. Futhermore, the proposed transformer model predicted battery life with high accuracy. This is expected to provide SoH information to consumers in a more intuitive manner and enable safer battery management.

The reference section at the end of the paper should be edited based on the following:

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