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SOC Prediction of Lithium-ion Batteries Using LSTM Model

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Abstract

This study proposes a deep learning-based LSTM model to predict the state of charge (SOC) of lithium-ion batteries. The model was trained using data collected under various temperature and load conditions, including measurement data from the CS2 lithium-ion battery provided by the University of Maryland College of Engineering. The LSTM model effectively models temporal patterns in the data by learning long-term dependencies. Performance evaluation by epoch showed that the predicted SOC improved from 14.8400 at epoch 10 to 12.4968 at epoch 60, approaching the actual SOC value of 13.5441. The mean absolute error (MAE) and root mean squared error (RMSE) also decreased from 0.9185 and 1.3009 at epoch 10 to 0.2333 and 0.5682 at epoch 60, respectively, indicating continuous improvement in predictive performance. This study demonstrates the validity of the LSTM model for predicting the SOC of lithium-ion batteries and its potential to enhance battery management systems.

Keywords: *Long short-term memory, Lithium ion battery, State of charge estimation, MAE, RMSE*

1. INTRODUCTION

Currently, major countries, including the United States and Europe, have introduced environmental regulations to reduce greenhouse gas emissions by 20-30% starting in 2020, which has promoted the use of renewable energy and led to rapid growth of the battery market [1]. Batteries play a key role in the smart grid and electric vehicle industries, and lithium-ion batteries are widely adopted as replacements for lead-acid batteries due to their high energy density and long lifespan [2]. In particular, batteries for electric vehicles require high capacity and a complex operating environment, and a systematic battery management system is essential to manage them safely and reliably [3].

SOC is a very important indicator in determining the condition of the battery and is defined as the ratio of the rated capacity to the remaining charge of the operating battery [4]. However, due to the nonlinearity and electrochemical reaction of the battery, SOC cannot be measured directly, and for this reason, various estimation methods have been studied. The current integration method, one of the existing SOC estimation methods, is simple and effective, but is affected by factors such as initial value, current sensor error, and battery deterioration [5]. The Kalman filter (KF) and its improved form, the extended Kalman filter (EKF), enable nonlinear system estimation for linear time-varying systems, but have the disadvantage of complexity of implementation and many parameters and conditions that must be considered during modeling [6-8].

To solve these problems, artificial intelligence-based SOC estimation methods have been proposed. Recently, with the explosive increase in data and the advancement of computer equipment, artificial intelligence technology has gained attention [9]. Artificial intelligence-based SOC estimation methods include

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artificial neural networks (ANN), support vector machines (SVM), fuzzy algorithms, and recurrent neural networks (RNN), and these methods provide high accuracy in various current ranges. RNNs can learn sequence data, and with the introduction of memory cells such as LSTM or GRU, learning on large-scale data over long periods has become possible. Recently, research has been conducted to estimate SOC in combination with the convolutional neural network (CNN) method.

Currently, artificial intelligence has become an important issue globally, and battery state-of-charge (SOC) prediction using deep learning deals with nonlinear battery characteristics in real-time and shows high adaptability to various battery types. In this paper, we propose a method to predict SOC using an RNN network with LSTM memory cells based on the characteristics of lithium-ion batteries.

2. RESEARCH MODEL

Recurrent neural networks (RNNs) emerged for modeling time series data but have problems such as long-term dependency and gradient vanishing. To overcome these shortcomings, the LSTM network was proposed in the mid-1990s. LSTM adds a cell state to the hidden state, which helps in learning long-term dependencies, making it widely used for time series data. This figure 1 shows the structure of the LSTM network for SOC estimation, using voltage (Vt), current (It), and temperature (Tt) as input data.

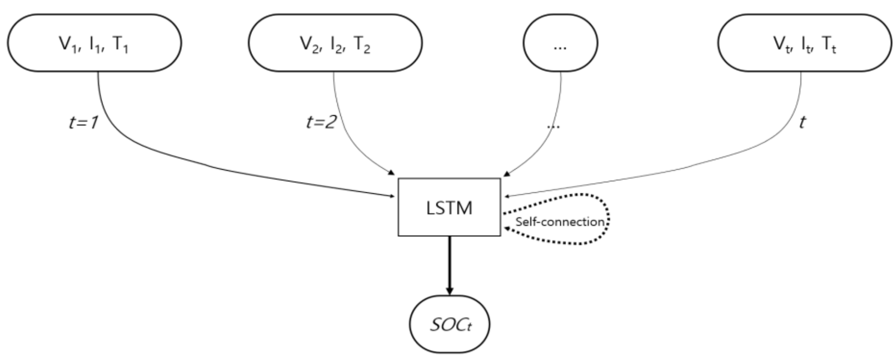

Figure 1. LSTM network structure for SOC estimation

For SOC estimation using an LSTM network, the input data consists of voltage (*Vt*), current (*It*), and temperature (*Tt*) at time step t. This input data is processed through an LSTM cell to estimate the SOC at that time step. The LSTM cell can process new inputs while remembering information from previous time steps.

This figure 2 shows the flow of information inside an LSTM cell, illustrating how the input gate, forget gate, and output gate operate.

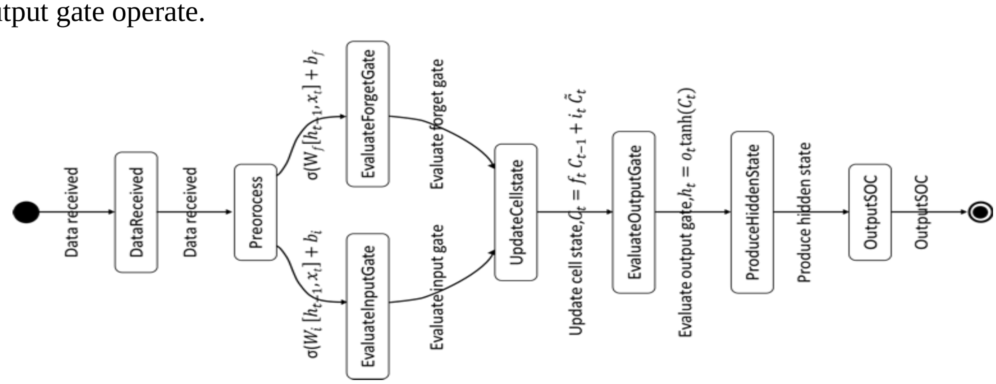

Figure 2. Flow diagram inside a forward-flowing LSTM cell

Inside an LSTM cell, there are input gates, forget gates, and output gates, each controlling the flow of information, with the cell state (*Ct*) handling long-term memory. Each gate combines the input data and the previous hidden state (*ht-1*) to decide what information to remember and discard. During the training process, a loss function is used to minimize the error between the predicted and actual values, with the mean squared error (MSE) being commonly used. This process helps the LSTM model to gradually improve its prediction accuracy.

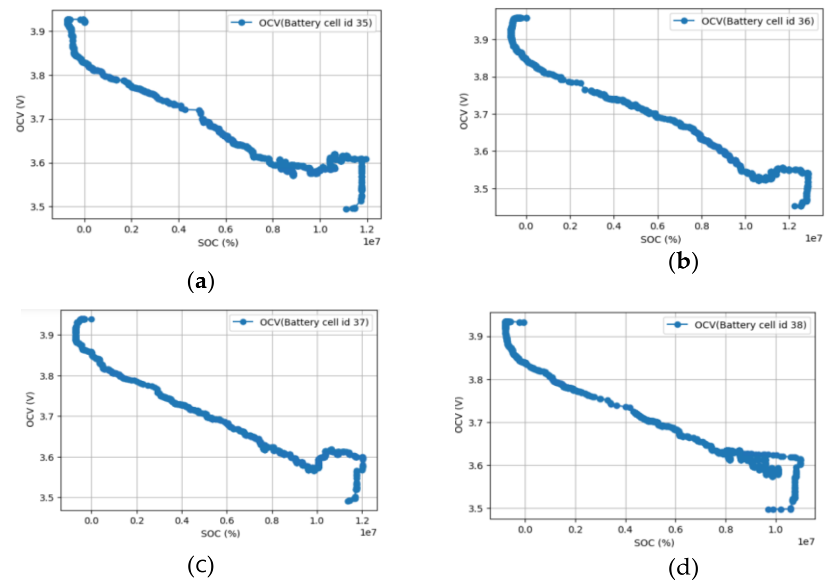

Figure 3. Comparison between SOC and OCV in (a), (b), (c), and (d) CS2 battery cell numbers 35, 36, 37, and 38 in Figure 3

This figure 3 compares the relationship between SOC and OCV for CS2 battery cells 35, 36, 37, and 38. Here, Cn represents the rated capacity, and i is the current at each time step. Although Cn is a variable value depending on the actual degree of battery aging, it is assumed to be constant in this paper since short-cycle data is used.

3. STRUCTURAL DESIGN OF LSTM MODEL

This section explains the characteristics of the battery and covers data preprocessing and implementation methods for the LSTM network model. It analyzes the learning ability and performance according to the LSTM structure and model parameter settings. To write the internal structure of the LSTM cell into a Python program, a library such as TensorFlow or Keras is used to perform calculations that update each gate and cell state.

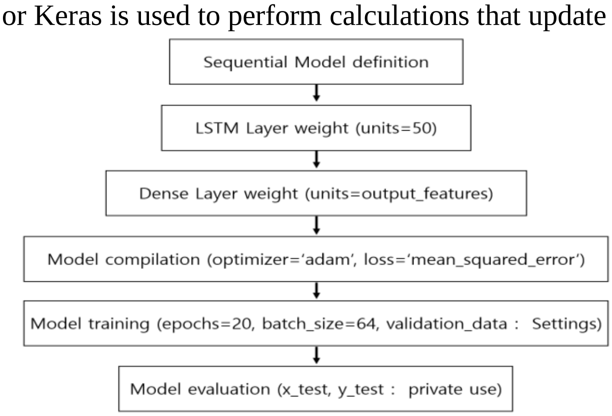

Figure 4. Flowchart for LSTM structure design

The LSTM model accepts input data, processes it through LSTM cells, and produces output data. Inside an LSTM cell, information is processed through several gates. Figure 4's pseudocode shows the structure of the LSTM model.

4. IMPLEMENTATION AND RESULTS

The software environment for the experiment was developed using Python version 3.10, and the artificial intelligence library used was the PyTorch-based MMDetection API. The hardware environment consisted of Windows 10 OS, an i9-9900K CPU, 128GB RAM, a 128GB GPU, and an NVIDIA RTX 6000.

Table 1. Types of battery data

Decision	Battery Type	Number of Data	Remarks
Battery Dataset	CS35	911	3931 rows × 22 columns
	CS36	950	
	CS37	1016	
	CS38	1056	
Total	4 Cell	3933	

In this paper, model parameters necessary for model construction or training process are set, and the actual SOC and predicted SOC are compared and analyzed according to epochs 10, 20, 30, 40, 50, and 60. Table 5 and Figure 9 show that as the epochs progress, the model tends to get closer to the actual SOC value, although it sometimes slightly overestimates or underestimates the SOC value at certain epochs. Epoch 60 shows the most accurate predictions, indicating that the model is gradually optimizing with sufficient training. Table 2 show the predicted SOC, MAE, and RMSE values for each epoch, and this data is used to analyze the model's training process and performance. As the epochs progress, MAE and RMSE values show a decreasing trend, indicating that the model's prediction accuracy is improving. The predicted SOC for epoch 10 was 14.8400, MAE was 0.9185, and RMSE was 1.3009, but by epoch 60, the predicted SOC was 12.4968, MAE was 0.2333, and RMSE was 0.5682, showing continuous improvement in model performance. Overall, as the number of epochs increases, the predicted SOC values gradually stabilize, and MAE and RMSE values decrease, indicating that the model is well-trained and its performance is improving.

Table 5. LSTM model performance across epochs

Epoch	Predicted SOC	MAE	RMSE
Epoch 10	14.8400	0.9185	1.3009
Epoch 20	12.6617	0.5693	0.8812
Epoch 30	12.4947	0.3403	0.6511
Epoch 40	12.6203	0.2706	0.5968
Epoch 50	12.5185	0.2331	0.5793
Epoch 60	12.4968	0.2333	0.5682

5. CONCLUSION

Accurate state of charge (SOC) prediction of lithium-ion batteries plays an important role in various applications such as electric vehicles and smart grids. Accurate estimation of SOC is essential to ensure efficient use, longevity, and safety of batteries. However, accurately estimating SOC is challenging due to the complex nonlinear nature of batteries and varying operating environments. This study proposes a method to estimate the SOC of lithium-ion batteries using deep learning, particularly LSTM models. LSTM can learn long-term dependencies from sequence data and effectively model temporal patterns in battery data. This study uses battery data collected from various charge and discharge cycles to train an LSTM model and evaluates the model's performance by epoch to derive the optimal model configuration. The results show that the predicted SOC at epoch 10 was 14.8400, higher than the actual value, but at epoch 60, the predicted SOC was 12.4968, closer to the actual value. Additionally, MAE and RMSE values decreased as epochs progressed, indicating improved model prediction performance. In conclusion, as the model learns, it gets closer to the actual SOC value, and the error rate consistently decreases. Therefore, this model can be evaluated as a useful tool for SOC prediction.

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