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NMC Lithium-Ion Batteries SOH Estimation Using CNN-LSTM Neural Network

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Abstract. Lithium-ion batteries have gained more place in the energy storage market thanks to their different advantages. However, their performance and safety decrease with ageing. Hence, the monitoring of their internal states is a mandatory condition to optimize their operations. The State of Health (SoH) of lithium-ion batteries is commonly quantified by the fade of the cell capacity. This paper presents a hybrid artificial neural network model for SoH estimation for electric vehicle applications. The estimation method combines the Long Short-Term Memory (LSTM) combined with the Convolutional Neural Networks (CNN) to estimate the SoH of NMC lithium-ion cells from voltage measurements. The model was trained and tested based on experimental data obtained from the cycling of four NMC cells. The cells are cycled with a dynamic current profile under a controlled temperature of 35 °C. The diagnosis model was tested for each cell using the Leave One Out Cross Validation (LOOCV) approach to evaluate the robustness against the cell's inconsistency.

Keywords. Lithium-ion batteries, ageing, state of health estimation, artificial neural networks.

1. Introduction

Lithium-ion batteries are one of the most used storage devices thanks to their numerous advantages such as: high energy density, high autonomy, fast charging, etc. Lately, they have been widely used in different applications such as the storage of renewable energies, power supply for mobile devices and electric vehicles.

The high performance of lithium-ion batteries degrades with time and operations. This degradation is expressed by a decrease in batteries' capacity and an increase of the internal resistance. To monitor the capacity fading of lithium-ion batteries, many studies [1] have suggested different methods to estimate the internal SoH (State of Health) which is defined as the ratio of the current battery capacity to its initial state. The lithium-ion batteries' SOH estimation is mainly achieved using model-based and data-driven approaches [1]- [17].

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Model-based methods are based on a mathematical representation of the physical model of lithium-ion batteries. These models are used to identify and estimate the internal parameters of the cells to assess their health status. N. A. Azis et al. [2] presented a method for SoC and SoH estimation using a dual Extended Kalman Filter on polynomial model of lithium-ion batteries. In [3], Y. Liang et al. used an Improved Adaptive Dual Extended Kalman Filter Based on Piecewise Forgetting Factor Recursive Least Squares in order to improve SoC and SoH estimation. P. Shrivastava et al. [4] presented a method for lithium-ion batteries model parameter identification Using Modified Adaptive Forgetting Factor-Based Recursive Least Square Algorithm. In [5], X. Liu et al. presented a method for SoH estimation of retired lithium-ion batteries based on Electrochemical Impedance Spectroscopy (EIS) and Back Propagation (BP) neural network. In addition, in [6], A. Laurin et al. presented a method for SoC and SoH estimation based an extended characterization of Li-ion cells, by establishing a precise electrical and ageing model. In [7], H. Obeid et al. proposed a higher Order Sliding-Mode Observers for Li-ION batteries SoC and SoH estimation.

Data-driven methods use experimental data to directly analyze the ageing of the batteries without the need to understand its ageing mechanisms. In [8], S. Bamati et al. proposed to use a solo nonlinear autoregressive with external input (NARX) network for SoH prediction. In [9], an Ensemble Learning Machine (ELM) was used to get a high accuracy of SoH estimation. In [10], Gaussian Process Regression (GPR) was used to analyze experimental data and to estimate the Li-ION batteries SoH. In [11], Z. Tan et al. proposed a 1D-CNN network to take benefits of its feature extraction ability for a good SoH estimation. In [12], D. Lu et al. proposed to use a Transfer Learning framework for SoH estimation by using a pre-trained CNN. In [13], A. Niraula et al. presented a comparative study between BP neural network, Support Vector Regression (SVR) and LSTM for SoH estimation in the electric vehicles. In [14], the authors provided a comparative study between three different data-driven algorithms (the nonlinear autoregressive neural network, convolutional neural network, and long short-term memory network) for the state of health estimation of lithium-ion batteries. The comparison results showed the superiority of LSTM.

To improve the robustness and accuracy of the diagnosis methods hybrid methods are also proposed. In [15], the authors proposed to combine back propagation neural network with dual Extended Kalman Filter to improve SoC and SoH estimation. In [16], the author presented a method based on ant lion optimization algorithm and support vector regression (ALO-SVR) to improve SoH estimation accuracy. In [17], the authors proposed a CNN-LSTM hybrid method for SoH estimation and Remaining Useful Life (RUL) prediction. The model showed good results compared to the alone LSTM neural network.

This paper investigates the use of the CNN-LSTM methods in battery capacity estimation for the evaluation of the battery ageing. This method uses the available voltage measurements under dynamic current profile to estimate the battery capacity, and consequently the battery SoH variation with ageing. The effectiveness of the method is verified with experimental data obtained from the cycling of four NMC cells.

The rest of the paper is structured as follows: Section II presents and details the algorithms used for the SoH estimation. Section III details the experimental protocol used to generate the dataset and the characteristics of the used lithium-ion cells. Section IV presents the architecture of the estimation model, the evaluation metrics and the results' analysis. Finally, a conclusion and summary are presented in Section V.

2. Methodologies and Algorithms

In this section, the algorithms and methods used will be presented and detailed.

2.1. LSTM

Long Short-Term Memory are one of the recurrent neural networks (RNN) that are mostly used for time series for the prediction of time series data. Lately, it has been widely used in the energetic field such as diagnostic and prognostic of lithium-ion batteries [18], and power time series data prediction [19]. An LSTM unit is composed of three gates: the forget gate, the input gate and the output gate that will be explained in detail in the following paragraphs.

- Forget gate

In this gate, mathematical calculations are done on the old memory cell and the new input in order to select the most significant information for the new output. The following equation expresses the calculation done in the forget gate:

$$f_t = \sigma\left(W_f . [h_{t-1}, x_t] + b_f\right) \tag{1}$$

Where;

- $[h_{t-1}, x_t]$ is the concatenation of the input array x_t and the previous output state h_{t-1};
- W_f and b_f are the weight and bias of the neuron, respectively.
- σ is the sigmoid function.

By multiplying the forget gate's output f_t, with the old memory cell C_{t-1}, the most irrelevant information (the closest to 1) are selected.

- Input gate

After selecting the irrelevant information, new calculations are done to select useful information from the new input. The mathematical calculations are expressed as follows:

$$i_t = \sigma(W_i . [h_{t-1}, x_t] + b_i) \tag{2}$$

$$\tilde{C}_t = tanh(W_c . [h_{t-1}, x_t] + b_c) \tag{3}$$

Where, i_t is the input gate's output and $\tilde{C}_t$ is the hyperbolic tangent function's result Then, a new calculation is done using i_t and $\tilde{C}_t$ in order to filter the new data and choose the most significant values, as expressed in the following equation:

$$C_t = f_t \times C_{t-1} + i_t \times \tilde{C}_t \tag{4}$$

The above equation allows updating the current memory cell C_t

- Output gate

After updating the memory cell and selecting the most irrelevant information, the next step is to calculate the new output as follows:

$$o_t = \sigma(W_o.[h_{t-1}, x_t] + b_o) \quad (5)$$

$$h_t = o_t \times \tanh(C_t) \quad (6)$$

Where, h_t is the new output value.

2.2. CNN

Convolutional Neural Networks are among the most popular types of neural networks. CNNs were developed to process high-dimensional data (images, videos, etc.) and showed high performance in image processing. Their biggest advantage is that each one of its units contains filters that are convoluted with the input data to extract the important features. The use of kernels is derived from classical image processing techniques (such as sharpening, blurring, etc.) and they use parameter sharing to greatly reduce the number of learnable variables.

Lately, a new version of CNN (CNN 1D) was developed to process one dimensional data and more specifically time series data, and it has been widely used for times series prediction such as stock price trend prediction [20], and temperature prediction [21]. CNN 1D are advantageous and preferable to CNN 2D in the processing of one dimension data for different reasons such as: the small computational complexity and ease of training and implementation.

Generally, a convolutional neural network is composed of the following layers:

- Convolutional layers: they extract features from the data using internal kernels (filters) and convolution mathematical operations.
- Pooling layers: they compress the data leaving only the most irrelevant information. These layers represent the biggest advantage of CNNs, which reduce the data size while keeping the most important information. Therefore, the processing can be accelerated.
- Fully connected layers: they combine the final characteristic information for the output.

2.3. Hybrid CNN-LSTM

The hybrid CNN-LSTM is a combination of CNN and LSTM networks. CNN is used for extracting the features and reducing the data size dropping out the most irrelevant characteristics. This filtering simplifies/optimizes the process of data extrapolation for LSTM network computation. Consequently, the hybrid CNN-LSTM can process big amounts of data in a short time delay. This combination has been widely used lately for the prediction of wind power [22], pulmonary tuberculosis incidence rate [23], and passenger flow [24].

3. Experimental Data

The dataset used is extracted from an experiment consisting on cycling Lithium-Ion cells at an ambient temperature of T=35°C. The cells are first charged using a CC-CV charging method until reaching a SoC of 100%. The cells are then discharged using dynamic current profile extracted from WLTC procedure until their voltage reaches the minimal value V_{min}. These operations are repeated during the first five days of the week. At the end of the week, the battery's performance is calculated during the check-up tests, which are done at 25°C. Figure 1 displays the experimental protocol. More details about the experiments and the test bench can be found in [25].

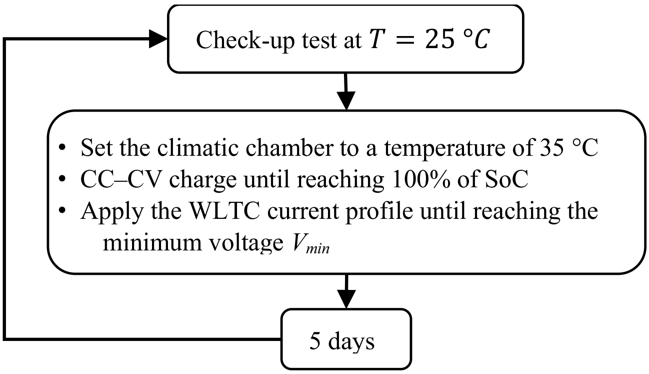

Figure 1. The experimental protocol of battery cycling.

WLTC (World-wide harmonized Light duty Test Cycle) is a standard driving cycle to evaluate the autonomy of light vehicles, fuel consumption, and CO2 emissions. The electrical load profile used for cells cycling is obtained considering electrical vehicles operating conditions and in particular, the speed and the acceleration profiles provided by the WLTC procedure.

During the check-up test, the capacity (C), and the energy (E) are calculated as given in the following equations:

$$C(Ah) = \int_0^{t_{end}} i(t).\,dt \tag{7}$$

$$E(Wh) = \int_0^{t_{end}} i(t) * U_b(t).\,dt \tag{8}$$

The lithium-ion cells used in these experiments are the Nickel Manganese Cobalt Chemistry/Graphite (NMC) cells. Table 1 provides their characteristics.

Table 1. The characteristics of the cycled NMC cells

Model Name	INR21700-30T
Diameter	21mm
Height	70.1 mm
Cathode materials	Lithium Nickel Manganese Cobalt Oxide
Anode materials	Graphite
Nominal capacity	3 Ah
Nominal voltage	3.6 V
Voltage range	2.5V – 4.2V
Rated charge current	4 A
Rated discharge current	10 A

4. Results and Analysis

In this section, the architecture of the model, the evaluation metrics and the obtained estimation results are presented.

4.1. The Architecture of the Model

As presented in Figure 2, the model input is the voltage variation obtained during the last WLTC cycle, while the estimated capacity (SoH indicator) is the corresponding output.

Figure 2. Estimation model.

The details of the architecture of the proposed model are depicted in Figure 3.

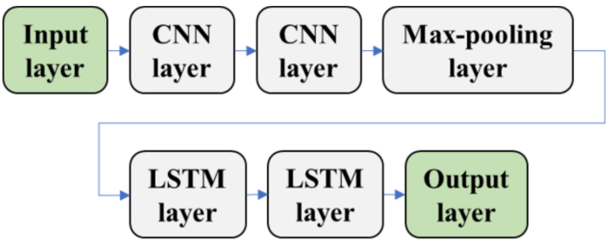

Figure 3. Detailed architecture of the estimation model.

4.2. Evaluation Metrics

For performance evaluation, the following errors are calculated between the estimated SoH $\tilde{y}_i$ and the actual SoH y_i for a set of N observation:

– Mean Absolute Percentage Error (MAPE)

The MAPE is used to determine the size of an error between predictions and actual values relative to the size of the data. The MAPE is given by the following equation:

$$MAPE = \frac{1}{N} * \sum_{i=1}^{N} \frac{|\tilde{y}_i - y_i|}{y_i} \quad (9)$$

– Mean Squared Error (MSE)

The MSE measures how far the predictions are from the actual values. The lower the MSE, the closer are the predictions to measurements. The MSE is expressed by the following equation:

$$MSE = \frac{1}{N} * \sum_{i=1}^{N} (\tilde{y}_i - y_i)^2 \quad (10)$$

– Mean Absolute Error (MAE)

The MAE (Mean Absolute Error) used to calculate the overall average amplitude between predictions and actual values is defined as follows:

$$MAE = \frac{1}{N} * \sum_{i=1}^{N} |\tilde{y}_i - y_i| \quad (11)$$

4.3. Estimation Results

To evaluate the performance and the robustness of the estimation model, we used the Leave-One-Out Cross-Validation (LOOCV) method. The LOOCV is a cross validation method where each observation is considered for validation and the other ones are used for training. In this study, the LOOCV method is applied to the data of the four cells. The data of each cell will be used for validation, and the data of the other three ones will be used for training. Figures from Figure 4 to Figure 7 show the estimated SoH for the cells in comparison with the measured SoH using the LOOCV method. Table II displays the different errors for the four cells.

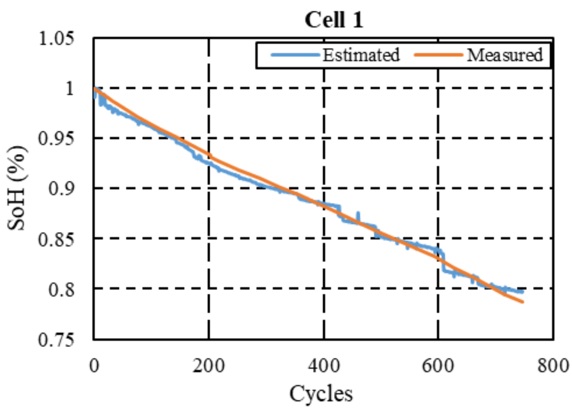

Figure 4. Cell 1 estimation results.

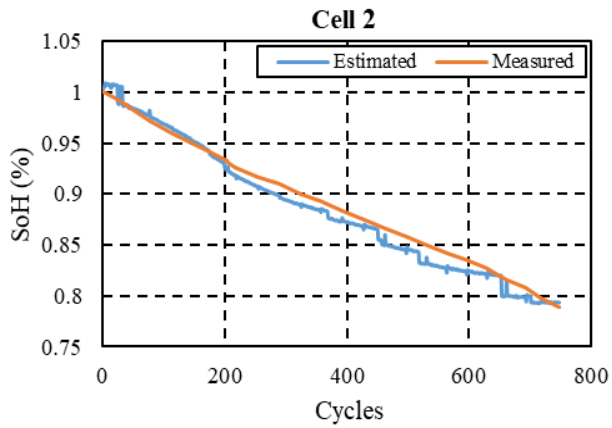

Figure 5. Cell 2 estimation results.

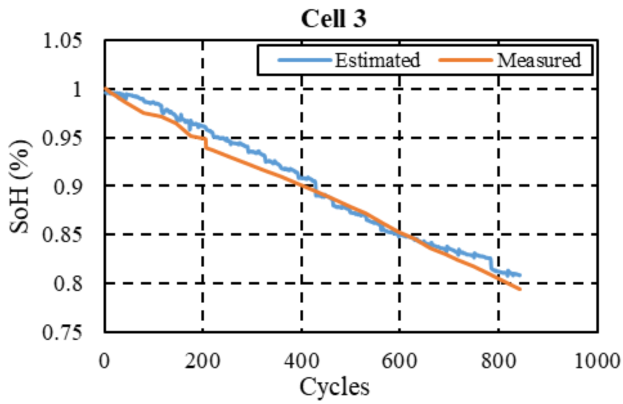

Figure 6. Cell 3 estimation results.

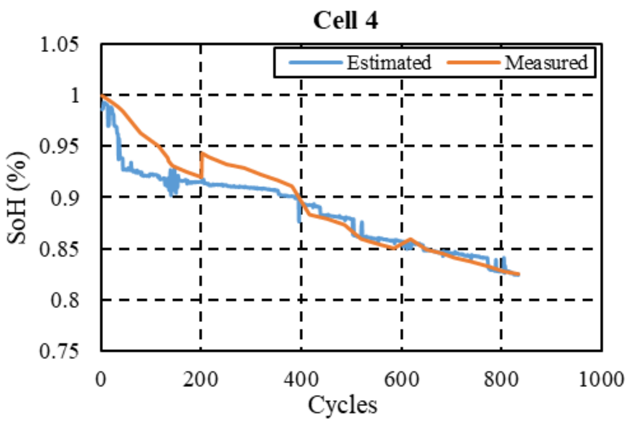

Figure 7. Cell 4 estimation results.

Table 2. Estimation results for NMC cell

	Cell 1	Cell 2	Cell 3	Cell 4
MAPE (%)	0.6095	0.9392	1.0014	1.3398
MSE	0.0009	8.7905e-05	0.0001	0.0003
MAE	0.0054	0.0082	0.0089	0.0124

The results in figures (figures 4-7) and the estimation errors in Table 2 show the effectiveness of method for the estimation of the capacity decreasing. The MAPE of the estimations is less than 1.40% for the four cells. The results also show the variation of the estimation errors between the cells, especially for the cell 4 which has a different ageing behavior in comparison with other cells. These variations are mainly due to the different ageing behaviors of the cells. Overall, the hybrid CNN-LSTM model show it efficiency and its robustness for the estimation of the SoH of the NMC cells based on the voltage measurements under WLTC current profile. The obtained results obtained in this study are consistent with those presented in [17] based on NASA open-source dataset.

5. Conclusion

This paper presented a hybrid neural network for lithium-ion batteries state of health estimation for vehicular applications. The used method combines the Convolutional Neural Network and the Long Short-Term memory. CNN is used to extract features from voltage measurements and the LSTM estimates the SoH from the extracted features. The experimental data are obtained by cycling four NMC cells under controlled temperature of 35 °C. The effectiveness of the method is verified under dynamic current profile extracted from WLTC procedure. The obtained results show that the mean absolute percentage error is less than 1.4 %.

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