State of Charge Estimation of Sodium-Ion Batteries Based on N-BEATS Neural Network

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2023 7th Asian Conference on Artificial Intelligence Technology (ACAIT) | 979-8-3503-5914-5/23/$31.00 ©2023 IEEE | DOI: 10.1109/ACAIT60137.2023.10528411

***Abstract*—The increasing penetration of renewable energy sources in the grid and the deficiencies of lithium batteries in terms of storage capacity have necessitated the use of sodium batteries as large scale energy storage devices in renewable energy systems. Accurate estimation of the State of Charge (SOC) of such batteries is of great significance. In this paper, we fabricated the CR2032 sodium-ion batteries and propose a novel method for the estimation of SOC of sodium-based coin cell using a Neural Basis Expansion Analysis for Time Serious (N-BEATS). The advantage of this method is that it does not require the input features to estimate the SOC, instead, the historical information of time series is used to predict the future information. Therefore, there is no need to collect external observations to achieve battery management system (BMS) cost savings. Experimental results show that the proposed method can substantially reduce the estimation error, with a mean absolute error (MAE) and root mean square error (RMSE) of less than 0.3669 % and 0.4549 %, respectively. This improved reliability of the BMS under the energy storage system (EES) is of great significance.**

***Index Terms*—State of charge, Sodium-ion batteries, N-BEATS, Energy storage systems**

I. Introduction

As the penetration of renewable energy in the national grid grows, so do its attendant problems and challenges. This is mainly reflected in the seasonal variation of power generation that exists for solar, wind and tidal energy, ect. This seasonal variation leads to instability in the grid, thus limiting the further increase of renewable energy penetration in the grid [1]. To meet these challenges, Zakariya et al. [2] proposed an energy storage scheme to regulate the indirectness problem that exists in renewable energy sources, energy storage system (ESS) are required for continuous energy harvesting and steady energy output [3]. Energy storage technologies that exist and feasible include electrochemical energy, thermal energy, thermochemical energy, electromechanical, and pumped hydro storage [4]–[6]. Among them, electrochemical energy storage is considered more practical for large-scale energy storage deployed in homes, cities and places that are out of reach of traditional electrical infrastructure away from the grid [7]. Lithium ion batteries(LIBs) have been commercially used on a large scale due to their high energy density as well as their mature technology. This is accompanied by the soaring price of lithium. As the reserves of lithium are not abundant and not uniformly distributed in nature. The above factors have hindered the use of LIBs as a material for large-scale electrochemical energy storage [8], [9]. Sodium ion batteries(SIBs) have received extensive research and attention due to the need for lithium replacement elements to achieve large-scale energy storage. The battery components and storage mechanisms of SIBs and LIBs are essentially the same except for the example carriers. And the intercalation chemistry and similarity of Na means that both can use similar compounds [10]. However, Na^+ (1.02 Å) are larger compared to Li^+ (0.76 Å), the difference in particle length also affects its phase

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stability, transport properties and interphase formation [11]. Sodium(23 g mol^{-1}) is also heavier than lithium(6.9 g mol^{-1}) and has a higher standard electrode potential (2.71 V vs. (standard hydrogen electrode)SHE as compared to 3.02 V vs. SHE for lithium); This means that the upper energy density limit of the SIBs must be lower than that of the LIBs [8]. The review [12] analyzed the progress of research on SIBs in recent years and concludes that the technology of SIBs is feasible for commercialization. Figure. 1 illustrates the working principle of SIBs and the structure of the coin cell based on sodium cell design used in this paper. The storage between lithium and sodium in terms of resources and reserves and public quantities also explains the inability of lithium to be used in large-scale energy storage applications [13]. Based on the above factors, SIBs is more promising than LIBs for future applications in the field of large-scale energy storage.

A. Literature review

Battery management systems (BMS) play a crucial role in ensuring the safe, reliable, and efficient operation of ESS. The BMS manages battery performance and SOH by monitoring battery voltage, current, temperature and state of charge(SOC), etc. The BMS is therefore a critical component of any ESS, and its proper functioning is essential to ensure the long-term reliability and performance of the system [14]–[16]. SOC is a crucial state quantity that represents the available charge of the battery. Its accuracy is critical to the reliability of the BMS [17]. In practice, SOC is often interfered by some non-linear factors and cannot be measured accurately [18]. Therefore, it can only be predicted by some physical quantities that are convenient to measure, such as current, voltage, temperature, etc [19]. So for any BMS, the estimation of SOC is still a challenging target. Existing methods for SOC estimation include open-circuit voltage (OCV) approach, Coulomb counting approach, as well as model-based filtering approach and machine learning approach [20].

Data-driven approach has become popular in recent years, thanks to the fact that it only requires input features to achieve the estimation of SOC and does not require specific formulas and models. The relationship between SOC and battery parameters is not linear due to the complex battery reactions and usage environments. This is why the calculation of SOC using the OCV approach and the coulomb counting approach often results in large errors [21]. Therefore, Data-driven approach have become an important tool for estimating SOC. Data-driven approach include filtering approach and machine learning approach. The latter one can achieve SOC estimation by viewing the battery model as a black box so that it does not need to be modeled but only by external conditions [22]. Li et al. [23] proposed a random forest regression approach to achieve the estimation of SOC for LIBs. Álvarez Antón et al. [24] used the support vector machine (SVM) technique to estimate the SOC of high capacity lithium ion phosphate ($LiFePO_4$) battery. Iman et al. [25]proposed a gaussion process regression (GPR) approach based on electrochemical impedance Spectroscopy (EIS) data to achieve SOC estimation of electric vehicles (EVs) batteries. Since the estimation of SOC is actually essentially a prediction problem about time series, some approaches with historical information processing capability have been widely studied [26]. Examples include autoregressive integrated moving average(ARIMA) [27], recurrent neural network (RNN) [28]. Since RNN often suffer from gradient vanishing and gradient explosion when dealing with longer time series, resulting in poor final convergence. Therefore, by using gating mechanism to induce long short-term memory (LSTM) and gated recurrent unit (GRU) to regulate the flow of information and gradients in the network, allowing them to learn long-term dependencies in the data [29]. Ephrem et al. [30]employed the LSTM to estimate the SOC, taking the comprehensive consideration of different temperatures into consideration, and achieved better practical effect. Meng et al. [31] proposed a approach to estimate the SOC using a momentum gradient algorithm to optimize the GRU convergence rate. Wu et al. [32] compared the estimation accuracy of conventional RNN and LSTM, GRU which adopts gating mechanism for lithium battery SOC, and the results proved the usefulness of gating mechanism in processing long time sequence data. Considering the complex physicochemical properties inside the cell. SOC may not only be related to the observed data outside the cell in the past. In other words, the exact value of SOC should be considered in combination with the observed data from the previous and future moments. Based on this feature of many time sequences, bidirectional gated recurrent units (BiGRU) and bidirectional long short-term memory (BiLSTM) were proposed [33]. The above mentioned data-driven approaches are based on predicting the SOC of a battery from features such as current, voltage, temperature, etc. The purpose of the model is to capture the relationship between features and SOC. Oreshkin et al. [34] proposed a neural network called N-BEATS, consisting of fully connected (FC) layers for time series prediction in 2019. This model is characterized by predicting future information from the historical information of the series, i.e., it does not need to capture the serial correlations between the inputs and outputs. N-BEATS was preferred by some studies to be a regression model [35], [36]. Kannan et al. [37] proposed a fusion model based on N-BEATS and deep neural network (DNN) for estimating the SOC of LIBs, and the results indicate that the method has good robustness and generalization ability. According to the above introduction of SIBs and SOC estimation methods, the objective is to propose a SOC estimation model that can be applied in the field of energy storage.

B. Key contributions

1 We propose to apply the N-BEATS neural network in the context of sodium battery energy storage for its SOC estimation. The model itself does not require input features since it uses the historical information of the sequence to predict the future information. Therefore, external observations such as voltage, current and temperature do not need to be collected.

2 The experiments were conducted to estimate the SOC of sodium batteries for each of the three cathode materials. The three cases were estimated for complete discharge process, discharge from 80%, and discharge from 60%, respectively.

3 R-squared, mean absolute error(MAE), and root mean squared error(RMSE) were used as the evaluation indexes for model estimation. The results show that N-BEATS presents a better estimation accuracy than the existing methods and provides a feasible solution for future large-scale energy storage BMS.

II. Methodology

A. Neural Basis Expansion Analysis for Time Series (N-BEATS)

Different from the above-mentioned RNN model and its derivatives, which view the time series prediction problem as a seq2seq problem, N-BEATS views it as a multiple nonlinear regression problem. Fig. 1 illustrates the architecture of the N-BEATS model. The leftmost box indicates that the entire model is a nonlinear regressor consisting of a combination of many FC layers. The future points are predicted by accepting historical information from the series. The FC layers are stacked on top of each other to achieve prediction and back-propagation information extraction, allowing learning of the context of the time series. The principle of doubly residual stacking can be seen in Eq. 3. by analyzing the two residual branches xb_k as a sequence of the input signal, running on the backward and forward prediction, respectively. Thus each block of N-BEATS can be viewed as a collection of FC layers with forward and backward prediction. Assume that the number of stacks in the model is M, the number of residual blocks in a stack is K, and there are N FC layers in a residual block. The input of xb_k represents the kth Block in a given stack. The outputs consist of the backcast $\widehat{xb}_k$ and the forecast $\widehat{yb}_k$. They are derived iteratively from Eq. 1 and Eq. 2.

$$h_{k,n} = FC_n(xb_k), h_{k,n} = ReLU(h_{k,n}) \tag{1}$$

$$\begin{aligned} \widehat{xb}_k &= B_k h_{k,n} \\ \widehat{yb}_k &= F_k h_{k,n} \end{aligned} \tag{2}$$

$$xb_k = xb_{k-1} - \widehat{xb}_{k-1} \tag{3}$$

where both B_k and F_k are the weights inside the kth residual block. Then the residual between the input and output of the kth residual block is used as the input of the $k+1$th residual block, and the operation principle can be seen in Eq. 3. The residuals xb_k of the input and output go to the next stack, while the forecast yb_k of all residual blocks are added up as the output of the corresponding stack. The calculation process can be seen in Eq. 4. The resulting output of the network is the summation of the outputs of all stacks ys_m and the result is input to the sigmoid function for nonlinear transformation.

$$ys_m = \sum_{i=1}^{K} \widehat{yb}_i \tag{4}$$

$$y = sigmoid(\sum_{i=1}^{M} ys_i) \tag{5}$$

III. Dataset description and experimental setup

A. Datasets

The sodium-ion battery dataset used in this paper was tested by the laboratory of the Institute of Carbon Neutralization, Shenzhen Institute of Advanced Technology, Chinese Academy of Sciences. Fig. 2 shows some of the voltage and current data for the three cells during the test. $Cell_1$ represents a SIB with Fe-Ti doped into the cell cathode material and tested in the voltage range of 1.5V-4.1V. $Cell_2$ has the same voltage test range as $Cell_1$, but with LiF doped into the cathode material. $Cell_3$ has the same cathode doping material as $Cell_2$, but with a voltage test range of 2.3 V-4.1 V. Each of the three cells were tested in a constant current charge/discharge protocol during the process. The test current of $Cell_1$ was 0.036 mA, the test current of $Cell_2$ was 0.012 mA, and the test current of $Cell_3$ was 0.016 mA. The current variation during the experiment and its bandwidth can be seen in the subplot which in the second row of Fig. 2.

B. Sequence processing

Due to the qualities of the N-BEATS model itself, there is no necessity to estimate the labels by the input features. Therefore, we constructed a SOC time series of length k $[SOC_1, SOC_2, ..., SOC_k]$. The intention is to be used to predict $[soc_{k+f}]$, and f is the estimation length. the SOC series is calculated by the Coulomb counting method.

C. Evaluation criteria

In considering the estimation performance of the adopted method, this paper chooses to evaluate it by MAE, RMSE and R-squared. RMSE can better reflect the effect of outliers, while MAE can reflect the general estimation error. R is then applied to evaluate the fit of the regression model and is often used together with other indicators to assess the model.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(SOC_i - \widehat{SOC_i})^2}{N}} \times 100\% \tag{6}$$

$$MAE = \frac{\sum_{i=1}^{N}\left|SOC_i - \widehat{SOC_i}\right|}{N} \times 100\% \tag{7}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(SOC_i - \widehat{SOC_i})^2}{\sum_{i=1}^{n}(SOC_i - \overline{SOC_i})^2} \tag{8}$$

where N represents total number of samples, $\widehat{soc_i}$ is the estimated value while soc_i is the actual value.

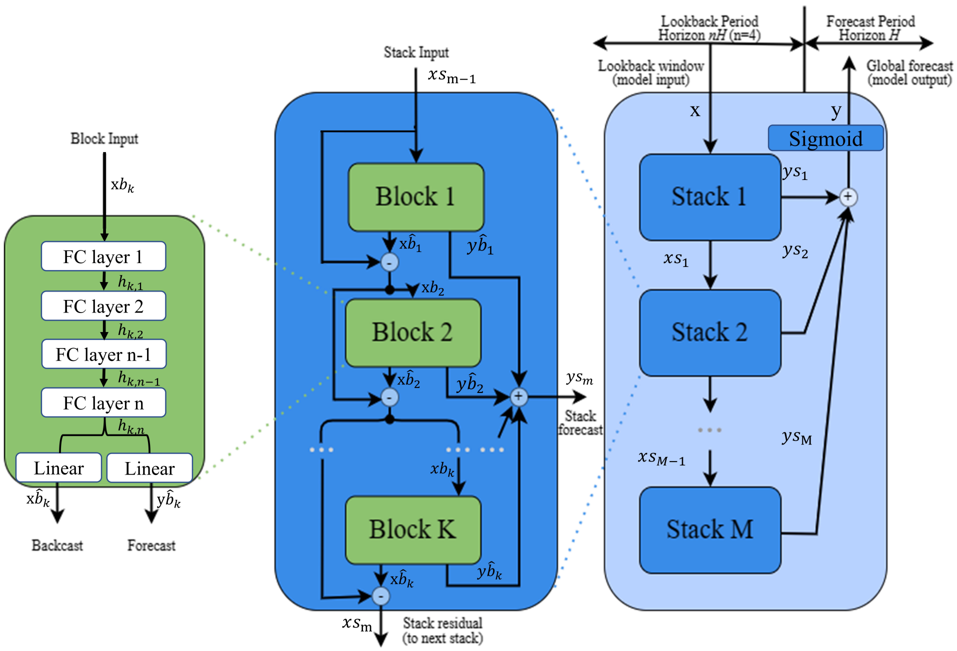

Fig. 1. The architecture of N-Beats.

TABLE I
Estimation results of Sodium cell SOC with N-BEATS and BiLSTM

Model	Data	RMSE(%)			MAE(%)			R-squared(%)		
		100%-0%	80%-0%	60%-0%	100%-0%	80%-0%	60%-0%	100%-0%	80%-0%	60%-0%
N-BEATS	$Cell_1$	0.2985	0.3014	0.1738	0.1640	0.1600	0.0869	99.9811	99.9800	99.9882
	$Cell_2$	0.2323	0.3382	0.2766	0.2008	0.2996	0.2511	99.9932	99.9785	99.9728
	$Cell_3$	0.1591	0.3071	0.4549	0.1435	0.2219	0.3669	99.9968	99.9815	99.9279
BiLSTM	$Cell_3$	0.8622	0.6058	0.7887	0.7082	0.4082	0.6633	99.9023	99.9289	99.7766

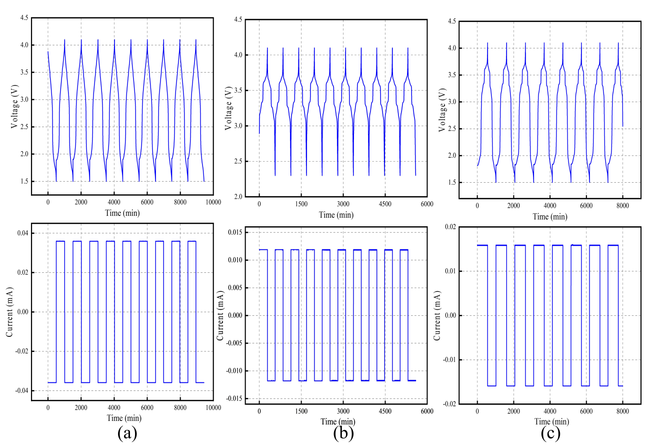

Fig. 2. Voltage and current data from three datasets at 25°C: (a)$Cell_1$; (b)$Cell_2$; (c)$Cell_3$.

IV. Experimental results and discussions

A. Experimental setup

For CR2032 type SIBs coin cell. The datasets were trained and tested under three operating conditions, respectively. $Cell_1$ is a sodium cell with equal proportions of Fe and Ti doped into the cathode material, and the voltage range is 1.5 V-4.1 V. $Cell_3$ is a sodium cell with LiF doped into the cathode material, and the voltage range is 2.3 V-4.1 V. $Cell_2$ has the same cathode material as $Cell_3$, and the voltage range is 1.5 V-4.1 V. The experiments estimated the three cell SOCs using the N-BEATS model from 100%, 80%, and 60% to complete discharge, respectively. In order to demonstrate the superiority of the N-BEATS model for SOC estimation of sodium batteries, the experiments were further estimated using the BiLSTM for the SOC of $Cell_3$ in the three discharge cases. Fig. 3 illustrates the estimated curves involved in the above experiments. The specific evaluation criteria for each experiment can be seen in Tab. I.

B. Experimental results

The evaluation criteria data in Tab. I were observed through the passages, and N-BEATS showed superior SOC estimation performance for all three discharge states in all three datasets. In all test cases with N-BEATS, the RMSE is less than 0.4549%, the MAE is less than 0.3669%, and the R-squared

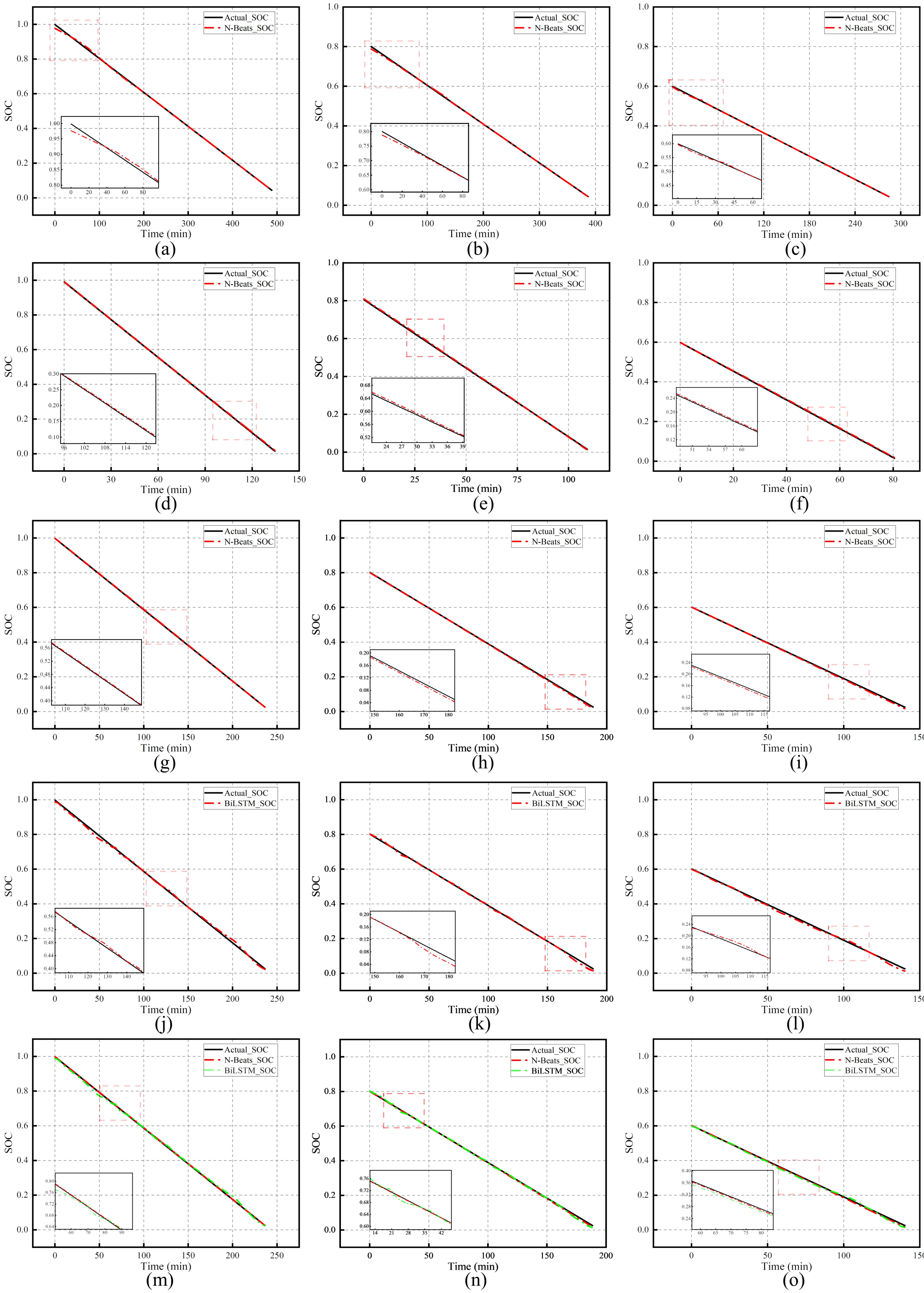

Fig. 3. Estimation results with N-BEATS and BiLSTM: (a-c) The SOC estimation results for $Cell_1$ are based on N-BEATS; (d-f) The SOC estimation results for $Cell_2$ are based on N-BEATS; (g-i) The SOC estimation results for $Cell_3$ are based on N-BEATS; (j-i) The SOC estimation results for $Cell_3$ are based on BiLSTM; (m-o) Comparison of SOC estimation results based on N-BEATS and BiLSTM for $Cell_3$.

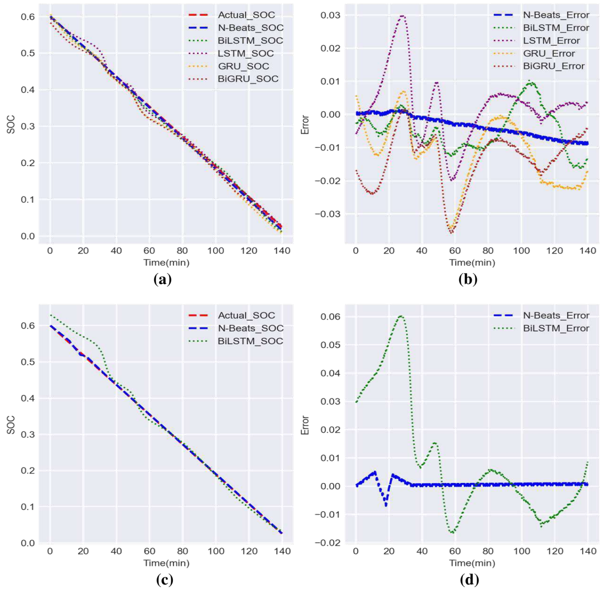

Fig. 4. SOC estimation and error of five algorithms. (a) SOC estimation; (b) SOC estimation error. Generalisability tests and errors. (c) SOC estimation; (d) SOC estimation error.

TABLE II
Performance comparison with RNN variants and generalisation ability tests.

Model	Train data	Test data	RMSE(%)	MAE(%)	R-squared(%)
			60%-0%	60%-0%	60%-0%
N-Beats	$Cell_3$	$Cell_3$	0.4549	0.3669	99.9279
LSTM			1.0294	0.7221	99.6253
BiLSTM			0.7887	0.6633	99.7766
GRU			1.5407	1.2607	99.1852
BiGRU			1.5960	1.3828	99.0601
N-Beats	$Cell_1$	$Cell_3$	0.15977	0.1195	99.9908
BiLSTM			2.3906	1.6508	98.2980

is greater than 99.9279%. By comparing the estimation results of the two models, N-BEATS and BiLSTM, for the three discharge conditions of $Cell_3$, it was found that the proposed model outperformed BiLSTM in all three evaluation criteria. By observation of the (m-o) subplot in Fig. 3, it can be viewed that N-BEATS shows few fluctuations and large frontal outliers during the estimation process. It shows a better tracking trend for 'Actual SOC' most of the time, and even if there is a small deviation, the curve is adjusted back in time.

To further validate the accuracy and generalisability of N-Beats estimates, the estimation results of four types of RNN variants and N-Beats are compared with the same dataset. The evaluation metrics are shown in Tab.II. It can be seen from Fig.4 that, compared with LSTM, BiLSTM, GRU and BiGRU, the estimated curves and results of N-Beats are closer to the actual SOC. Then, in order to prevent overfitting situations, the generalization ability test is performed on N-Beats and BiLSTM. From the Fig. 4 (d), we can observe that N-Beats achieve better trend tracking after a short period of adjustment. As comparted to N-Beats, BiLSTM takes longer to adjust and have a greater fluctuations.

V. Conclusion

This study fabricated and tested a button half battery with model number CR2032. And three sodium battery datasets were successfully obtained by doping Fe-Ti and LiF to its cathode material and changing the charge/discharge voltage range, respectively. And the estimation of their SOC by N-BEATS is proposed. The model is constructed by combining the fully connected layers into residual blocks, and the residual blocks into stacks, and the model as a whole is constructed from several stacks. Since the model does not need to predict labels by inputting features, but by predicting future sequences with past information of the sequences, it does not need to collect external observations. Experiments are tested for three data sets starting from 100%, 80%, and 60% discharge to 0% SOC sequences. The results show that the RMSE of SOC under different operating conditions estimated using the N-BEATS model is less than 0.4549%, the MAE is less than 0.3669%, and the R-squared is greater than 99.9279%. Among them, the RMSE is even as low as 0.1591% in the SOC estimation for $Cell_3$ discharged from 100%. By comparing the accuracy of N-BEATS and BiLSTM in estimating SOC for $Cell_3$, it is concluded that the former outperforms BiLSTM for all evaluation criteria.This study demonstrates the validity and promise of the adopted model in the field of SOC estimation for SIBs.

Future work will be conducted in three main areas. The first is to improve the estimation accuracy of the model by continuing to optimize it; the second is to test more data of SIBs under more conditions, taking into account factors such as temperature; The third is to study the generalization ability of N-BEATS in the field of SOC estimation.

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