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online state of charge estimation of lithium-ion batteries using gated recurrent unit neural network and a least mean square adaptive filter

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Abstract: State of charge (SOC) estimation of lithium-ion batteries is the most important role of a battery management system. to improve the SOC estimation speed and accuracy in the operational environment, a novel method is proposed by combining a gated recurrent unit (GRU) neural network and a least mean square (LMS) adaptive filter. First a GRU network is used to estimate the SOC based on the battery measurement data. Then the LMS filter is used for online error reduction through unpredicted operation conditions, the LMS is a lite adaptive filter that updates its coefficient based on operation conditions with low computation cost. To verify the method robustness, its performance was checked under constant and varying temperature for standard drive cycles like UDDS and LA92. The proposed method is able to estimate SOC with less than 10-min discharge voltage, current and temperature data as the input with an error of less than 0.6% during working hour. Therefore, compared with conventional methods like LSTM and GRU the proposed GRU-LMS method has better speed and accuracy in the SOC estimation.

1 Introduction

energy storage devices play a key role in a wide range of applications like smart grids, electric vehicles, and portable electronics, and they are used to enhance operations, reliability, and efficiency of systems [1].Lithium-ion batteries are widely used as energy storage due to their high-power density, high-energy density and long life [2]. In order to ensure safe and reliable battery operation, the battery management system (BMS) is necessary. BMS manages all the control and management facilities related to the battery like state monitoring and estimation, charge and discharge control, temperature control, battery protection, and cell balancing.

The most important task of BMS is accurate SOC estimation because it helps to improve the battery's life and safety by avoiding overcharge and over-discharge of the battery[3]. It defines as a ratio of the available capacity of the battery to its rated capacity [4]. SOC is like the fuel gauge in a car and is necessary for the reliable operation of the system, it provides the current state of the battery and helps the BMS to charge and discharge the battery at the best level for battery life increase. Estimating SOC is challenging and it is impossible to measure it directly. Furthermore, the uncertainty of a battery's performance under different operational and environmental conditions causes a challenge to the estimation of SOC [5].

According to the literature SOC estimation methods can be categorized into four categories, amp-Hour integration method, open circuit voltage method, model-based estimation method, and data-driven estimation method [6]. amp-Hour integration method is an easy and fast method but this method is dependent to initial SOC which is challengeable, equally it suffers from error accumulation which leads to inaccurate estimation. open circuit voltage method uses the OCV-SOC (Open Circuit Voltage State) table for SOC estimation [7]. although this method is simple and reliable it is too slow so it is not appropriate for online applications.

Model-based estimation methods like Kalman Filter produce a highly reliable estimation as they can mitigate the inaccuracies caused by measurement errors or changing work conditions because this method implements closed-loop feedback control [8,9]. Nevertheless, this method depends on the characteristics of battery models, and any error in calculating battery parameters _which is predictable in operational conditions_ will affect this method's accuracy [6,10].data-driven estimation method is independent of any battery model because it assumes the battery as a black box, nonetheless the training data and method is very important in this method.

In recent years, deep learning methods becomes extremely popular, Nowadays, machine learning algorithms play a key role in our lives, Advances in deep learning models, especially recurrent neural networks and long short-term memory, offer some effective ways to predict battery SOC [11-17]. a deep learning method can adaptively learn the battery parameters by itself based on measured signals like voltage and current [7], Since the SOC is not only dependent on the current measured variables but also related to the historically measured information, the recurrent neural network (RNN) has been widely used for SOC estimation [18].

In [19] authors introduce an RNN with LSTM to perform accurate SOC estimation for Li-ion batteries. In [6] Ren et al. use the particle swarm optimization algorithm in order to optimize the key parameters of LSTM, results show that the network can tolerate noises. In [7] a convolution-gated recurrent unit (CNN-GRU) network is proposed for the SOC estimation of lithium-ion batteries. Chen et al. [18] introduced the novel neural network method by combining an autoencoder neural network with the conventional gated recurrent unit, this network is noise resistant and shows a better nonlinear mapping relation between the measurement data and the SOC. Kang et al. [20] proposed Radial Basis Function Neural Network which eliminates the battery degradation's effect on the SOC estimation accuracy. Some researchers combine the amp-Hour integration method and Kalman filter with the deep learning method in order to use their advantages Simultaneously. In [21], a deep neural network (DNN) is constructed to estimate the SOC in the charging process and the estimation results can be used as the initial SoC of the ampere-hour counting method. Yang et al. [22] use an unscented Kalman filter to filter out the noises and reduce LSTM estimation error. In [23], a combination of the Coulomb counting method with the deep neural network method is proposed which enables fast and accurate SOC estimation with an error of less than 2.03% over the entire battery SOC range.

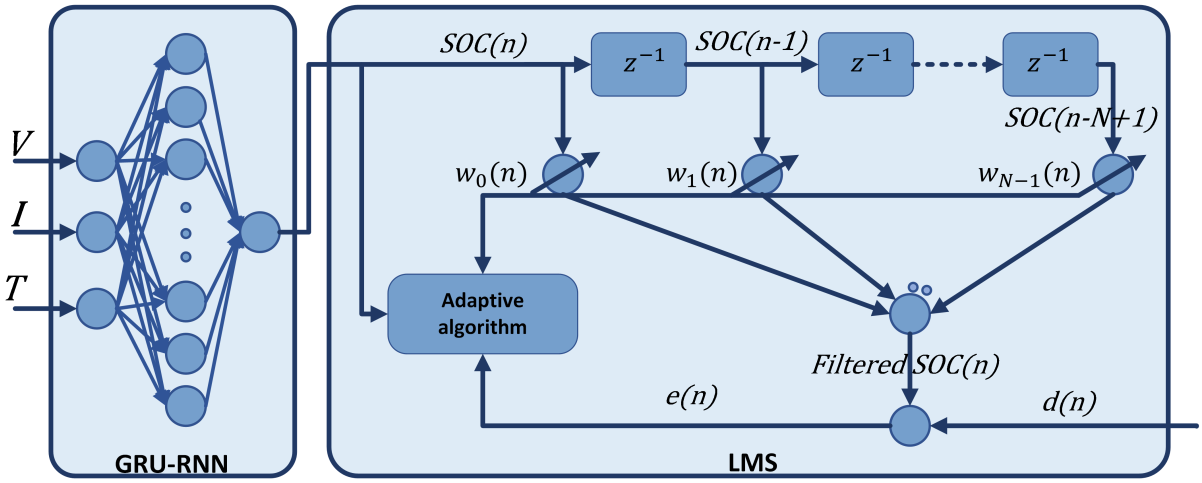

Fig. 1: Proposed method architecture

Adaptive filters have been widely used in various applications like prediction, noise canceling, and system identification due to their simplicity and robustness [24]. Authors in [10] tried to specify the conditions for implementing real-time adaptive prediction filters. Huang et al. [7] provide a predictor which combines LMS and LSTM-RNN in Wireless Sensor Network.

These filters can automatically change their coefficient to adapt to new conditions. Although these filters are easy to use and need a little memory, they have significant speed and accuracy. On the other hand, data-driven methods especially deep learning-based methods become popular for SOC estimation. Despite many advantages, these methods require numerous and accurate training data that have a reasonable similarity with the test data. It is practically impossible to simulate all events during working hours so the method which adapts to operational conditions through working hours seems to be necessary. Hence a hybrid method that uses the advantages of adaptive filters and deep learning simultaneously has been introduced in this paper.

The remainder of this paper is organized as follows; section 2 introduced the architecture of the proposed method. In Section 3 the battery specification and data experiment were introduced and in section 4 the simulation result was discussed.

2 SOC ESTIMATION METHOD

In order to cover the gap between the laboratory and operational environment, a SOC estimation method has been introduced in this paper. The schematic of the proposed method is shown in Fig.1. A string of cell voltage, current and temperature in m time steps has fed into the GRU-RNN network and the estimated capacity as the network's output will pass through the LMS filter. The principles of the LMS filter and the GRU network are presented below.

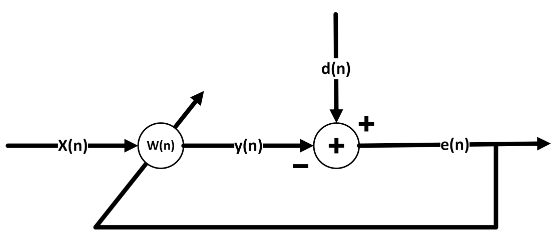

Fig. 2: LMS filter archtecture

2.1 LMS filter

The adaptive filter has been used in various applications[25]. Among different types of the adaptive filter, the LMS is a simple predictor and needs low computational complexity and memory. It also has a good performance in predicting time-series data. Unlike other alternative methods like the Kalman filter, the LMS doesn't need any information on the statistics of the environment [26]. The structure of the LMS algorithm is illustrated in Fig.2.

as an autoregressive process, the LMS filter is able to change its coefficient matrix quickly in operational conditions. During the training process, the LMS filter compares the prediction outputs with the desired outputs and tries to minimize the error between the prediction and desired by updating the weights of the coefficient matrix. A detailed presentation of the algorithm is given next.

$$y(k) = W(k)X^T(k) \tag{1}$$

Where $X^T(k)$ is transposition of input vector in time step k, and for a filter of size N, $X(k)$ is represented as follow:

$$X(k) = [x(k-1), x(k-2), x(k-3), \ldots, x(k-N)] \tag{2}$$

The initial vector of W is set to 0, which obviously is not a good choice, Anyway the weights can be updated as follow:

$$W(k+1) = W(k) + \eta X(k)e(k) \tag{3}$$

where η is the learning rate, which determines the performance of the algorithm. The large value of η boosts the convergence speed however it decreases the accuracy while the small value of η certifies the accuracy of the algorithm. $e(k)$ is an error which defined as:

$$e(k) = d(k) - y(k) \tag{4}$$

In this paper, the input vector is the SOC which is estimated using the GRU algorithm and the desired output outlined from the coulomb counting (CC) method. Although The CC method is a simple and fast method, it suffers from cumulative error. here we used the CC method just for modeling the SOC changes so this issue can't cause a problem in the proposed method.

2.2 GRU Algorithm

RNN network has an excellent performance on time series data, hence it can be a good candidate for SOC estimation [19]. Unlike other neural networks, the RNN network consists of some copies of a unique unit that are connected like a chain, this structure allows

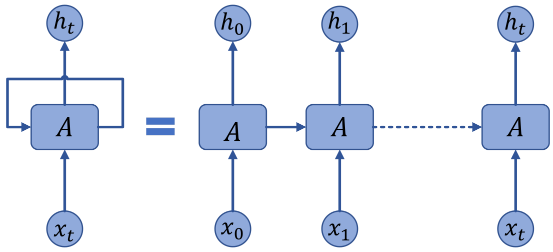

Fig. 3: a recurrent neural network schematic

information to be passed from one step of the network to the next [27]. The RNN schematic is shown in Fig.3.

Simple RNN network suffers from gradient vanishing and gradient explosion, in order to solve these problems LSTM and GRU are established[11,12]. In compression with LSTM, the GRU cell has a simpler structure due to one less gate [28]. Therefore, the number of parameters under the same network structure in GRU is less than in LSTM, which can reduce the risk of overfitting and boost the convergence rate while its performance is just like LSTM cell [18]. So, in this paper, GRU-RNN is chosen for SOC estimation.

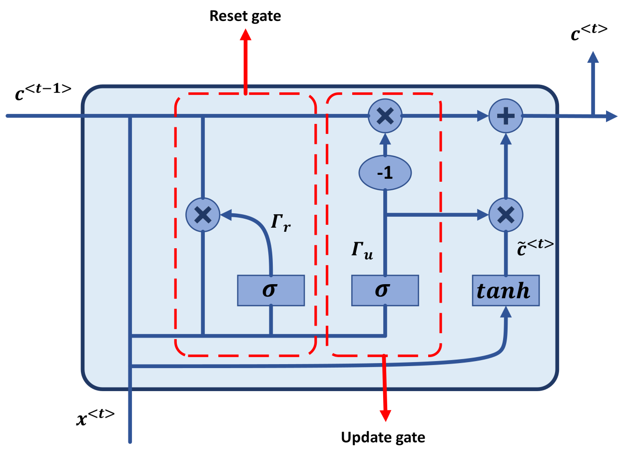

Fig. 4: a recurrent neural network schematic

GRU architecture is shown in Fig.4, in compression with simple RNN, the GRU-RNN has a relevance gate which is responsible for controlling the retention of historical information, and an update gate which controls the effect of the previous cell state and the current input on the new cell state [28]. information from the current input and Information from the previous hidden state which can be considered as the memory of the network is passed through the sigmoid function, so the Values come out between 0 and 1. The closer to 0 means to forget, and the closer to 1 means to keep. the sigmoid function is shown in Equation (9). The mathematical calculation process of GRU can be represented by the following equations.

$$\tilde{c}^{<t>} = \tanh(W_c[\Gamma_r * c^{<t-1>}, x^{<t>}] + b_c) \tag{5}$$

$$\Gamma_u = \sigma(w_u[c^{<t-1>}, x^{<t>}] + b_u) \tag{6}$$

$$\Gamma_r = \sigma(w_r[c^{<t-1>}, x^{<t>}] + b_r) \tag{7}$$

$$c^{<t>} = \Gamma_u * \tilde{c}^{<t>} + (1 - \Gamma_u) * c^{<t-1>} \tag{8}$$

where Γ_r, Γ_u, $\tilde{c}^{<t>}$, $c^{<t>}$ are the reset gate, the update gate, the candidate cell state, and the current new cell state, respectively; $x^{<t>}$is the input; network weights and bias are denoted by W and b Respectively; σ is the sigmoid function shown in Equation (9), and $\tanh$ function shown in Equation (10).

$$\sigma(x) = \frac{1}{1 + e^{-x}} \tag{9}$$

$$\tanh(x) = \frac{e^{2x} - 1}{e^{2x} + 1} \tag{10}$$

In this paper, the input dataset for training the network is given by $D = \{(\psi_1, SOC_1^*), (\psi_2, SOC_2^*), \ldots, (\psi_N, SOC_N^*)\}$, where SOC_k^* and ψ_k are the observable state-of-charge value and the vector of inputs at time step k, respectively. the vector of inputs is defined as $[V(k), I(k), T(k)]$, where $V(k)$, $I(k)$ and $T(k)$ are the voltage, current and temperature of the battery measured at time step k, respectively. As you can see for considering any other parameter for SOC estimation, we can just add it to the input vector and retrain the network.

In order to obtain a single estimated SOC value at time step k the hidden state $c^{<t>}$ passes to a fully-connected layer, the equation is as follows:

$$SOC_k = W_{fc} * c^{<t>} + b_{fc} \tag{11}$$

W_{fc} and b_{fc} are the fully-connected layer's weight matrix and biases, respectively. during the training process, the weight matrixes and biases are updated based on the difference between estimated and measured SOC. the mean absolute error is a good candidate for a loss function, which its equation is as follows:

$$MAE = \frac{\sum_{i=1}^{n} |SOC_i - SOC_i^*|}{n} \tag{12}$$

Where SOC_i, SOC_i^* are the estimated and measured value of SOC at time step i.

The Adam optimizer is implemented for updating the weight and bias matrixes based on the gradient of the loss function.

3 Battery specification and data experiment

machine learning methods need large amounts of data for training, and perform weakly when the test data differ greatly from train data. Batteries are used in a wide range of operating conditions. hence data covering these conditions is essential to build accurate models [29]. In this paper, the datasets are collected by the tests on a lithium nickel cobalt aluminum oxide (NCA) battery manufactured by Panasonic company. The main parameters of the battery are presented in Table 1.

These datasets are collected by the battery research group at the University of Wisconsin-Madison, and consist of a random combination of different typical drive cycles like US06, HWFET, UDDS, and LA92. Using these unique datasets which consist of several drive cycles, provides an extended range of realistic operating conditions for training the GRU network. In order to generate the train and test data for the GRU network, the battery was subjected to a selection of drive cycles. For each discharge test, the battery had fully charged with a constant current rate of 2.9 A (1C) and constant voltage (4.2 V), and the charging process terminated when the current fell below the cut-off current (50 mA). the details of the battery testing method are explained in [19].

The voltage, current, and capacity of a battery under four drive cycles are shown in Fig.5. The negative current causes the battery to discharge, so the voltage varies from 4.2 V to an empty state at 2.5 V.

Table 1 Panasonic 18650PF cell parameters

Parameter	Value
Nominal Open Circuit Voltage	3.6V
Min / Max Voltage	2.5V / 4.2V
Capacity	Min. 2.75 Ah / Typ. 2.9 Ah
Minimum Charging Temperature	$10^{\circ}C$
Mass / Energy Storage	48g / 9.9Wh
Cycles to 80% Capacity	500 (100% DOD,$25^{\circ}C$)
dc resistance	43 $m\Omega$

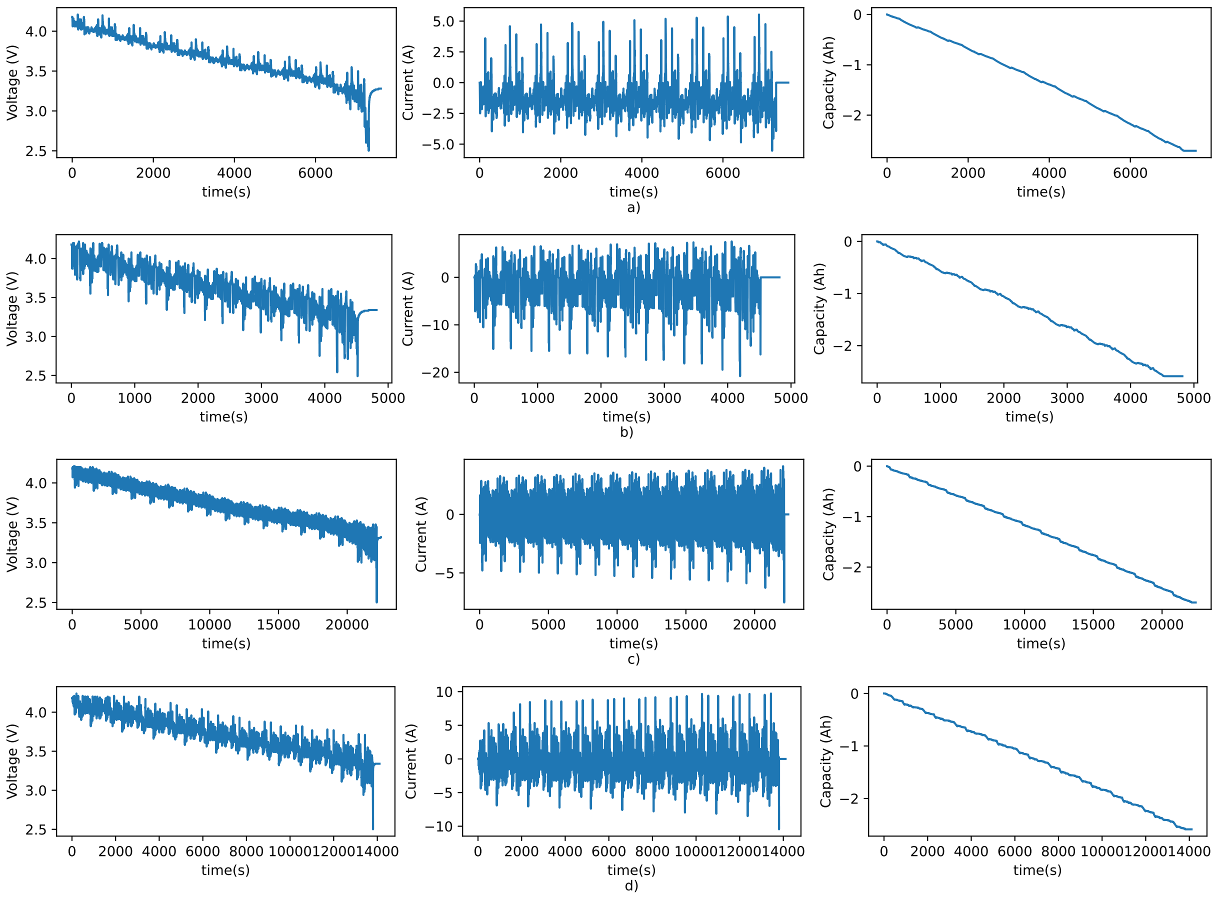

Fig. 5: voltage, current and amp-hour for standard drive cycles: a)HWFT, b)US06, c)UDDS, d)LA92

positive current (charge current) refers to regenerative braking which causes some growth in voltage amplitude within driving cycles. The capacity value is calculated by the Coulomb counting method. In this method, the SOC value is obtained by integrating the current, as shown in e.g. (13).

$$SOC = SOC_0 + \frac{\int idt}{C_n} \tag{13}$$

where SOC_0 is the initial value of SOC, C_n corresponds to the nominal capacity, i represents the battery current and t is the time.

the datasets for machine learning are susceptible to being inconsistent, missing, and noisy. Applying a deep-learning algorithm to this data would not lead to quality results because the algorithm could not identify the features effectively. So, data processing is essential to train an efficient model. missing or Duplicate values may give an incorrect view of the overall statistics of data, therefore in the first step, we eliminate these values from the dataset. In the next step, we normalize the input values, Normalization gives equal importance to each variable by scaling the value of numeric columns in the dataset to a common scale, so that variables with bigger numbers could not steer model performance in one direction.

4 Modeling and simulation

As mentioned in previous sections, the input vector is defined as $[V(k), I(k), T(k)]$ where the $V(k)$, $I(k)$, and $T(k)$ are the measured voltage, current and, temperature of the cell at time step k, respectively. the network has trained on 7 mixed drive cycles and the performance of the network was tested by different data. The MAE, RMSE, and MAX errors have been used as network performance metrics. The formulation of MAE was presented in e.g. (12).The formulation of RMSE and MAX are as follows:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(SOC_i - SOC_i^*)^2}{n}} \tag{14}$$

$$MAX = \max(SOC_i - SOC_i^*) \tag{15}$$

The next two subsections show the proposed method's robustness and accuracy when performed on a dataset recorded at a fixed temperature and at variable temperatures, respectively.

4.1 SOC estimation at constant ambient temperature

The RNN layer consists of 500 neurons. the number of the network's parameters is 756000 in the GRU network while the LSTM network has 1006000 trainable parameters, so the computation cost and the train time will be fewer in the GRU network. The results in Table 3 show that with an equal number of epochs and computational nodes the GRU has even better performance than LSTM. In RNN networks, the length of the input vector can directly affect the network performance, because in time series data the previous time steps are important in the current time, there is always a tradeoff between the network's accuracy and training cost in order to elect the proper input sequence length. here the length of each sequence was 500 during training time which means this network will need less than 10 minutes for SOC estimation. it is necessary to mention the network is able to predict SOC with fewer input data but its accuracy will decrease. The comparison between different sequence length accuracy is presented in Table 2. As you can see, by increasing the input length, the error decreases. Anyway, the decrease in estimation error is not linearly proportional to input length because going from 250 to 500 decreases MAE by about 40% while, going

Table 2 SOC estimation accuracy of GRU with various input sequence length

Sequence length	MAE %	RMSE %	MAX %
250	1.19	1.39	6.14
500	0.74	0.96	4.57
1000	0.54	0.69	3.94

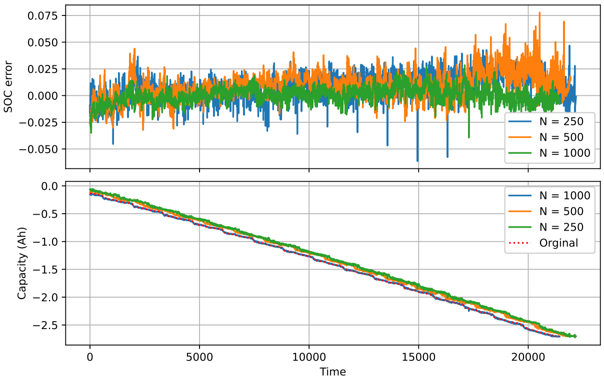

Fig. 6: Different sequence length SOC error and estimated Capacity

Table 3 SOC estimation accuracy of the proposed method compared with GRU and LSTM

Method	MAE %	RMSE %	MAX %
LSTM	0.88	1.06	5.1
GRU	0.74	0.96	4.57
GRU+LMS	0.53	0.68	2.3

from 500 to 1000 offers only a 15% enhancement in MEA. The estimated error and results of different depths of input vector over time are shown in Fig.6.

The LMS filter was used in this paper in order to real-time correction of GRU's estimated SOC. The predicted SOC fed to the filter of size 5 and its learning rate was 0.0017.

The MAE, RMS, and MAX performance metrics for LSTM, GRU, and the proposed method are outlined in Table 3. Despite more accuracy, the GRU has less computational cost than LSTM. As the results in Table 3 show, GRU offers about 15% improvement under the same condition. It is also trained in less time. So, it is reasonable to elect GRU as the SOC estimator. In order to improve GRU accuracy and robustness we used LMS filter in this paper. By filtering the GRU output using LMS filter the estimation error decreases from 0.74% to 0.53% which offers about a 30% reduction in MAE error, which is more accurate than a trained network with 1000 input vector length. It means that by adding a lite adaptive filter like LMS we can Cut the estimation time in half. Which is really important in real-time applications. Fig.7 shows the proposed method and GRU result over time.

In order to verify the estimation performance of the proposed method for covering different drive cycles, we tested the result for specific drive cycles and trained the network using the rest of the datasets. Here, we choose US06 and LA92 drive cycles for verifying the performance and generalization. Obviously, any other drive cycle can be chosen. The SOC estimation result and error for these drive cycles are shown in Fig.8. Besides, The MAE, RMS, and MAX performance metrics for these drive cycles are outlined in Table 4.

4.2 *SOC estimation at varying ambient temperatures*

During working hours, the ambient temperature can change due to the climate or the geographical location within which the battery operates. In order to validate the proposed method's performance

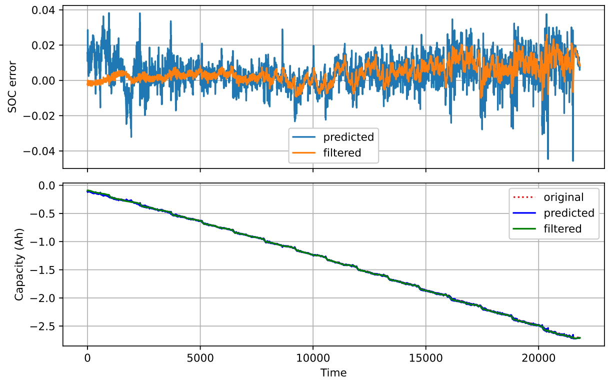

Fig. 7: Results of SOC estimation and SOC error at constant ambient temperature

Table 4 SOC estimation accuracy of the proposed method for US06 and LA92 drive cycle

Drive cycle	Method	MAE %	RMSE %	MAX %
US06	GRU	1.24	1.64	7.13
	GRU+LMS	0.91	1.19	4.23
LA92	GRU	0.95	1.16	10.72
	GRU+LMS	0.73	0.94	3.78

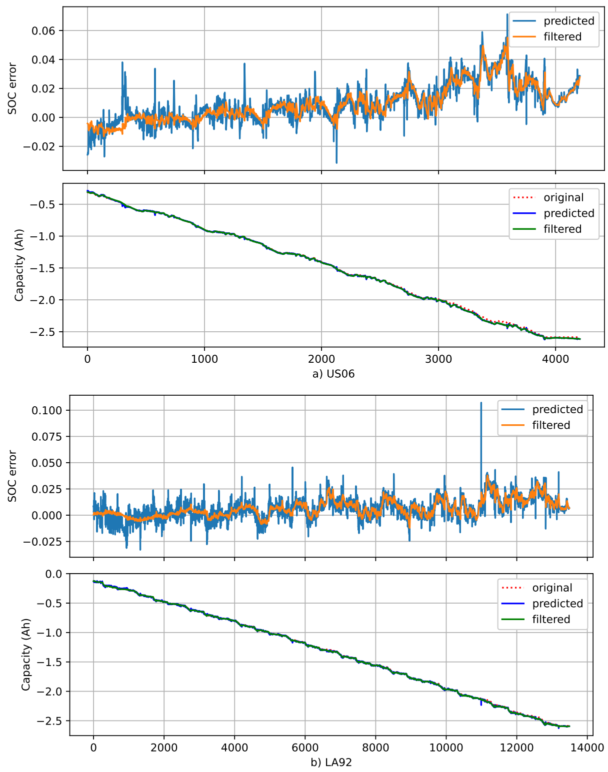

Fig. 8: Results of SOC estimation and error for a)US06 drive cycle and b)LA92 drive cycle

under varying ambient temperatures, the GRU-LMS network was trained using a larger dataset consisting of 20 drive cycles which were recorded under fixed ($10^{\circ}C$, $25^{\circ}C$) and variable ambient temperatures. In variable ambient temperature, the drive cycles are recorded with a starting chamber temperature of $10^{\circ}C$, which is then allowed to drift upwards such that the battery temperature rises up to $25^{\circ}C$ during the drive cycle. The SOC, voltage, current, and temperature of a sample drive cycle is illustrated in Fig.9. The GRU

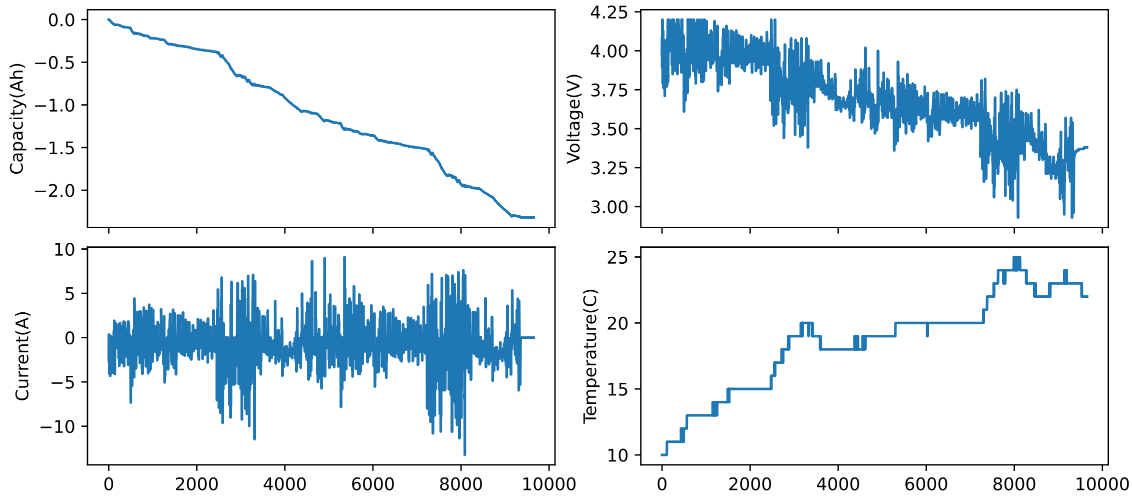

Fig. 9: SOC, voltage, current and temperature of a sample drive cycle under variable temperature

network used in this part is unrolled for 500 time steps and contains 500 nodes. The performance of the GRU-LMS network is shown in Fig.10. The MAE, RMS, and MAX metrics achieved over varying ambient temperatures are 0.66, 3.69, and 0.89 respectively. so, the performance of the proposed method is good over varying temperatures.

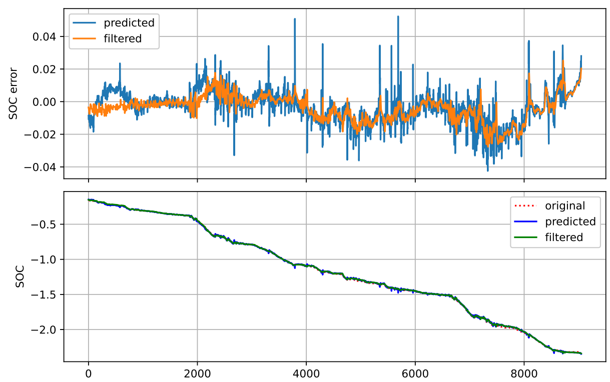

Fig. 10: Results of SOC estimation and SOC error in Varying Temperature

5 Comparative performance analysis

To illustrate the proposed method's efficiency against other methods we compared the results with other works in the literature. The proposed method offers competitive SOC estimation performance when compared to other algorithms in the literature which are illustrated in Table 5. In [19] the authors introduced a LSTM network to estimate the SOC for four standard drive cycles with an error of 0.77%, although this method has good accuracy for standard conditions, the error increases when the operating condition changes. In [18], an auto-encoder network combined with GRU network for boosting the robustness of the GRU against the noise, the introduced method's error is 1.19% for noisy data. the auto-encoder network has a good performance for noise canceling but its calculation cost is high. To improve the accuracy and the robustness of the LSTM network against the noise the authors in [22] combined the unscented Kalman filter with LSTM, and they succeeded to decrease the error to 0.82%. in [21], a deep neural network composed of two convolutional, max pooling, and GRU layers have been introduced. The estimation error is 0.8% but this deep neural network needs a huge data for training and is prone to overfitting. However, the proposed GRU-LMS offers the following advantages:

Table 5 Comparation results of SOC estimation error for six studies

Method	MAE %	RMSE %	MAX %
Reference [18]	1.19	1.51	-
Reference [19]	0.77	1.11	3.69
Reference [21]	-	0.8	2.5
Reference [22]	0.82	0.93	-
This paper	0.53	0.68	2.3

- The LMS filter has a low computational cost so the hardware cost and the calculation time decreases.
- As an adaptive filter, the LMS filter can adapt its coefficient based on operational conditions, therefore the estimation error will decrease through the unpredicted condition.
- Compared with other methods in the literature the proposed method offers about 30% enhancement in SOC estimation.

6 Conclusion

to introduce an accurate and fast method for mapping between the battery state of charge and measurement variables like current, voltage and temperature, the GRU-LMS method is proposed by combining the GRU-RNN and the LMS filter. The GRU has a good performance to obtain an accurate mapping between the battery SOC and measured variable, it also needs less computation compared to LSTM so it trains faster and it is resistant to overfitting. The estimated SOC was fed into the LMS filter to reduce estimation error during the operational condition. The LMS filter is a lite predictor which adjusts its coefficient online based on environmental conditions so it can improve the algorithm's robustness against unhandled working conditions. The simulation results show this hybrid method is more accurate than a single GRU, and filtering the GRU's output using LMS filter offers about 30% improvement in estimation results.

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