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An Improved Bidirectional Gate Recurrent Unit Combined with Smoothing Filter Algorithm for State of Energy Estimation of Lithium-ion Batteries

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***Abstract*—The accurate estimation of state of energy (SOE) is the key to the rational energy distribution of lithium-ion battery based energy storage equipment. This paper proposes an improved bidirectional gate recursive element combined with a time-varying bounded layer based smooth variable structure filtering algorithm. First, based on the solid temporal nature of the estimated parameters, a BiGRU neural network structure is constructed to strengthen further the influence of past and future information on the current estimates. Then, based on the traditional variable structure filtering, a time-varying bounded layer smoothing mechanism with saturation restriction (TS-VBL) is proposed to smooth the output of BiGRU to obtain a more accurate estimate. Finally, the test was conducted under 15℃ hybrid pulse power characterization (HPPC) and 35℃ Beijing bus dynamic stress test (BBDST). Compared with other algorithms, the BiGRU-TSVSF algorithm has a minor maximum estimation error of 0.00495 and 0.00722, respectively. The experimental results show that the algorithm has high precision and robustness and is of great value to the energy storage research of energy storage equipment.**

Keywords-state of energy; smooth variable structure filtering; bidirectional gate recurrent unit; time-varying bounded layer; energy storage

I. Introduction

In the past, society's massive consumption of energy not only brought the world energy crisis and caused severe environmental pollution. Lithium-ion batteries are widely used as energy storage equipment sources due to their advantages of green environmental protection, low energy consumption, and long cycle life. Among them, the most typical is the research and development of new energy vehicles [1]. However, with the extensive promotion and use of products using lithium-ion batteries as energy storage devices, there have been false energy displays, fast power consumption, and even explosions due to overcharge and over-discharge or environmental factors [2, 3].

The accurate and effective estimation of SOE can better solve the problem of battery energy distribution and ensure the safe operation of the battery. Standard SOE estimation methods include ampere-hour product (AHI), battery equivalent circuit model (ECM) based method, neural network model, and other methods [4-6]. Although the ampere-hour integration method [7] is simple and easy to estimate, the output depends on the initial value, and errors accumulate with the integration, resulting in inaccurate estimates. ECM is usually combined with a Kalman filter (KF) to estimate SOE [8, 9]. For example, Lai et al. [10] proposed a novel SOE method using a particle filter (PF) and extended Kalman filter (EKF) insensitive to uncertain total available energy loss and ambient temperatures, and the maximum error is less than 3%. Although the method based on ECM can improve the estimation accuracy of SOE, the accuracy of the ECM model will directly affect the estimation accuracy, which requires much time to establish the mode. The neural network model [11] does not require the construction of ECM and has good generalization ability for different battery types.

Recurrent neural networks (RNN) can well characterize sequence problems, introduce the concept of "memory," and fully capture the influence of other moments on the output of the current moment [12, 13]. Due to the problems of gradient disappearance and long-term dependence of RNN, long-period memory (LSTM) is proposed. LSTM introduces cell states based on traditional RNN, which can select and save input information [14, 15]. Although GRU, as a variant of LSTM, has similar functions, GRU has a more straightforward structure, which can improve the estimated speed of the model [16-18]. To further improve the accuracy of the algorithm and reduce the influence of noise interference on the result, a hybrid method [19, 20] combining a neural network model and filtering algorithm can be constructed. Compared with other literature [21-23], most are based on one-way LSTM or GRU combined with an improved KF algorithm. This paper fully explores the data series' characteristics, improves the model's memory ability, and proposes the BiGRU-TSVSF algorithm based on the KF algorithm. The main contributions of this paper are as follows.

(1) Build a bidirectional GRU model for multi-directional information "memory".

(2) Construct SVSF based on a time-varying bounded layer for smooth denoising of nonlinear solid data.

(3) Experimental analysis based on different temperatures and working conditions proved the accuracy and robustness of the algorithm.

II. Mathematical analysis

A. bidirectional gate recurrent unit

GRU is simple in structure and can reflect the time series problem well. It can solve the gradient problem of traditional RNN and the problem of a small information range. However, a single GRU can only take information from one direction and preserve it as a "memory." To improve the accuracy of SOE estimation, a BiGRU network model is constructed in this paper. Capture information from both positive and negative directions and determine the output value at the current moment, thereby strengthening the influence of past and future information on the output. The structure of BiGRU is shown in Figure 1.

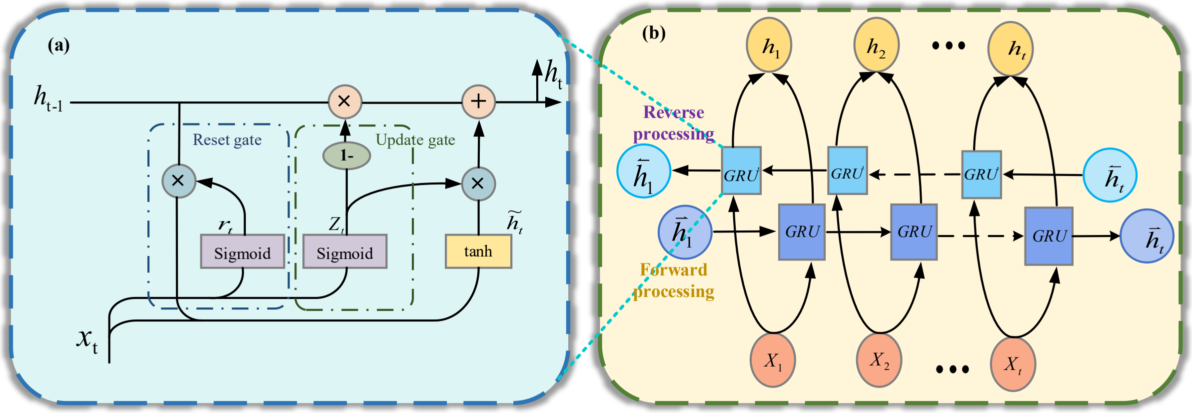


Figure 1. Improved RNN structure diagram. (a) GRU single-celled structure. (b) BiGRU.

As can be seen from Figure 1(b), the GRU consists of a reset gate and an update gate. It can be seen from Figure 1(c) that the current hiding layer state h_t and the current input x_t, and the forward hiding layer state $\vec{h}_t$ and forward hiding layer state $\overleftarrow{h}_t$ are jointly determined by three states. The hidden layer formula is shown in Formula 1.

$$\begin{cases} \vec{h}_t = GRU(\vec{h}_{t-1}, x_t) \\ \overleftarrow{h}_t = GRU(\overleftarrow{h}_{t+1}, x_t) \\ h_t = w_t \vec{h}_t + v_t \overleftarrow{h}_t + b_t \end{cases} \tag{1}$$

Where, w_t and v_t are the weights of the forward and reverse hidden states respectively, and b_t is the bias corresponding to the hidden layer state at time *t*.

B. Improved Smooth variable structure filtering based on time-varying boundary layer

The Smooth bounded layer principle (SSVSF) is introduced into the SVSF algorithm, which can not only be applied to nonlinear solid systems but also solve the problem of filtering, which is not apparent due to the measurement noise and inappropriate initial conditions in the KF algorithm. In addition, the SSVSF algorithm uses the smooth bounded layer to smooth and filter the results effectively. Also, it ensures the stability of the estimation process, avoiding the problem of SVSF estimation trajectory oscillation. The algorithm principle diagram of SSVSF is shown in Figure 2(a).

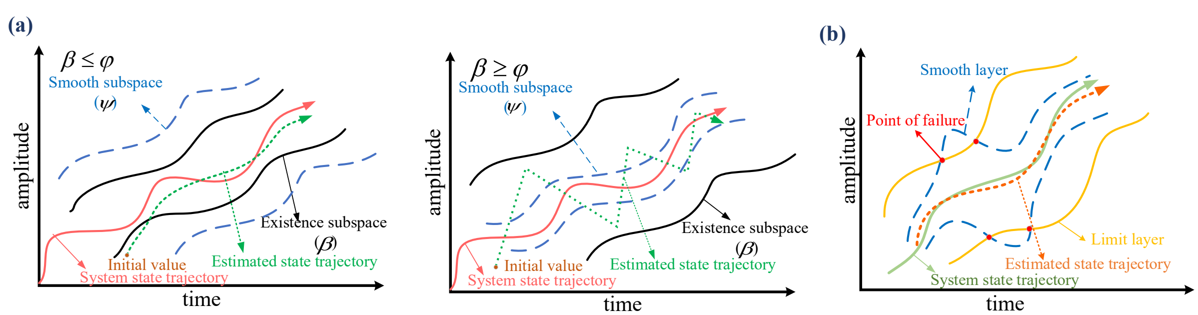


Figure 2. Improved SVSF algorithm. (a) SSVSF algorithm principle diagram. (b) TSVSF algorithm principle diagram.

In Figure 2(a), β represents the initial existential boundary and φ represents the smooth boundary. It can be seen that when $\beta \leq \varphi$, the estimated state trajectory is stable output. However, when $\beta \geq \varphi$, the output of the estimated state trajectory fluctuates sharply, which will lead to the reduction of output accuracy. To solve the above problems, based on the smooth bounded layer, this paper introduces the principle of time-varying bounded layer (TVBL) to form the TSVSF smooth filtering algorithm, which restricts the smooth bounded layer, to ensure the smooth output of the estimated results. The principle is shown in Figure 3(b). As can be seen from it, when the boundary of the smooth bounded layer deviates from the standard trajectory, the limiting layer will conduct real-time saturation restriction to keep the estimated trajectory in a stable state so that the SOE estimate after accurate filtering can be obtained. The calculation process is mainly divided into four steps, as shown below.

The first step is the prediction stage.

$$\begin{cases} \hat{x}_{k+1|k} = A\hat{x}_{k|k} + Bu_k \\ P_{k+1|k} = AP_{k|k}A^T + Q_k \\ \hat{z}_{k+1|k} = C\hat{x}_{k+1|k} \\ e_{k+1|k} = z_{k+1} - \hat{z}_{k+1|k} \\ S_{k+1} = CP_{k+1|k}C^T + R \\ E_{k+1} = |e_{k+1|k}| + \gamma|e_{k|k}| \end{cases} \tag{2}$$

Where, $\hat{x}_{k+1|k}$ is the state estimation matrix; $P_{k+1|k}$ is the covariance matrix; $\hat{z}_{k+1|k}$ is the measurement estimation matrix; $e_{k+1|k}$ is a new information or measurement error; S_{k+1} is defined as the measurement error covariance matrix. E_{k+1} is defined as the variable of error; $\boldsymbol{A}$ is the transfer matrix of state x from $k\text{-}1$ to time k; $\boldsymbol{B}$ is the input matrix; $\boldsymbol{C}$ is the measurement matrix γ is a positive diagonal matrix where the elements satisfy $0 < \gamma_{ii} < 1$.

The second step is to calculate a smooth boundary layer.

$$\psi_{k+1} = ((diag(E_{k+1}))^{-1}CP_{k+1|k}C^T S_{k+1}^{-1})^{-1} \tag{3}$$

The third step, calculate the gain. In this step, different gain calculation formulas must be selected according to the size of the smooth bounded and restricted layers.

$$K_{k+1} = C^{-1}diag(E_{k+1})\psi_{k+1}^{-1} \tag{4}$$

The width of the smooth bounded layer is smaller than that of the limiting layer, and the gain is calculated as shown in Formula 5.

$$K_{k+1} = C^{-1}diag((E_{k+1} \circ sat(e_{k+1|k}, \psi))[diag(e_{k+1|k})]^{-1} \tag{5}$$

The fourth step, update the stage.

$$\begin{cases} \hat{x}_{k+1|k+1} = \hat{x}_{k+1|k} + K_{k+1}e_{k+1|k} \\ P_{k+1|k+1} = (I - K_{k+1}C)P_{k+1|k}(I - K_{k+1}C)^T + K_{k+1}RK_{k+1}^T \\ \hat{z}_{k+1|k+1} = C\hat{x}_{k+1|k+1} \\ e_{k+1|k+1} = z_{k+1} - \hat{z}_{k+1|k+1} \end{cases} \tag{6}$$

C. Overall structure of BiGRU-TSVSF algorithm

To obtain accurate SOE estimates, the BiGRU-TSVSF combined algorithm is proposed. The battery's current, voltage, and temperature data tested under specific conditions are used as inputs to the BiGRU model. The trained BiGRU model collects the information before and after and outputs the SOE with the current input values. At this time, the SOE value may cause the curve to produce burrs due to the internal uncertainties of the model, and the error value becomes more extensive. Therefore, the SOE output of BiGRU is taken as the input of TSVSF and smoothed to reduce the error and improve the model's accuracy. The overall framework of the BiGRU-TSVSF algorithm is shown in Figure 3.

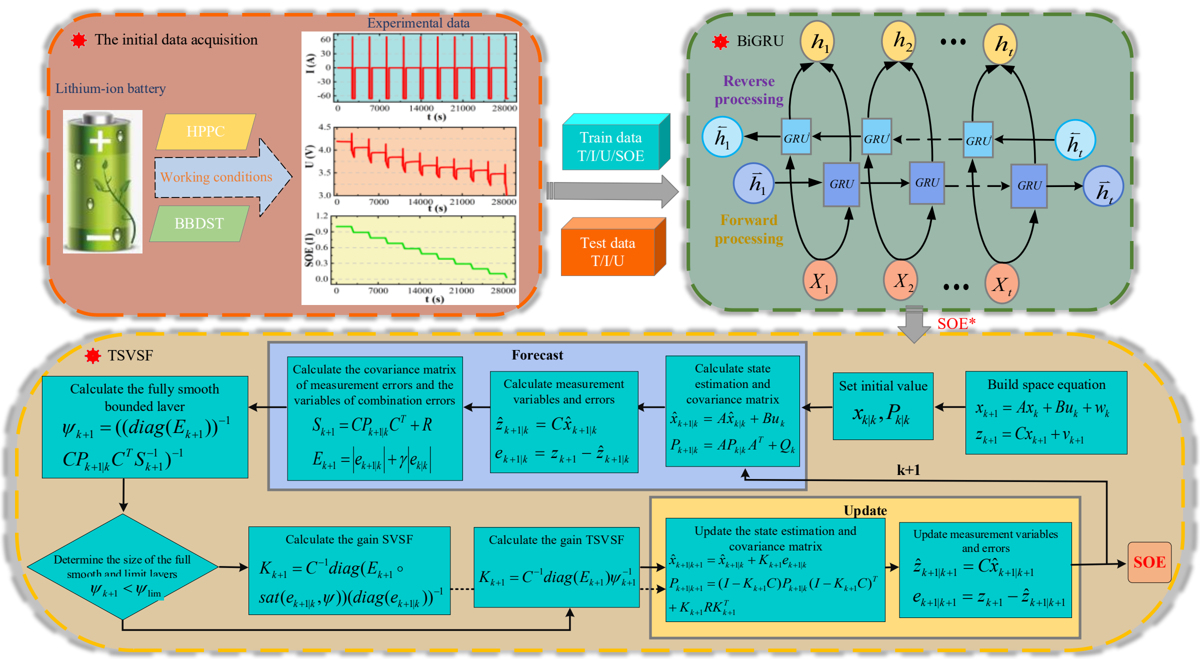


Figure 3. BiGRU-TSVSF algorithm framework

To further analyze the accuracy of the estimated results, this paper uses mean square error (MSE) and mean absolute error (MAE) as evaluation indicators to compare and analyze the results. Their expression is shown in Formula 7.

$$\begin{cases} MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \\ MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \end{cases} \tag{7}$$

Where, y_i indicates the true value. $\hat{y}_i$ is the estimate; $\overline{y_i}$ is the average.

III. Experimental analysis

A. Lithium-ion battery test platform design

The ternary material has replaced the previously widely used lithium cobalt oxide cell, which is widely used in high-tech equipment. This research is based on a 72Ah ternary lithium-ion battery cycle charging and discharging experiment. The experimental configuration is divided into five parts: temperature test chamber, charge and discharge test, lithium-ion battery, PC, and BMS. The lithium-ion battery test platform is shown in Figure 4.

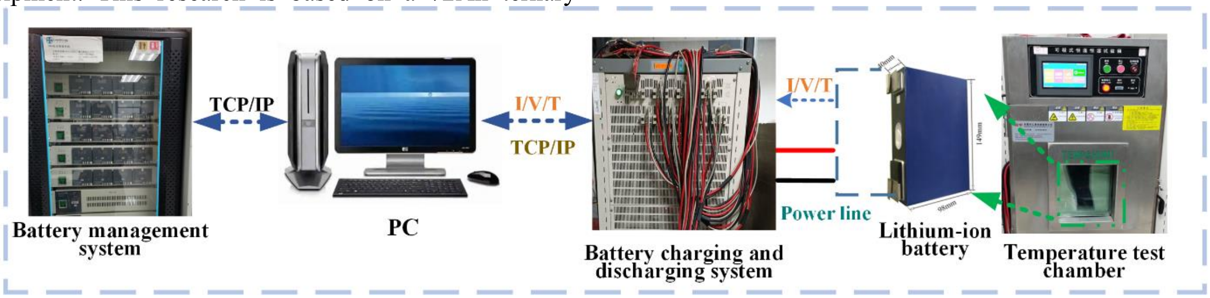
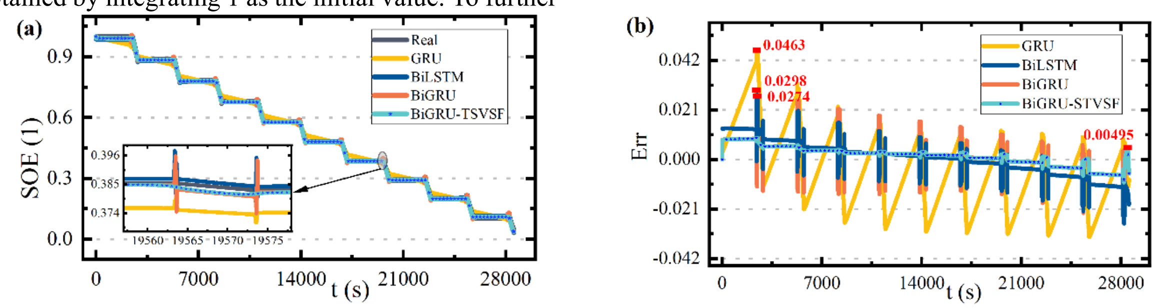


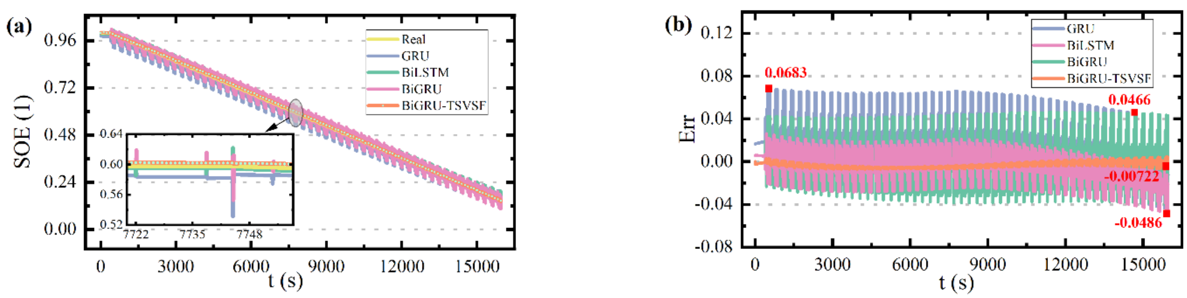
Figure 4. Lithium-ion battery test platform

B. Comparative analysis of SOE estimation results

This paper uses HPPC at 15℃ and BBDST at 35℃ as training data and test data of the BiGRU network model. Among them, SOE and theoretical SOE values in the training data are obtained by integrating 1 as the initial value. To further reflect the performance of this algorithm, the SOE output values of GRU, BiLSTM, and BiGRU were also obtained and compared in this experiment under the condition that the model hyperparameters and the number of iterations were consistent. SOE estimation results are shown in Figure 5.



(A) 35℃BBDST-15℃HPPC. (a) SOE result. (b) Error comparison.



(B) 15℃HPPC-35℃BBDST. (a) SOE result. (b) Error comparison.

Figure 5. The comparison of algorithm GRU, BiLSTM, BiGRU, and BiGRU-TSVSF under different working conditions

The comparison graph of the four algorithms shows that the bidirectional network has higher estimation accuracy than the unidirectional network. The comparative analysis of errors shows that the SOE estimation errors of GRU and BiGRU are 0.0463 and 0.0298 under HPPC and 0.0683 and 0.0466 under BBDST. Compared with the output error of BiLSTM and BiGRU, their SOE estimation results are familiar. Under HPPC and BBDST, the maximum error of BiLSTM and BiGRU is 0.0274,0.0298, and 0.0486, 0.0466, respectively, and the difference between them is minimal. However, compared with BiLSTM, BiGRU has a more straightforward structure and faster model estimation speed, so it is a good choice for this study. In addition, by comparing the SOE estimation results and errors of BiGRU and BiGRU -TSVSF, it is evident that the TSVSF algorithm proposed in this paper can perform smooth filtering operations on SOE from the BiGRU model. Finally, the HPPC and BBDST estimation error reaches 0.00495 and 0.00722, respectively. The SOE error analysis of different algorithms proves that this algorithm has high precision and robustness. To further reflect the performance of the algorithms, this study also conducted a comparative analysis of the performance indicators of MSE and MAE for the four algorithms, as shown in Figure 6.

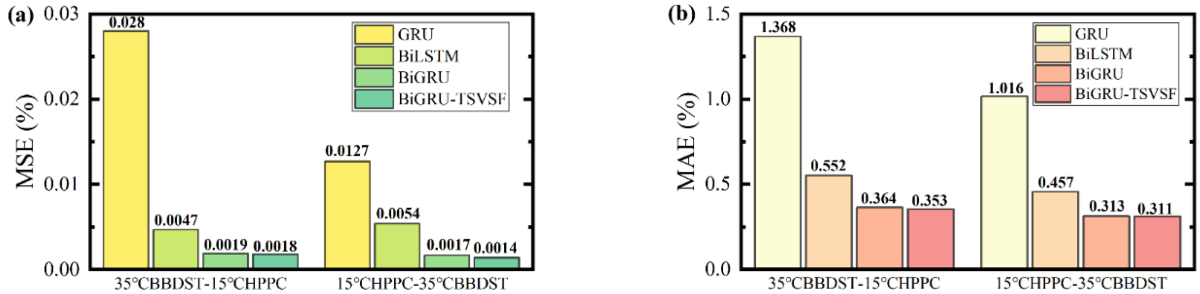


Figure 6. MSE and MAE results under HPPC and BBDST conditions. (a) The results of MSE. (b) The results of MAE.

According to the MSE and MAE results of the four algorithms under different working conditions, it can be seen that this algorithm is the minimum value under both working conditions. The smaller the value, the smaller the output error of the model and the better the fitting effect with the theoretical value. Under HPPC and BBDST, the MSE values of the BiGRU-TSVSF algorithm are 0.0018% and 0.0014%, and the MAE values are 0.353% and 0.311%. The experimental results show that the proposed BiGRU-TSVSF algorithm can be applied to complex processes at different temperatures, and the SOE estimation accuracy is high.

IV. Conclusion

To accurately estimate the SOE of lithium-ion batteries under various complex conditions, improve the efficiency of energy storage distribution to ensure the safe operation of the battery system. In this paper, an improved BiGRU-TSVSF algorithm is proposed. The mechanism of bidirectional information capture satisfies the nature of SOE's time series data. The SOE output of BiGRU is filtered and denoised by the SVSF algorithm with a time-varying bounded layer. HPPC at 15°C and BBDST test data at 35°C are used for interactive data estimation to improve the model's generalization ability. Under HPPC conditions, the maximum error, MSE, and MAE of the BiGRU-TSVSF algorithm are 0.00495, 0.0018%, and 0.0014%, respectively. Under BBDST conditions, the maximum error, MSE, and MAE of the BiGRU-TSVSF algorithm are 0.00722, 0.353%, and 0.311%, respectively. This algorithm has the best performance index compared with GRU, BiLSTM, and BiGRU. Experimental results show that this algorithm has high accuracy, robustness, and generalization ability. This algorithm can be applied to SOE estimation and other state parameters of lithium-ion.

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