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Generalized Regression Neural Network Based State of Charge Estimation for Lithium-Ion Battery with Ambient Temperature Consideration

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ABSTRACT

Obtaining an accurate mapping relationship between lithium-ion battery open-circuit voltage (OCV) with the state of charge (SOC) at different ambient temperatures is the basis for its accurate SOC estimation in the whole ambient temperature range. However, the experimental test of the OCV-SOC correspondence takes a lot of time; and it is obviously impossible to perform the test at all temperatures. To achieve accurate SOC estimation at different ambient temperatures with a lower experimental cost, a model-based SOC estimation method is proposed in this paper. First, based on generalized regression neural network (GRNN), an OCV-SOC mapping model for the whole ambient temperature range is established. Second, a new diagonalization of matrix adaptive cubature Kalman filter (DMACKF) is proposed, which enhances the filtering stability and realizes the adaptive update of noises in the recursive process. Finally, combined with the forgetting factor recursive least squares (FFRLS) algorithm, the proposed SOC estimation method is verified under the DST conditions at three temperatures. The root mean square errors (RMSEs) of SOC estimation results are within 0.4% at each temperature.

Keywords: lithium-ion batteries, state of charge, different ambient temperature, generalized regression neural network

1. INTRODUCTION

Lithium-ion batteries are widely used in new energy electric vehicles and energy storage systems due to their advantages of high energy density and environmental protection [1]. However, due to the temperature sensitivity of lithium-ion batteries, an advanced battery management system (BMS) that considers the influence of temperature is very important to ensure the reliable and safe operation of electric vehicles [2]. State of charge (SOC) is the most important and basic parameter in BMS. Realizing accurate estimation of SOC under different ambient temperatures is not only the basis for the accurate state of health estimation in BMS, but also has great reference value for proposing reasonable battery thermal management solutions [3].

Pang et al. [4] proposed an improved lithium-ion battery dual-polarization model considering ambient temperature influence. But it was assumed that the parameters of the battery model only change due to the ambient temperature. Wu et al. [5] conducted research on the lithium-ion battery SOC estimation method under a wide temperature range. But the used filter algorithm did not consider the changed noise in the estimation process. Moreover, the above researches were all based on the premise that the known open-circuit voltage (OCV) and SOC data of lithium-ion batteries at the target temperature.

However, it is obviously impossible to obtain the OCV-SOC data at all ambient temperatures. It is very important to map the OCV-SOC correspondence over the whole temperature range through the OCV-SOC data at partly known temperatures. Essentially, the OCV-SOC mapping is a nonlinear regression fitting problem. Therefore, considering the powerful nonlinear fitting capability and flexible network structure of the generalized regression neural network (GRNN), which has high fault tolerance and robustness. We have built a GRNN network model of OCV with SOC and ambient temperature to obtain the OCV-SOC correspondence in the whole ambient temperature range.

2. PROPOSED METHOD

2.1 Generalized regression neural network

The GRNN is a kind of radial basis neural network, whose structure is analogous to the radial basis function network as well. But a summation layer is added between the pattern layer and the output layer, while the weight connection between the hidden layer and the output layer in the feedforward neural network is omitted. In the summation layer of GRNN, two types of neurons are used to perform arithmetical summation and weighted summation on the outputs of all neurons in pattern layers respectively, in which there is only one neuron for arithmetical summation, and the number of neurons for weighted summation is equal to the dimension of the output vector in the samples. In the output layer, the outputs of the weighted summation neurons in the summation layer are divided by the output of the arithmetic summation neuron, and the obtained results are the output of each neuron in the output layer.

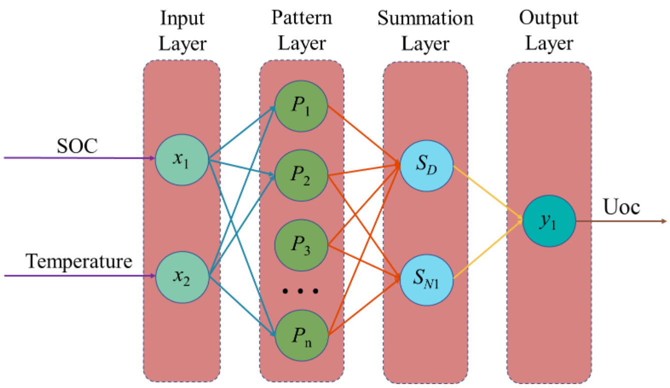


Fig. 1 GRNN structure

The structure of GRNN proposed in this paper is shown in Fig 1. The GRNN was trained through the data obtained from the low current test at 0°C, 10°C, and 20°C ambient temperature, where the SOC and temperature were used as input vectors, corresponding to the OCV as the output vector. Therefore, the number of neurons in the input layer, summation layer, and output layer was 2, 2, and 1 respectively. The number of neurons in the pattern layer was the number of samples in the training set.

2.2 Diagonalization of matrix adaptive cubature Kalman filtering

To improve the estimation performance of the cubature Kalman filter (CKF) algorithm, we replaced the Cholesky decomposition of the covariance matrix in the filtering process with the method of matrix diagonalization [6]. The square root matrix obtained by this method is a theoretical square root matrix, which could retain the original eigenspace information of the covariance matrix. The process makes the transmission of covariance more accurate and can effectively improve the filtering accuracy.

After that, according to the principle of window estimation, the adaptive update of the process noise Q and the observation noise R was realized in the CKF recursion process.

2.3 Joint algorithm

In this paper, based on the OCV-SOC test data at the known temperatures, an OCV-SOC mapping model was established through GRNN. After that, the CKF algorithm was improved to enhance the filtering accuracy and stability in the recursive process. Finally, the forgetting factor recursive least squares (FFRLS) algorithm was combined to update the other parameters of the battery model and complete the SOC estimation of the lithium-ion battery at the other ambient temperatures, whose OCV-SOC test data was unknown. The flow chart of the joint algorithm is shown in Fig 2.

The simulation process of the proposed method in this paper was executed on MATLAB software, and all the codes used will be shared in the final manuscript if requested.

3. RESULTS OF THE GRNN-DMACKF METHOD

3.1 OCV-SOC validation results of GRNN

To verify the fitting accuracy of OCV-SOC by the proposed GRNN model at different ambient temperatures, the low-current test SOC datasets at 30°C, 40°C, and 50°C were used as input, and the GRNN fitting surface was shown in Fig 3. The fitting errors were shown in Fig 4. Meanwhile, to further verify the fitting accuracy, the root mean square error (RMSE) of the SOC fitting results was calculated, as shown in Table 1.

Table 1. RMSE of OCV at various ambient temperatures

Temperature/°C	30	40	50
RMSE/V	0.0074	0.0097	0.0118

It can be seen from Fig 4 and Table 1 that the trained GRNN model had high fitting accuracy, the RMSE at each temperature did not exceed 0.012V. The proposed model could accurately map the corresponding relationship of OCV-SOC at each ambient temperature.

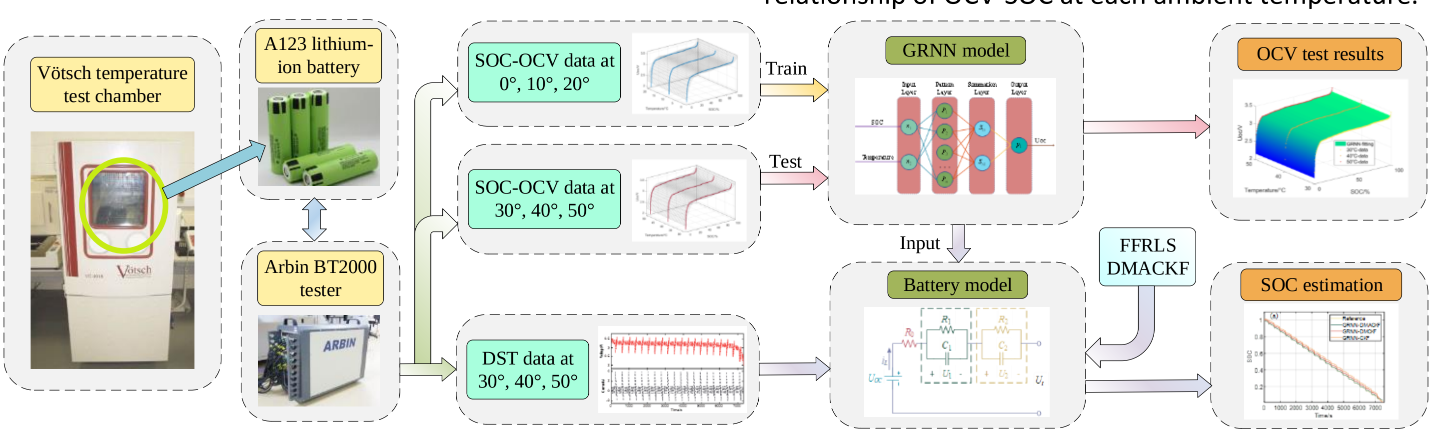


Fig. 2 Flow chart of the GRNN-DMACKF method

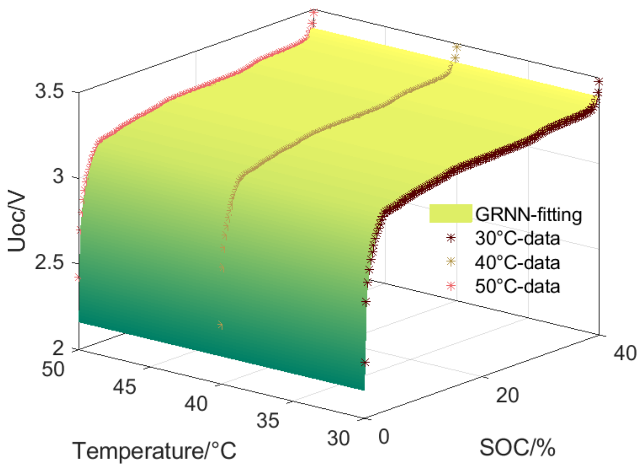


Fig. 3 GRNN fitting surface of OCV-SOC

3.2 SOC estimation results

To verify the effectiveness of the proposed method, we completed the SOC estimation of the experimental A123 lithium-ion battery under DST working conditions at 30°C, 40°C, and 50°C. Besides, the SOC estimation results based on the CKF and DMCKF were compared.

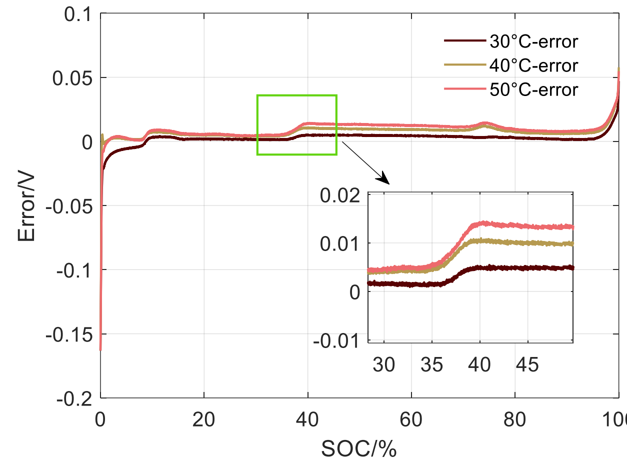
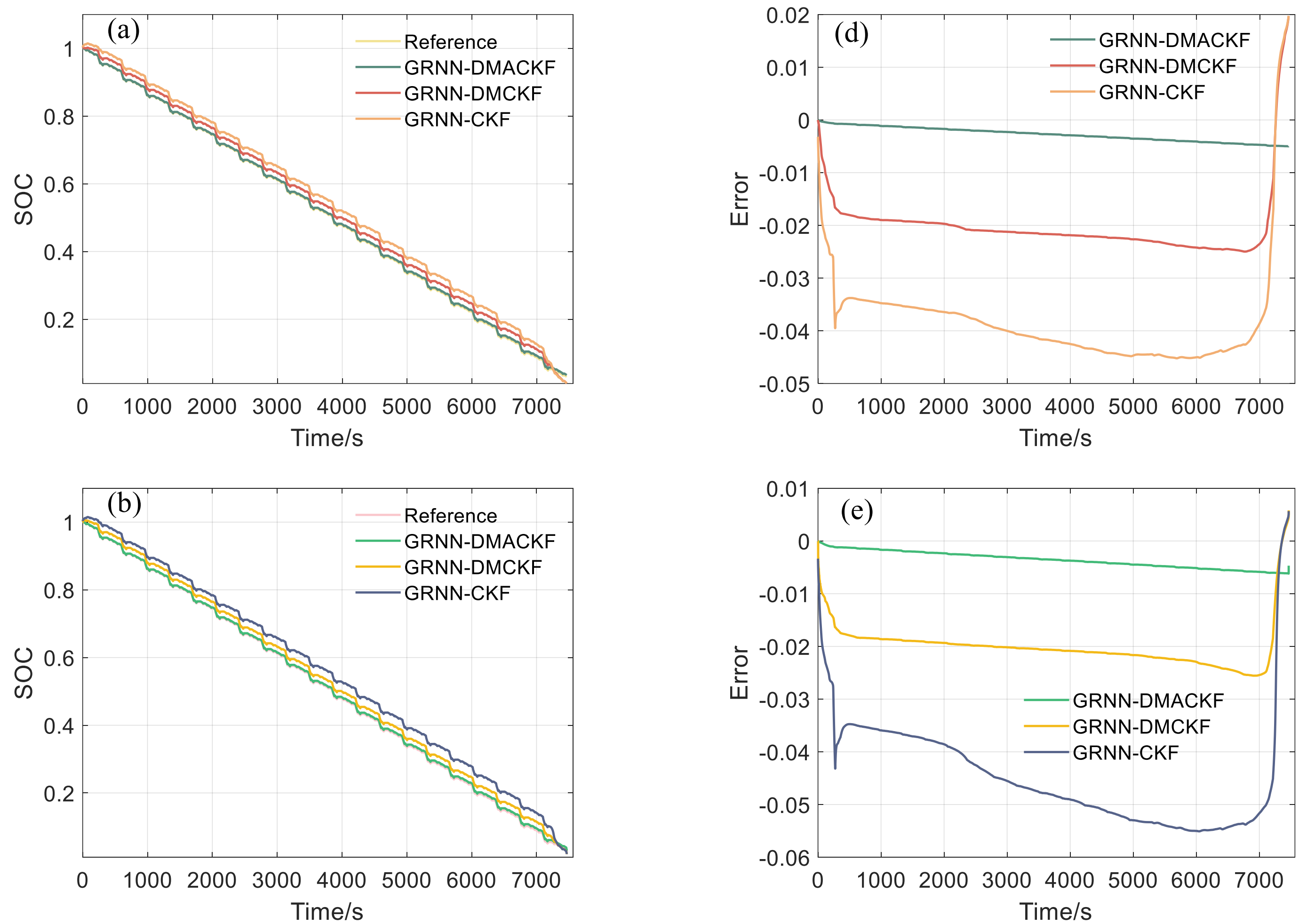


Fig. 4 GRNN fitting errors of OCV-SOC

The SOC estimation and error results were shown in Fig 5. Meanwhile, to further verify the robustness of the proposed method, the RMSEs of the SOC estimation results were also calculated respectively, as shown in Fig 6. The experimental data used in this paper is from the CALCE battery research group at the University of Maryland.



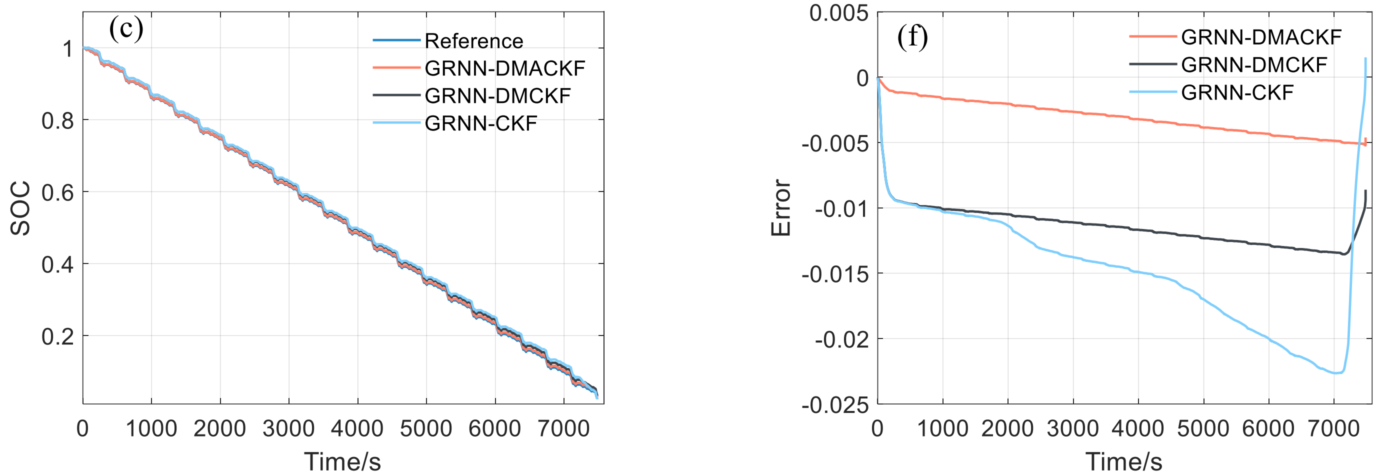


Fig. 5 SOC estimation results. (a) results at 30°C; (b) results at 40°C; (c) results at 50°C; (d) errors at 30°C; (e) errors at 40°C; (f) errors at 50°C;

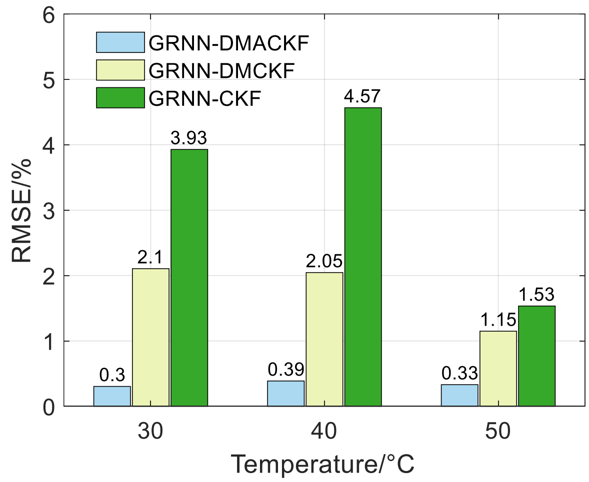


Fig. 6 RMSEs at three ambient temperatures

As shown in Fig. 5 and Fig. 6, the SOC estimation errors based on CKF increased very fast at the beginning of the recursion. Although the subsequent SOC estimation results conform to the changing trend of reference, the errors remained at a relatively high state. But when the covariance matrix in CKF had been optimized, the SOC estimation errors in the estimation process were significantly reduced. However, the divergence phenomenon of the estimation results in the low SOC interval still existed, which was mainly due to the intensified polarization of the lithium-ion battery in the low SOC interval and the fixed noise of the basic CKF algorithm. After realizing the adaptive update of noise in the filtering process, not only the initial SOC estimation results could quickly converge to the vicinity of reference, but also the divergence phenomenon in the entire SOC interval had disappeared.

4. CONCLUSION

In this paper, firstly, by establishing a GRNN model, an accurate fitting relationship of the experimental battery's OCV-SOC in the whole temperature range was successfully obtained. Secondly, the state estimation algorithm in SOC estimation was enhanced by improving the standard CKF. Finally, combined with the FFRLS, the SOC estimation of the lithium-ion battery under DST working condition at different ambient temperatures was completed. According to the OCV-SOC fitting results, without the low-current test data of the experimental battery at the target temperatures, the trained GRNN model could still map the OCV-SOC correspondence of the lithium-ion battery at the temperature with high accuracy. Meanwhile, the proposed DMACKF algorithm could achieve high precision SOC estimation at each temperature; the RMSE based on GRNN-DMACKF at each temperature did not exceed 0.4%.

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