International Conference on Applied Energy 2019
Aug 12-15, 2019, Västerås, Sweden
Paper ID: 1085

COOPERATIVE ESTIMATION OF SOC AND SOH FOR LITHIUM-ION BATTERY BASED ON A THERMO-ELECTRO-AGING MODEL

Qianqian Liu[a, b], Zehua Li[a], Xiaolin Xu[a], Bo Chi[c], Jianhua Jiang[a,*]
a) School of Artificial Intelligence and Automation, Key Laboratory of Education Ministry for Image Processing and Intelligent Control, Huazhong University of Science & Technology, Wuhan 430074, China
b) China-EU Institute for Clean and Renewable Energy, Huazhong University of Science & Technology, Wuhan 430074, China
c) School of Materials Science and Engineering, State Key Laboratory of Material Processing and Dye and Mold Technology, Huazhong University of Science and Technology, Wuhan 430074, China
*Corresponding author: Jianhua Jiang Tel: (+86) 15827271233 Fax: (+86) 027-87557273
Email address: jiangjh@hust.edu.cn

ABSTRACT

This paper presents a cooperative estimation approach for SOC and SOH with the consideration of temperature and aging. The co-estimation is realized by using a co-estimator which is a combination of a model-based algorithm and a data-driven technique for joint SOC and SOH estimation, and by a developed thermo-electro-aging coupling model which can reflect the dynamic and static characteristics of the parameters related to the SOC and SOH. In this co-estimator, unscented Kalman filter (UKF) and long short-term memory recurrent neural network (LSTM RNN) are designed to estimate SOC and SOH respectively and update mutually as temperature and current input; an optimized dual-time scale strategy based on slow-varying SOH and fast-varying SOC characteristics is implemented. Simulation results indicate that compared with the popular dual EKF and the UKF, the proposed algorithm gains higher accuracy and faster error convergence speed, and its estimate error for SOC and SOH are statistically less than 0.4% and 0.21% respectively under a wide range of condition.

Keywords: lithium-ion battery, battery model, state of charge, state of health

NONMENCLATURE

Abbreviations	
SOC	State of charge
SOH	State of health
LSTM RNN	Long short-term memory recurrent neural network
EKF	Extended Kalman filter
UKF	Unscented Kalman filter
MAE	Mean absolute error
C-rate	Discharge rate

1. INTRODUCTION

The lithium-ion battery has been widely used in modern technologies, e.g. smart grid and electric vehicles, for its advantages of small size, high energy density, long life, and no memory effect [1]. Accurate online estimation of the SOC (state of charge) plays a pivotal role in the battery management system for protecting the battery from over-charge/discharge which causes battery degradation and potentially hazardous situations. The SOC has an intimate connection with the SOH (state of health), which indicates capacity degradation due to repeated cycles or long-term storage. As battery ages, SOC-only estimation, such as Coulomb counting, unscented Kalman filter (UKF), extended Kalman filter (EKF) can cause large errors, and inaccurate SOC, in turn, can mislead SOH calibration [2]. Therefore, the joint estimation of SOC and SOH is advantageous. Dual SOC and SOH estimation strategies such as PI observer [3], dual EKF [4], and FPGA [5] to estimate SOC and SOH simultaneously have been presented and improved accuracy of SOC estimation. However, when the temperature dependence of

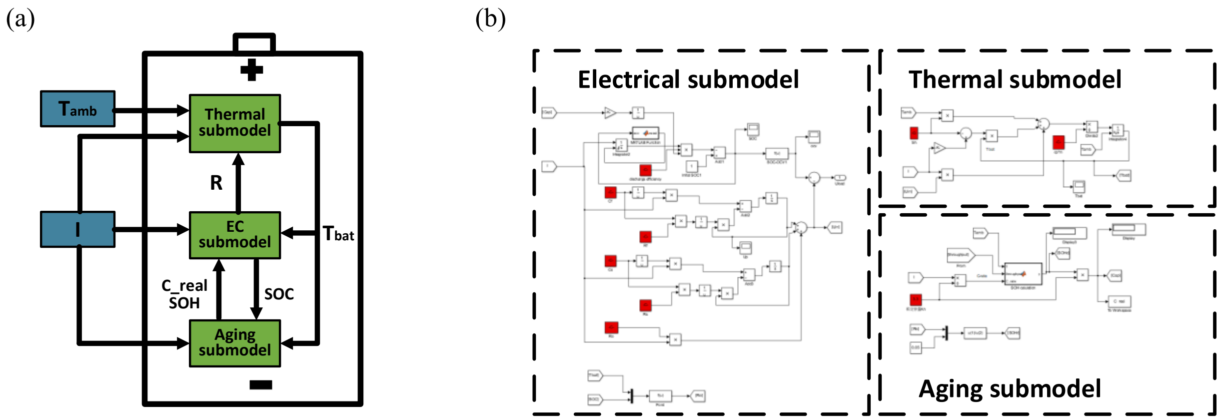


Fig. 1. Layout of the thermo-electro-aging coupling model. (a) Signals circulating among submodels of the battery; (b) the realization of the coupling model on MATLAB/Simulink platform

SOC/SOH is poorly considered or overlooked, the dual estimators tend to produce divergent errors as temperature varies: the deviation of SOC can be over 2.8% at 40 ℃, and over 5.2% at 60 ℃ [2]. Temperature predominates both battery electrical characteristics and degradation behaviors by stimulating physical particle movement and electrochemical side effects which is necessary to be examined in both SOC and SOH estimation.

This paper aims at developing a cooperative SOC and SOH estimation strategy considering thermal and aging activities to optimize the precision of SOC/SOH estimation under a wide range of condition and lifespan. A thermo-electro-aging coupling model is first developed to accurately reflect the dynamic/static characteristics and coupling relationships of SOC and SOH related parameters, and reduce computation of models. Considering the facts that SOC can be explicitly resolved by electrical model, while data-driven method with simplicity and sufficient accuracy is more practical for SOH prediction than existing computationally heavy aging models, it is appropriate that a model-based algorithm and a data-driven method are selected separately and integrated cooperatively to observe SOC and SOH jointly. The UKF algorithm (unscented Kalman filter) and the intelligent LSTM RNN (long short-term memory recurrent neural network) are therefore chosen to estimate SOC and SOH correspondingly while promoting mutually in regard to variables of temperature and current. The main idea of the cooperative estimator is: due to the mutual update between the SOC and SOH estimators, model parameters varying with temperature and aging factors, such as temperature, current, SOC and throughout, are calibrated continuously and quantified accurately, and therefore state observer with more favorable performance can be obtained. Furthermore, a dual time-scale strategy is applied in the cooperative estimation algorithm to separate the update frequency of SOC and SOH observers so as to adapt to the fast-varying SOC and slow-changing SOH, i.e., the SOH estimator works in slow speed while SOC estimator fast speed.

2. THERMO-ELECTRO-AGING MODEL FOR LITHIUM-ION BATTERY

The lithium-ion battery is a very complex system with highly coupling electrical, thermal, and degradation behaviors. Based on the electrothermal characteristics and working principles of the battery, a coupling model is developed by integrating an electrical submodel, a thermal submodel, and an aging submodel to give comprehensive information on the dynamic and static characteristics of the battery (Fig. 1). Current and temperature are detected as inputs to the model, and the specific structure of each submodel is introduced below.

For the electrical submodel, a widely used 2RC equivalent circuit [6] is referred to represent electric behavior of lithium-ion batteries. Based on the Coulomb counting equation and Kirchhoff's law, the state space equation of battery is obtained as:

$$\begin{bmatrix} SOC \\ U_b \\ U_p \end{bmatrix}_{t+1} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1-\dfrac{T_s}{R_b(SOC)\cdot C_b} & 0 \\ 0 & 0 & 1-\dfrac{T_s}{R_p(SOC)\cdot C_p} \end{bmatrix} \begin{bmatrix} SOC \\ U_b \\ U_p \end{bmatrix} + \begin{bmatrix} -\dfrac{\eta T_s}{C_{\_real}} \\ \dfrac{T_s}{C_b} \\ \dfrac{T_s}{C_p} \end{bmatrix} I \qquad (1)$$

where R_o is internal ohmic resistance, R_b*C_b is diffusion impedance, R_p*C_p is charge transfer impedance, T_s denotes sample time which is 1 second in this case, η denotes the coulomb efficiency. η is simplified as a constant which is 1 when charging and 0.985 when discharging. The load voltage U_B is taken as the observed quantity:

$$U_B = U_{oc}(SOC) - I \cdot R_o - U_b - U_p \tag{2}$$

The open circuit voltage (Uoc) is found as a nonlinear function of SOC which can be represented by polynomial:

$$U_{oc} = \sum_{0}^{i} a_i \cdot SOC^i \tag{3}$$

Internal resistances change with both SOC and temperature, which can be expressed in binary Taylor expansion formula as:

$$R_m = \sum_{k}^{l} \sum_{j=0}^{k} c_{kj} \cdot T^j \cdot SOC^{k-j}, R_m = R_o, R_b, R_p \tag{4}$$

To facilitate the analysis of the thermal submodel, several reasonable assumptions are first made: (i) the temperature is uniform inside the battery; (ii) the radiant heat is ignored; (iii) the specific heat (C_p) and heat transfer coefficient (h) of the battery are constant. According to these assumptions, the heat conservation equation is easily established as:

$$\frac{dT_{bat}}{dt} = \frac{Q}{C_p \cdot m} - s \cdot h \frac{T - T_{amb}}{C_p \cdot m} \tag{5}$$

Where m is the battery mass, s is the battery area, and T_{amb} is the ambient temperature. The heat source term Q is the sum of polarization heat and entropic heat according to Bernardi model[7]:

$$Q = I(U_{oc} - U_B) - I \cdot T \cdot \frac{dU_{oc}}{dT} \tag{6}$$

For power battery, the capacity attenuation is generally used to indicate SOH as:

$$SOH = \frac{C_{\_real}}{C_{\_rated}} \times 100\% \tag{7}$$

However, eq.7 is inconvenient for direct use of SOH estimation, and thus an Arrhenius equation-based battery life model mapping aging factors to SOH is referred [8] as:

$$SOH = 1 - B \cdot \exp(-\frac{E_a}{R \cdot T}) \cdot A_n^{\ z} \tag{8}$$

Where R is gas constant, N is cycle numbers, z is a factor which has an experienced value of 0.55, A_n is the throughput which can be calculated as:

$$A_n = N \cdot \Delta SoC \cdot C_{\_real} = \int I \cdot dt \tag{9}$$

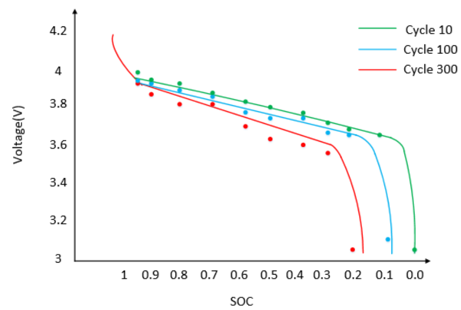
Pre-exponential factor (B) can be fitted as an exponential function of discharge rate, and activation energy (E_a) is a linear function of discharge rate. It is beneficial to add correction factors (k_1~k_6) to determine E_a (eq.10) and B (eq.11) for calibrating the characteristics difference between batteries. So far, the physical model has been built as a whole.

$$E_a = k_1 \cdot C\text{-rate} + k_2 \tag{10}$$

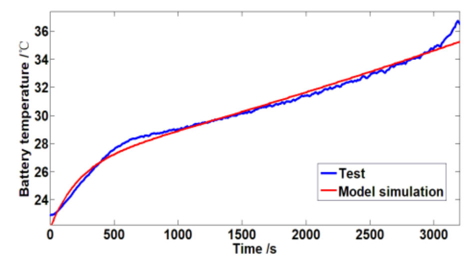
$$B = k_3 \cdot e^{k_4 \cdot C\text{-rate}} + k_5 \cdot e^{k_6 \cdot C\text{-rate}} \tag{11}$$

A previous test dataset collected from an 18650-type lithium-ion battery is used to identify the model. Procedures described in [9] were followed to identify internal resistance and capacitance by discharge experiment test data. Least squares method is utilized to optimize parameters by minimizing the root mean squared error (RMSE) of the measurements and model

(a) Load voltage results



(b) Battery temperature results



(c) SOH results

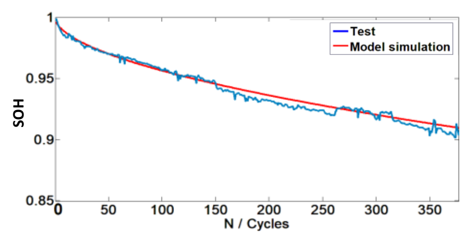


Fig. 2. The coupling model simulation vs. experiment measurement.

response. The model is built in Simulink environment, and the simulation results in the 1 C cycling test at 23℃ is shown in Fig. 2, which show good matches between the model and measurements.

3. COOPERATIVE ESTIMATION OF SOC AND SOH BASED ON UKF AND LSTM RNN

Model-based UKF and intelligent LSTM RNN are selected to estimate SOC and SOH separately. The UKF-based SOC estimator has been studied in [10], so we'd like to focus on the SOH estimation method and the combination of the two algorithms.

Battery aging is significantly influenced by dynamic operation conditions and historical states. LSTM RNN has a proven capability to perform mapping in highly nonlinear systems and well-designed structure to remember historical information for a long time. The LSTM RNN is trained by over 3500 samples under different temperatures and discharge rates to map between the input variables (C-rate, throughput, SOC, and ambient temperature) and the SOH. The mini-batch-based back propagation optimization algorithm is introduced to train LSTM RNN with a mini-batch size 40 and learning rate of 0.08 in this case.

It usually takes dozens of hours for observable SOH shift, while few seconds for SOC variation. Estimating SOC and SOH on the same time scale is inefficient. In order to alleviate this problem, the UKF and the LSTM RNN are designed to work at different time-scale with tolerable estimation error. *f* and *s* are defined as the timer indicators of SOC (fast) observer and SOH (slow) observer respectively. Define the time-scale separation indicator of two timer as

$$N = f / s \tag{12}$$

Whenever a SOC or SOH estimation process is finished, its corresponding timer is added. As UKF updates in micro steps, we define $t_{s,0} = t_{s-1,N}$ to manage the macro step when the LSTM NN should step in. The time-scale of SOC and SOH is thus separated so as to adapt to the fast-varying SOC and slow-varying SOH. Fig.3 demonstrates the flow chart of the cooperative estimator of SOC and SOH based on UKF and LSTM RNN (shortly called as UKF-NN estimator hereinafter) proposed in this paper. On the fast time-scale, the UKF calculates the state and observation value according to state space equation (eq.1) and observation equation

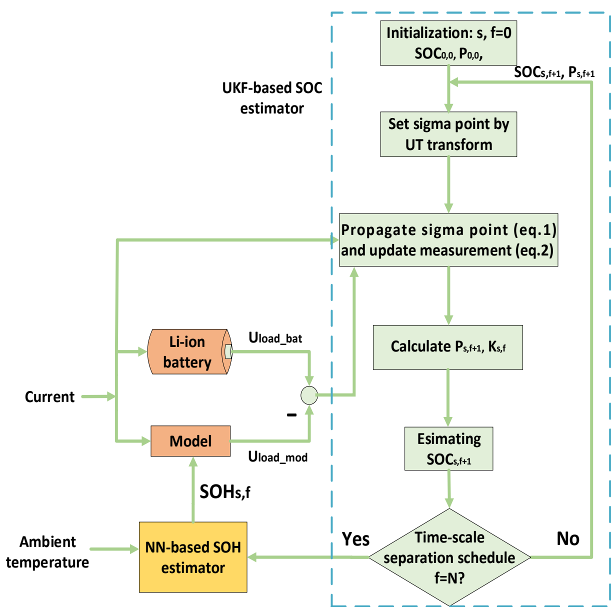


Fig. 3. Flow chart of the UKF-NN estimation algorithm.

(eq.2). The load voltage difference between the measurement and calculation determines the covariance matrix (*P*) and Kalman matrix (*K*), which further define the estimated SOC. When the SOC estimate ends, the SOC timer increases. Whenever SOC timer counts to *N*, the SOH timer is updated and LSTM RNN starts to predict SOH and update model parameters. The SOH timer adds, and the updated model goes to the next step for SOC estimation. The process moves on to estimate SOC continuously and predict SOH periodically.

4. SIMULATION AND RESULTS

The validated coupling model and the UKF-NN estimator are constructed to verify the performance of the co-estimator (Fig. 4). Gaussian noises with standard deviations of 200 mA, 10 mV, and 0.05 ℃ are added to the measured current, voltage and temperature data, respectively, to simulate sensor noises. The validated coupling model is deemed as the object whose states are observed by estimator. A sequence of dynamic hybrid pulse load (see Fig. 5) collected from real EVs driving data is used.

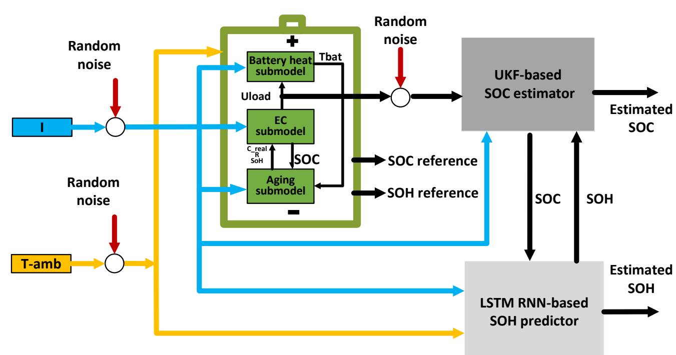
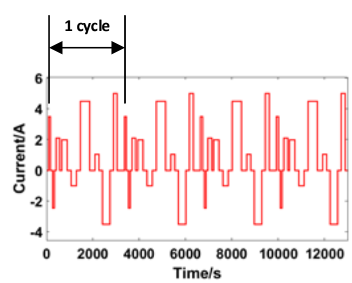


Fig. 4. Schematic diagram of the verification system



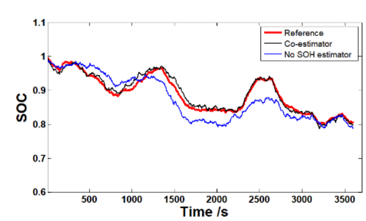


Fig. 5 Fig. 6

(left) Fig. 5. Dynamic hybrid pulse load
(right) Fig. 6. SOC estimation results of the UKF-NN vs. UKF when the SOH=0.82

4.1. Comparison between the UKF-NN estimator with the UKF-based SOC estimator

During battery aging, the UKF-NN estimator can update parameters by periodically introducing the estimated SOH, so its SOC estimation accuracy is improved compared to the SOC-only estimator. A case simulates an aged battery whose SOH has fallen to 0.82, nearly retired, to compare the performance between the UKF-NN estimator and the SOC-only method, i.e. UKF, as shown in Fig. 6. The MAE (mean average error) of the UKF-NN estimator and UKF are 0.38% and 4.34% respectively which means a 4% accuracy improvement. Actually, the SOC-only estimator performs worse as further degradation happens. When the battery retires, the SOC estimation accuracy of the SOC-only estimator decreases to 85.2%, while of the UKF-NN estimator is 98.3%. In a word, the co-estimation shows consistent reliability through the battery lifespan.

4.2. Comparison between the UKF-NN estimator with dual EKF co-estimator

The dual EKF is a commonly used technique which uses two EKF running in parallel to estimate SOC and SOH simultaneously. In order to investigate the performance of the proposed estimation methodology, the dual EKF method is also realized for comparison with 0.5 and zero initial error (see Fig. 7). the MAE and convergence speed of the UKF-NN estimator and dual EKF are statistically recorded in Table 2. As we can see, the MAE of the proposed method and dual EKF are 0.40%/0.29% and 3.09%/2.38%, the convergence speed are 24/15 s and 1600/1085 s separately, implying the proposed UKF-NN estimator performs far better than the dual EKF estimator and is more feasible for application.

Table 1. MAE and convergence speed comparison between the UKF-NN estimator and dual EKF under 0.5/zero initial error.

0.5/zero initial error	MAE	Convergence speed (s)
Dual EKF	3.09%/2.38%	1600/1085
UKF-NN	0.40%/ 0.29%	24/15

4.3. Estimation results at different temperatures

Because the ambient temperature changes rapidly and greatly introducing many uncertainties into battery property, it is necessary to examine the estimators' adaptivity to various temperature. In this section, the results of SOC estimate in dynamic hybrid pulse load test, and the results of SOH estimate in cycling tests are illustrated at different temperatures for the UKF-NN estimator.

Three cycles of dynamic hybrid pulse load are input to the verification system to evaluate the SOC estimation under a wide range of temperatures. SOC estimation results of the UKF-NN estimator at four ambient temperature conditions (-10, 0, 15, and 30 ℃) are shown in Fig. 8. As temperature increases, the SOC varies more dramatically. Nevertheless, the UKF-NN estimator firmly follows the real value, and its MAE is consistently less than 0.38% under four temperatures.

Fig. 9 illustrates the SOH estimation when the battery is charged/discharged repeatedly by 1 C current at three temperatures which are extreme low (-10 ℃), room temperature (23 ℃) and extremely high (40 ℃). As the temperature increases, the SOH estimation error gradually increases: the MAE are 0.06%, 0.10% and 0.21% from low to high temperature, which remain high accuracy for practical application.

In a word, the proposed model-based and data-driven cooperative SOC and SOH estimator achieves accurate and fast estimation under various operating conditions, which demonstrate the high performance of the method and its potential for real-time application with moderate chips.

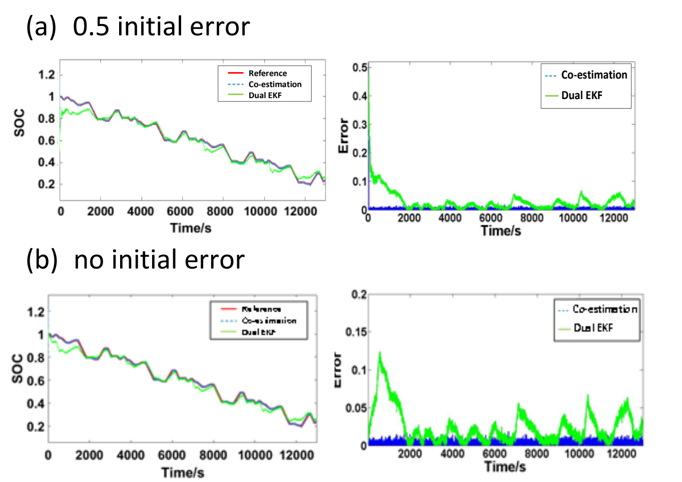


Fig. 7. The UKF-NN co-estimator vs. dual EKF with/without initiall error. Plot SOC estimation results (left column) and error (right column) under (a) 0.5 initial error, and (b) no initial error.

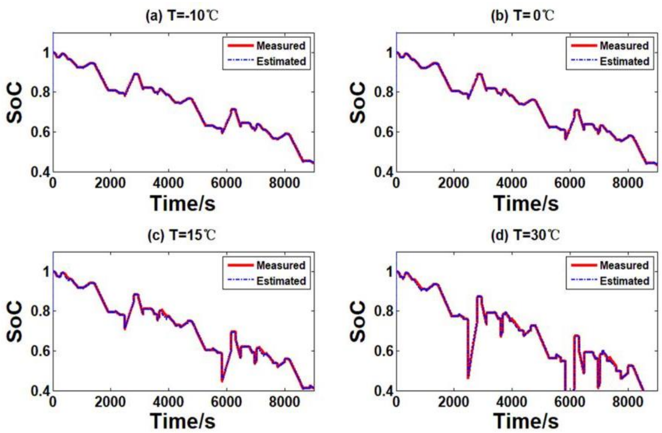
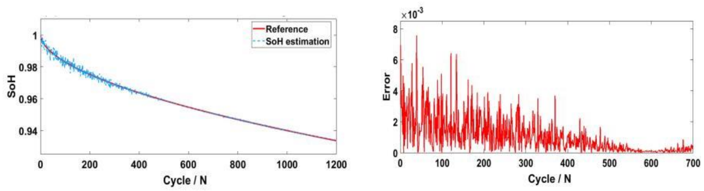
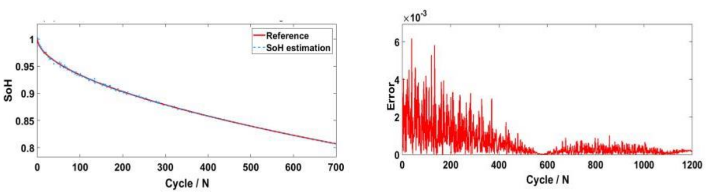


Fig. 8. Comparisons between the estimated SOC and the reference SOC at four different temperatures.

(a) T=-10 ℃



(b) T=23 ℃



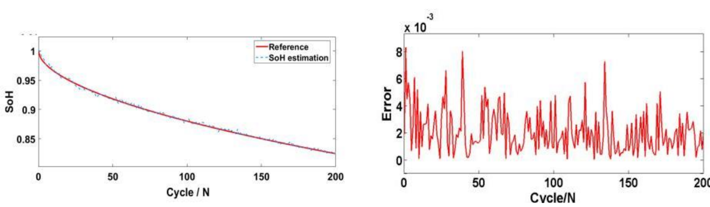


Fig. 9. The SOH estimation results at different temperatures. Plot the SOH estimation results (left column) and estimation error (right column).

(c) T=40 ℃

5. CONCLUSION

This work mainly proposes a cooperative estimation approach of state of charge and state of health for lithium-ion batteries to handle issues of the complex degradation characteristics and temperature effects, which can cause deteriorating performance to states observer.

The main contributions of this work are: (i) a novel thermo-electro-aging coupling model is developed to accurately reflect the coupling relationship and dynamic and static characteristics of parameters related to SOC/SOH; (ii) a model-based algorithm (unscented Kalman Filter) and a data-driven technique (long short-term memory recurrent neural network) are integrated as a cooperative estimator to observe SOC and SOH jointly to balance the accuracy and complexity of existing methods; (iii) effects of temperature and aging factors are captured by the carefully organized cooperative estimator.

Simulation results verify the high-fidelity of the proposed methods against aging effects, temperature variation, and noises, which endow its promising application in practical use, such as EVs.

REFERENCE

[1] Truchot C, Dubarry M, Liaw B Y. State-of-charge estimation and uncertainty for lithium-ion battery strings[J]. Applied Energy, 2014, 119(C):218-227.

[2] Kong S N, Moo C S, Chen Y P, et al. Enhanced coulomb counting method for estimating state-of-charge and state-of-health of lithium-ion batteries[J]. Applied Energy, 2009, 86(9):1506-1511.

[3] Cacciato M, Nobile G, Scarcella G, et al. Real-Time Model-Based Estimation of SOC and SOH for Energy Storage Systems[J]. IEEE Transactions on Power Electronics, 2016, 32(1):794-803.

[4] Dai H, Wei X, Sun Z, et al. Online cell SOC estimation of Li-ion battery packs using a dual time-scale Kalman filtering for EV applications[J]. Applied Energy, 2012, 95(2):227-237.

[5] Zou Y, Hu X, Ma H, et al. Combined State of Charge and State of Health estimation over lithium-ion battery cell cycle lifespan for electric vehicles[J]. Journal of Power Sources, 2015, 273:793-803.

[6] He H, Zhang Y, Xiong R, Wang C. A novel Gaussian model based battery state estimation approach: state-of-energy. Applied Energy 2015; 151:41–48

[7] Bernardi D, Pawlikowski E, Newman J. General energy balance for battery systems[J]. Journal of the Electrochemical Society, 1984, 132(1):5-12

[8] Wang J, Liua P, Hicks-Garner J, et al. Cycle-life Model for Graphite-LiFePO4 Cells[J]. Journal of Power Sources,2011,196:3942-3948.

[9] Hu C, Youn B D, Chung J. A multiscale framework with extended Kalman filter for lithium-ion battery SOC and capacity estimation[J]. Applied Energy, 2012, 92(none):694-704.

[10] He Z, Dong C, Pan C, et al. State of charge estimation of power Li-ion batteries using a hybrid estimation algorithm based on UKF[J]. Electrochimica Acta, 2016, 211:101-109

