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Online Double-layer System Identification Scheme for Battery State-of-Health Prediction

Cetengfei Zhang[1], Quan Zhou[1], Min Hua[1], Chongming Wang[2], Hongming Xu[1*]

1 Department of Mechanical Engineering, University of Birmingham

2 Institute for Future Transport and Cities, Coventry University

(*Corresponding Author: h.m.xu@bham.ac.uk)

ABSTRACT

The battery is the primary power source of electrified vehicles (EV). Prediction of battery performances with digital models is essential for both the R&D stage and real-world operation. However, the battery model developed in the R&D stage is not suitable for all real-world conditions, and it will be good if it can be optimized online. This paper proposes an Online Double-layer System Identification (ODSI) scheme to calibrate a battery model for State-of-Health (SoH) prediction with measured data. To determine the unified settings for the base battery model, the ODSI scheme firstly conducts robust optimization in the lower layer based on offline particle swarm optimization (PSO). It then incorporates a deep convolutional neural network (DCNN) to the base model to enable knowledge transfer from offline optimization to online adaption for SoH prediction under different working conditions. By reducing the size of the learning dataset, the study indicates that the proposed scheme has high robustness of uncertainty management. Besides, the ODSI scheme saves the computation resource by avoiding training from scratch.

Keywords: Intelligent Energy system; Battery digital modelling; System Identification; Particle swarm optimization; convolutional neural network

1. INTRODUCTION

Modern transportation is moving towards the electrification of vehicles in order to reduce the dependence on fossil fuels. The battery plays a significant role in the power source of electrified vehicles. Particularly, the lithium battery is popular in the automotive industry because of its notable dynamic performances[1][2]. With the trend of digitalization in all engineering fields, digital modelling of the lithium battery is widely researched[3][4].

For battery modelling, three types of battery models are studied[5], [6]: 1) the electrochemical-based model; 2) the mathematical-based model, and 3) the equivalent circle based model. The electrochemical model mainly focuses on the internal working mechanism of the battery. Computational fluids dynamics and thermal propagation calculations are needed for a typical electrochemical model[5], this causes a bulky workload in battery control applications. For the mathematical models of battery, large amounts of the experimental are needed for numerical regression of the physical behaviors[7]. Thus, for convenience and flexibility, the equivalent circle model is often chosen for digital modelling applications. According to recent research[3], the second-order RC equivalent circle model (SECM) (as known as the two RC models) is valid and chosen as the battery plant model for control applications. In SECM modelling, multiple factors need to be modified to represent the actual features of the battery[5]. Modelling modification and calibration are widely researched by different parameter identification approaches[8]–[10].

For the practical automotive engineering applications of lithium batteries, one of the factors that cannot be ignored is the degradation problem[11], [12]. Typically, this problem is assessed using the state of health (SOH) of the battery for two reasons: 1) increase of the internal resistance. 2) loss of capacity[13]. Since the internal resistance cannot be measured directly, regular battery aging evaluation uses model-based and

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data-driven methods. The former depends on significant empirical experiences; the latter can be achieved efficiently by machine learning[14].

However, for the complex automotive engineering environment, digital models of batteries are continuously developed from scratch, which requires significant computation resources. Then for the end-of-life problem, more data will be dealt with manually in the prediction process. In this paper, a double layer battery identification system is constructed to address this demand. For the battery PI, this approach only deals with the battery performance of voltage and current. Then for SOH prediction, the performance data of the battery is obtained from the digital model and used as the input for battery cycle testing for learning and evaluation.

The rest of this paper is organized as follows: Section 2 demonstrates system structure including the lower layer adaptive PSO modelling optimization and the upper layer CNN model of battery SOH prediction. Section 3 presents the experimental setup. Section 4 presents the results and the discussion. The conclusion is made in section 5.

2. THE MECHANISM OF THE DOUBLE-LAYER STRUCTURE

The structure of this system consists of an upper layer and a lower layer. The upper layer is a battery digital model with a PSO-based PI optimization. The lower layer is a battery SOH prediction model with a DCNN structure for real-time prediction.

2.1 The digital model of the battery

Based on the existing research[3], [10], a second-order equivalent circle model (SECM, known as two RC model) is chosen as the battery plant model. The governing equation of two RC models illustrated by figure 1 are listed in Eq.1.

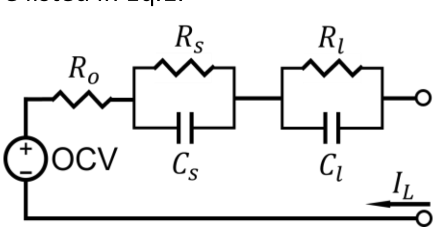

Fig. 1. The second order RC equivalent circle model

$$\left.\begin{aligned} U_o &= I_L R_o \\ U_s &= \frac{I_L}{C_s} - \frac{U_s}{R_s C_s} \\ U_l &= \frac{I_L}{C_l} - \frac{U_l}{R_l C_l} \\ U_t &= U_{OCV} - U_s - U_l - U_o \end{aligned}\right\} \quad (1)$$

where R_o is Ohm resistance, C_s and R_s are equivalent capacitance and equivalent resistance for the short-term performance (activation polarization). C_l and R_l are for the long-term performance (concentration polarization). I_L is current, and U_{OCV} is the open circle voltage.

From the suggestion of [5], this SECM can be further modified considering the SoC variation. The general battery equation is shown as Eq.2.

$$\left.\begin{aligned} \mathrm{C_{cap}} &= \mathrm{X_1} \\ \mathrm{V_{oc}} &= \mathrm{X_2}\exp(\mathrm{X_3 V_{soc}}) + \mathrm{X_4} + \mathrm{X_5 V_{soc}} + \mathrm{X_6 V_{soc}}^2 + \mathrm{X_7 V_{soc}}^3 \\ \mathrm{R_{series}} &= \mathrm{X_8}\exp(\mathrm{X_9 V_{soc}}) + \mathrm{X_{10}} \\ \mathrm{R_{short}} &= \mathrm{X_{11}}\exp(\mathrm{X_{12} V_{soc}}) + \mathrm{X_{13}} \\ \mathrm{C_{short}} &= \mathrm{X_{14}}\exp(\mathrm{X_{15} V_{soc}}) + \mathrm{X_{16}} \\ \mathrm{R_{long}} &= \mathrm{X_{17}}\exp(\mathrm{X_{18} V_{soc}}) + \mathrm{X_{19}} \\ \mathrm{C_{long}} &= \mathrm{X_{20}}\exp(\mathrm{X_{21} V_{soc}}) + \mathrm{X_{22}} \end{aligned}\right\} \quad (2)$$

where $\mathrm{X_1}$ to $\mathrm{X_{22}}$ are defined by a sensitive analysis[15], they are all influenced by the instant SoC level of the battery. In this paper, a general battery model is built based on eq.1 and eq.2. by MATLAB and Simulink. Then, these 22 parameters are optimized for calibrating the digital model.

2.2 The offline PI optimization of battery digital model

Since the parameters identification for the 22 dimensions is a large-scale numerical problem[16], the PSO is chosen to optimize the model with the 22 parameters of battery (as eq.2). In this paper, as demonstrated in the green part of Fig.2 (Offline layer), the recorded current data from pulse charge-discharge experiments of the battery is applied as input to the digital model. Its corresponding voltage data is used as a comparison target for the PI optimization. Mathematically, the PI optimization can be described as:

$$\left.\begin{aligned} &[\mathrm{X_1}, \mathrm{X_2}, \dots \mathrm{X_{22}}] = \operatorname{argmin}(\mathrm{J_{vlt}}) \\ &\text{s.t.}\begin{cases} \mathrm{J_{vlt}} = \sqrt{\frac{\sum_{i=1}^{T}(\mathrm{V_{sim}} - \mathrm{V_{ref}})^2}{\mathrm{T}}} \\ \mathrm{X_1} \in [0.5\mathrm{X_{1ref}},\ 1.5\mathrm{X_{1ref}}] \\ \dots \\ \mathrm{X_{22}} \in [0.5\mathrm{X_{22ref}},\ 1.5\mathrm{X_{22ref}}] \end{cases} \end{aligned}\right\} \quad (3)$$

where the $\mathrm{X_1}, \mathrm{X_2}, \dots \mathrm{X_{22}}$ are 22 numerical parameters in the Eq.2. The $\mathrm{J_{vlt}}$ is the root mean square error (RMSE) between the simulated voltage $\mathrm{V_{sim}}$ and the reference data of voltage $\mathrm{V_{ref}}$.The $\mathrm{X_{1ref}}$, $\mathrm{X_{2ref}}$ … $\mathrm{X_{22ref}}$ are values from the reference for the extraction of Li-ion battery mathematical model[5]. The upper and lower limits of searching spaces for each numerical parameter are set empirically with 50% variations for the reference values. With such searching spaces, the PSO is used to optimize

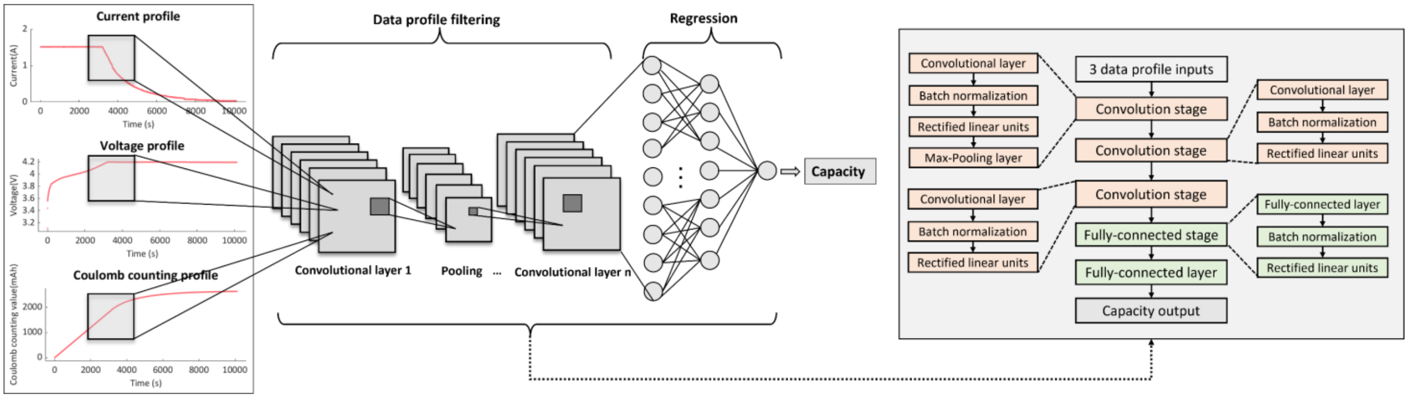

Fig. 2. The architecture of online DCNN

the parameters in conducting an accurate battery model with the smallest RMSE. The particle updating process is presented mathematically as :

$$\left.\begin{aligned} v_{k+1} &= \omega \cdot v_k + c_1\,\epsilon_1 \cdot (gb_k - x_k) + c_2 \cdot \epsilon_2 \cdot (lb_k - x_k) \\ x_{k+1} &= x_k + v_{k+1} \end{aligned}\right\} \quad (4)$$

where v_k is the velocity vector at the k-th (k=1, 2, …j-1, j, …) iteration in updating the position of the particles for the 22 parameters; x_k is a 20×22 matrix with 20 group sizes and 22 dimensions ($\mathrm{X}_1, \mathrm{X}_2, \dots \mathrm{X}_{22}$ in this paper), this matrix represents the positions of all individual particle at the k-th (k=1, 2, …j-1, j, …). The ω is an inertia weight factor in controlling the exploration and exploitation; $c_1 = c_2 = 2$ are two weighting factors. $\boldsymbol{\epsilon_1}$ and $\boldsymbol{\epsilon_2}$ are two random numbers between 0 and 1 in increasing the randomness. lb_krepresents the local best position found by the individual particles; gb_k is the global best position for all particles. The pseudo code of PSO algorithm is shown as

Algorithm 1 The hybrid termination methods in the PSO process

while k < maximum iterations number
  for each particle *i* the swarm **do**
    update the best position x_{id} by Equation 1 &2
    calculate the fitness function $\mathrm{J}_{\mathrm{vlt}}$
    update the p_i & p_g
  end for
  if $\mathrm{J}_{\mathrm{vlt}}$fulfills the termination threshold
    break
    return $\mathrm{J}_{\mathrm{vlt}}$, x_{id} , p_i , p_g
  end if
end

Fig. 3. The pseudo-code of the PSO algorithm

2.3 *The online prediction of the battery SOH*

Due to the difficulty of direct measuring the internal resistance, this paper mainly concentrates on the SOH of the capacity loss. When the capacity of the battery drops to a particular value (i.e. 80%), the battery is considered as the end of life (EOL). Inspired by recent researches [17]–[19], a deep convolutional neural network (DCNN) is applied in this subsection for the evaluation and prediction of the battery's degradation status.

In Fig.2, the current, voltage and the Coulomb counting of battery (represent the state of charge) are the inputs of the DCNN; the output is the instant capacity of the discharge phase, which indicates the battery SOH. Mathematically, the inputs are expressed by a matrix as:

$$Input = \begin{bmatrix} I_1^k & V_1^k & C_1^k \\ I_2^k & V_2^k & C_2^k \\ \vdots & \vdots & \vdots \\ I_t^k & V_t^k & C_t^k \end{bmatrix}_{t\times 3} \quad (5)$$

where the I_t^k, V_t^k and C_t^k are the tested current value, voltage value and coulomb counting value at the t-th in the k -th iteration of the charge-discharge test, respectively. The matrix is $t \times 3$ size, where the t is time steps for each iterative test, in this paper $t = 3500$.

As the right part of Fig.2, this DCNN consists of three convolution stages and two fully-connected stages. the input size is defined as $3500 \times 3 \times 1$ by referencing the previous study [18], as Eq.4. In the first convolutional layer, the number of filters (kernels) is set as 20, with a size of 2×1. The stride is set as the size of 1×1 and padding of $[0,0,1,1]$. The data then is fed into a batch normalization layer to accelerate the calculation speed and reduce the gradient vanishing. After the rectified linear unit (ReLU), the processed data is into a max-pooling layer.

Similarly, the second and third convolution stages have 32 kernels and 40 kernels, respectively. For convolutional layers with a the same stride size of 3×1. The rest two fully-connected layers have both 50 layers. Finally, after a regression, the single capacity value is output. These parameters are set initially from the

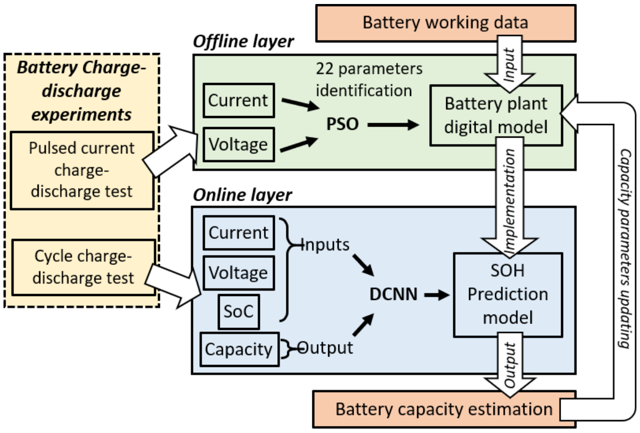

Fig. 4. The architecture of the double layer system

reference then tuned empirically by an amount of experimental simulation in pursuing a trade-off between an accurate result with a fast calculation speed. This DCNN will be trained by the experimental data first, then be implemented into an online application for battery SOH estimation.

2.4 The integration between offline and online

The architecture of the whole system is shown in Fig.4. Based on the content of the previous two subsections, an integration is conducted to pass the data between the two layers. There will be circulated feedback in updating the capacity parameter in the battery digital model to generate corresponding voltage and state of charge values for the battery as inputs of the online layer. With input of current requirements, this closed-loop system can predict future capacity variations as data of longer time spans being fed.

3. EXPERIMENTAL SETUP

In this section, the database is chosen of the 18650 Li-ion battery from the NASA database [20]. Namely B0005, B0006 and B0007. In this database, two kinds of experiments are done: 1) Regular charge-discharge cycle test, where the battery is charged by a constant current (2A) until reached cut-off voltage 4.2V, then discharged with 2A current until the voltage reaches 3.2V. 2) Pulsed charge-discharge cycle test, where the battery is discharged from 4.2V with pulse current 1A for 10 minutes and rest for 20 minutes.

Among these, the data of pulsed charge-discharge is used to develop the battery digital plant model; the data of regular charge-discharge is implemented to train the DCNN for the battery degradation evaluation and prediction. Finally, the data is applied to validate the learning results of the previous two structures. The database is implemented as Table. 1 below.

For the battery SOH prediction model, these three experimental data (B0005, B0006 and B0007) are used to train the DCNN. As in Table 2, the data ratio is the proportion of the data in neural network learning. Three sets of data are used to train the network with different data ratios.

Finally, a cross-validation will be conducted to explore the robustness of the system. By trimming the training data for the DCNN, prediction results of the system will be compared with data of battery capacity loss from experiments.

Table. 1 Data implementation for different purposes.

Database items	Usage
Pulsed charge-discharge	2RC model development
Regular charge-discharge	SOH estimation study

Table. 2 Offline learning setup for DCNN SOH estimation.

Data ratio	Database		
0.5	B0005	B0006	B0007
0.6			
0.7			
0.8			

Table. 3 Cross-validation setup for battery SOH prediction.

B0005	B0006	B0007
Learning	Validation	Validation
Validation	**Learning**	Validation
Validation	Validation	**Learning**

4. RESULTS AND DISCUSSION

4.1 Battery digital modelling

After the PSO optimized relative parameters, the voltage performance of the battery model in the pulsed discharge simulation is shown in Fig.4. The root-mean-square error (RMSE) is calculated as 0.0045. This is

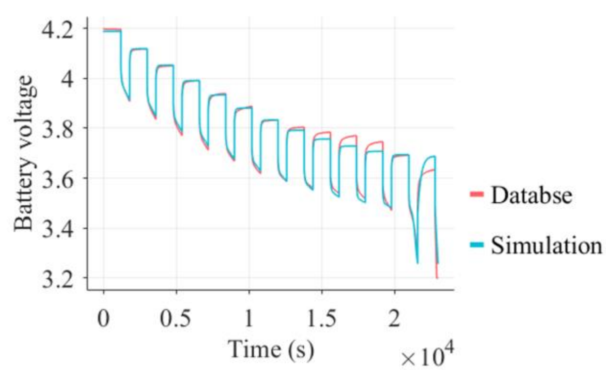

Fig. 5. Performance of voltage comparison for battery modelling

considered as an applicable 2RC model in applying to the later combined platform.

4.2 *Battery SOH estimation*

In this section, the DCNN is mainly trained and tested in having an accurate result of the battery's capacity estimation. Figure 6 a) b) and c) shows the local learning results for the DCNN in the ODSI for each learning database (B0005, B0006 and B0007). It is obtained that in Figure 6 a), the local learning process for the B0005 battery database has the most considerable fluctuation for the capacity loss estimation. Figure.6 b) and c) performance similar learning results. Table 3 presents the RMSE for learning results of the DCNN as in Figure 6. The RMSE of the B0005 database has the largest RMSE. However, in B0006 and B0007 databases, the performance of this DCNN is rarely influenced by the learning data ratio once it is larger than 0.6. The estimation results were used in updating the value of capacity variation in the digital model of the battery.

Table.4 Learning and cross-validation result in RMSE

Data ratio	RMSE		
	B0005	B0006	B0007
0.5	0.0245	0.0210	0.0156
0.6	0.0166	0.0154	0.0133
0.7	0.0185	0.0151	0.0120
0.8	0.0121	0.0134	0.0115

4.3 *Model prediction for cross-validation*

After the local training, the developed platform from each battery dataset is used to cross-validate with each database. Figure. 7 a), b), and c) demonstrate the results of the cross-validation. The system is pre-trained (in section 4.1 and 4.2) by three battery databases, respectively, then have the prediction comparison with each database.

In figure 7 a), the pre-trained ODSI from B0005, B0006 and B0007 are validated for the B0005 experimental database. It can be obtained that deviations exist between the three prediction results and the B0005 experimental database. The reason is considered from two factors: firstly, the 2RC model has its cumulating system error due to the dynamic training environment; Secondly, the training database of B0005 is considered to have more noise and scarce data as training input. These may cause the later prediction results to have high precision but low accuracy. In figure 7 b), the ODSI pre-trained by B0007 performs the best accuracy in predicting the battery capacity loss. The system pre-trained by B0006 has the most significant error, and the

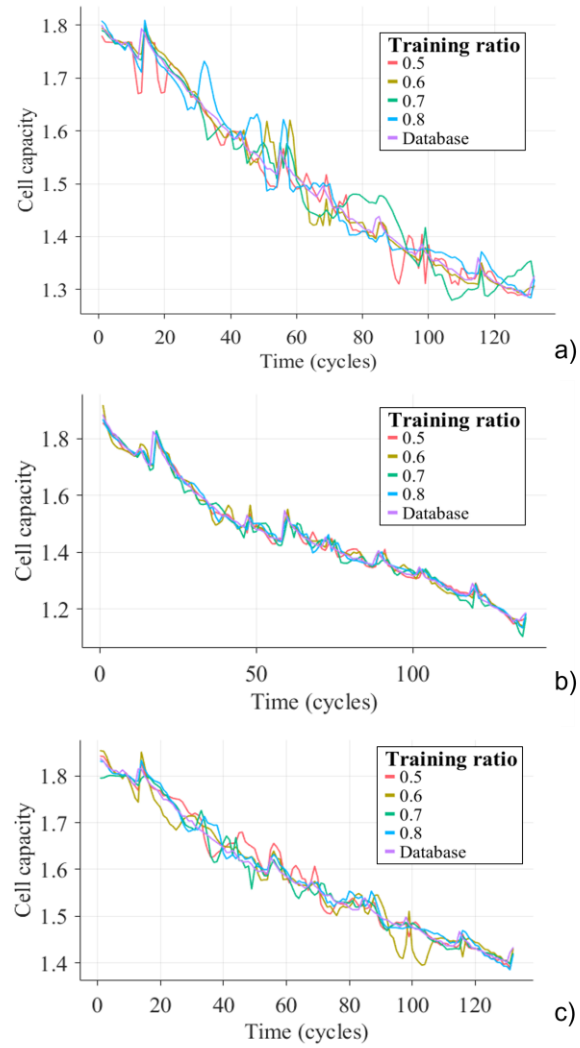

Fig. 6. The DCNN learning result for battery SOH estimation for B0007 validation dataset

system pre-trained by B0005 is obtained with errors in a middle stage. In figure 7 c), all the systems pre-trained by the three experimental databases prominently predict the battery capacity loss. It is considered that the database of B0007 is the most general case for the battery degradation of the capacity loss. Overall, the ODSI platform shows the ability in predicting battery capacity loss by only requiring a current input.

5. CONCLUSION

This paper presents a new online double layer system identification scheme for SOH estimation and prediction of the battery, with an experimental study based on cross-validation. The conclusions can be made as follows:

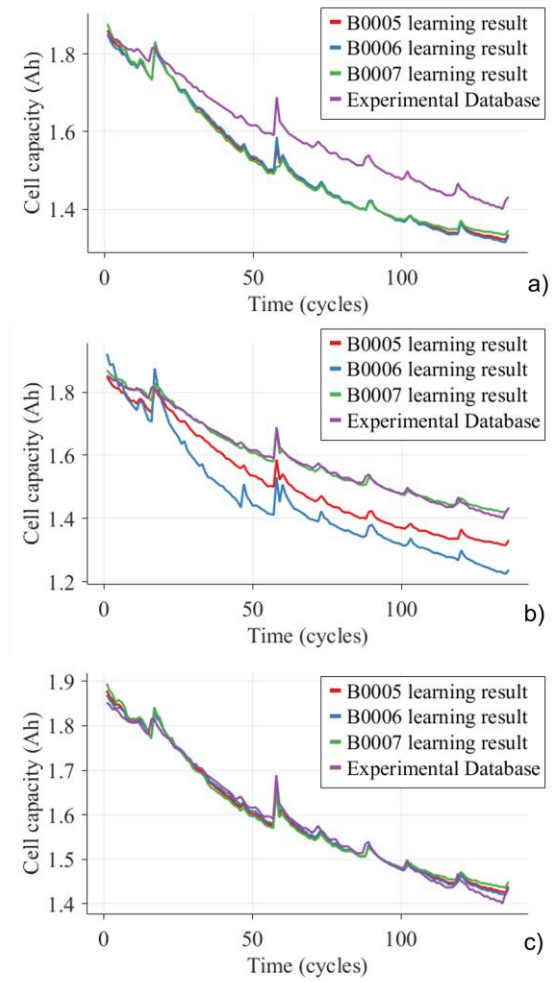

Fig. 7. The DCNN learning result for battery SOH estimation for B0006 validation dataset

1. By introducing this ODSI, the battery can be modeled during real-time applications. The closed-loop mechanism of this system gives instant feedback between the 2RC model and the neural network, compared to the traditional RC model with SOH consideration.
2. Different to the battery models of the pure neural network, the proposed system shows an advantage in avoiding a model training from scratch. By direct supporting from the 2RC model in the offline layer, the online DCNN can save calculation time in the health estimation.
3. Moreover, by feeding more existing data into the system, the instant feedback between two layers of this ODSI enables the system to further predict a capacity loss for battery degradation.

In the future, this system will be further developed into the package level in supporting applications for electrified vehicles. However, this online system still needs further exploration for the data sensitive analysis in avoiding large deviations during its working process of the self-feedback loop.

REFERENCE

[1] J. Wang *et al.*, "Cycle-life model for graphite-LiFePO4 cells," *J. Power Sources*, vol. 196, no. 8, pp. 3942–3948, 2011, doi: 10.1016/j.jpowsour.2010.11.134.

[2] Q. Zhou *et al.*, "Multi-step Reinforcement Learning for Model-Free Predictive Energy Management of an Electrified Off-highway Vehicle," *Appl. Energy*, vol. 255, no. 2019, pp. 588–601, 2019.

[3] X. Hu, S. Li, and H. Peng, "A comparative study of equivalent circuit models for Li-ion batteries," vol. 198, pp. 359–367, 2012, doi: 10.1016/j.jpowsour.2011.10.013.

[4] Q. Zhou, D. Zhao, B. Shuai, Y. Li, H. Williams, and H. Xu, "Knowledge Implementation and Transfer With an Adaptive Learning Network for Real-Time Power Management of the Plug-in Hybrid Vehicle," *IEEE Trans. Neural Networks Learn. Syst.*, pp. 1–11, 2021.

[5] A. Seaman, T. Dao, and J. Mcphee, "A survey of mathematics-based equivalent-circuit and electrochemical battery models for hybrid and electric vehicle simulation," vol. 256, pp. 410–423, 2014, doi: 10.1016/j.jpowsour.2014.01.057.

[6] S. Li, S. Member, and B. Ke, "Study of Battery Modeling using Mathematical and Circuit Oriented Approaches," pp. 1–8, 2011.

[7] V. R. Subramanian, J. E. Soc, V. R. Subramanian, and V. Boovaragavan, "Mathematical Model Reformulation for Lithium-Ion Battery Simulations : Galvanostatic Boundary Conditions Mathematical Model Reformulation for Lithium-Ion Battery Simulations : Galvanostatic Boundary Conditions," 2009, doi: 10.1149/1.3065083.

[8] X. Lai, W. Gao, Y. Zheng, M. Ouyang, J. Li, and X. Han, "Electrochimica Acta A comparative study of global optimization methods for parameter identi fi cation of different equivalent circuit models for Li-ion batteries," *Electrochim. Acta*, vol. 295, pp. 1057–1066, 2019, doi: 10.1016/j.electacta.2018.11.134.

[9] V. Sangwan, A. Sharma, R. Kumar, and A. K. Rathore, "Equivalent circuit model parameters estimation of Li-ion battery : C-rate , SOC and Temperature effects."

[10] S. Zhou, X. Liu, Y. Hua, X. Zhou, and S. Yang, "Adaptive model parameter identification for lithium-ion batteries based on improved coupling hybrid adaptive particle swarm optimization- simulated annealing method," *J. Power Sources*, vol. 482, no. September 2020, p. 228951, 2021, doi: 10.1016/j.jpowsour.2020.228951.

[11] X. Li, Z. Wang, and J. Yan, "Prognostic health condition for lithium battery using the partial incremental capacity and Gaussian process regression," *J. Power*

Sources, vol. 421, no. January, pp. 56–67, 2019, doi: 10.1016/j.jpowsour.2019.03.008.

[12] X. Han, M. Ouyang, L. Lu, J. Li, Y. Zheng, and Z. Li, “A comparative study of commercial lithium ion battery cycle life in electrical vehicle: Aging mechanism identification,” *J. Power Sources*, vol. 251, pp. 38–54, 2014, doi: 10.1016/j.jpowsour.2013.11.029.

[13] Y. Li *et al.*, “Data-driven health estimation and lifetime prediction of lithium-ion batteries: A review,” *Renew. Sustain. Energy Rev.*, vol. 113, no. July, 2019, doi: 10.1016/j.rser.2019.109254.

[14] Y. Li, D. Stroe, Y. Cheng, H. Sheng, and X. Sui, “On the feature selection for battery state of health estimation based on charging – discharging profiles,” *J. Energy Storage*, vol. 33, no. September 2020, p. 102122, 2021, doi: 10.1016/j.est.2020.102122.

[15] M. Chen, S. Member, and G. A. Rinc, “Accurate Electrical Battery Model Capable of Predicting Runtime and I – V Performance,” vol. 21, no. 2, pp. 504–511, 2006.

[16] I. Rahman, P. M. Vasant, B. S. M. Singh, and M. Abdullah-Al-Wadud, “On the performance of accelerated particle swarm optimization for charging plug-in hybrid electric vehicles,” *Alexandria Eng. J.*, vol. 55, no. 1, pp. 419–426, 2016, doi: 10.1016/j.aej.2015.11.002.

[17] S. Shen, X. Chen, C. Hu, M. K. Sadoughi, and M. Hong, “Online estimation of lithium-ion battery capacity using deep convolutional neural networks,” *Proc. ASME Des. Eng. Tech. Conf.*, vol. 2A-2018, pp. 1–8, 2018, doi: 10.1115/DETC2018-86347.

[18] S. Shen, M. Sadoughi, and C. Hu, “Online Estimation of Lithium-Ion Battery Capacity Using Transfer Learning,” pp. 2019–2022, 2019.

[19] C. Vidal, S. Member, P. Kollmeyer, E. Chemali, and A. Emadi, “L I - ION B ATTERY S TATE OF C HARGE E STIMATION USING L ONG S HORT -T ERM M EMORY R ECURRENT N EURAL N ETWORK WITH T RANSFER L EARNING,” 2019.

[20] B. Bole, C. S. Kulkarni, and M. Daigle, “Adaptation of an electrochemistry-based Li-ion battery model to account for deterioration observed under randomized use,” *PHM 2014 - Proc. Annu. Conf. Progn. Heal. Manag. Soc. 2014*, pp. 502–510, 2014.