

# Digital Twin-Driven Estimation of State of Charge for Li-ion Battery

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**Abstract**— Under the net-zero carbon transition, lithium-ion batteries (LIB) plays a critical role in supporting the connection of more renewable power generation, increasing grid resiliency and creating more flexible energy systems. However, poor useful life and relatively high cost of batteries result in barriers that hinder the wider adoption of battery technologies e.g., renewable resources storage. Furthermore, the useful life of a battery is significantly affected by the materials composition, system design and operating conditions, hence, made the control and management of battery systems more challenging. Digitalisation and artificial intelligence (AI) offer an opportunity to establish a battery digital twin that has great potentials to improve the situational awareness of battery management systems and enable the optimal operation of battery storage units. An accurate estimation of the state of charge (SOC) can indicate the battery's status, provide valuable information for maintenance and maximise its useful life. In this paper, a digital twin-driven framework based on a hybrid model that connects LSTM (long short-term memory) and EKF (extended Kalman filter) has been proposed to estimate the SOC of a li-ion battery. LSTM provides more accurate initial SOC estimations and impedance model data to EKF. According to experimental results, the developed battery digital twin is considered less dependent on the initial SOC conditions and is deemed more robust compared to traditional means with a lower RMSE (root mean squared error).

**Keywords**—digital twin, lithium-ion battery, battery management system, state of charge.

## I. INTRODUCTION

Lithium-ion batteries (LIB) play an important role in the net-zero carbon transition, which enables applications ranging from electric vehicles to grid-scale energy storage due to their wide temperature range, high power density and low memory effect [1, 2]. Maximising battery life is a challenge due to the impact of operating conditions on batteries degradation, such as over-charging and over-discharging, low energy utilisation attributed to inconsistent pack configuration; high and low-temperature working conditions, etc. [3, 4]. To ensure working safety and maximise working life, the battery management system (BMS) is usually indispensable for understanding, quantifying and predicting battery performance in real-world conditions [5]. State of Charge

(SOC), as one of the most important parameters of batteries, represents the remaining available capacity of the battery and plays an important role in health management and remaining useful life prediction (RUL) [6]. Accurate and reliable SOC can not only indicate the remaining available capacity of the battery but also provide guidance for avoidance of overcharge/over-discharge [7]. However, existing external electrical sensors cannot measure it directly. As such, accurate SOC estimation is still a popular area of research and a variety of researchers dedicated to exploring efficient, accurate and robust SOC estimation algorithms [8].

While there are many methods to create digital models of batteries, the models usually have lacked accurate real-world data to back them up. In addition, there are not the same batteries that are treated equally throughout their life. Batteries degrade at different rates, subject to different operations conditions and charging/discharging methods. This further emphasises the need for real-world data to be combined with machine learning. Although the concept of Digital Twin (DT) technology was first introduced by Michael Grieves [9] in 2002, researchers have been limited in their exploration of DT technology. Since 2015, with breakthroughs in technologies such as wireless communications, machine learning and cloud computing, DT technology has developed in leaps and bounds [10, 11]. Integrating machine learning and the digital twin, not only could estimate batteries SOC utilizing real-world data but could be used to update BMS via the cloud to change algorithms or parameters to optimise the performance of the battery as the cells age and maximise battery life [12].

This paper proposed a digital twin framework of the battery for more accurate state-of-charge estimation. In Section 2, the existing studies on SOC estimation and the researches of battery digital twin are reviewed, and the battery digital twin framework is proposed. In Section 3, the proposed method and algorithms are demonstrated, where the LSTM calibrates the SOC status and impedance model accuracy before the EKF estimates the online SOC. Section 4 presents a case study on the Li-ion battery datasets for validating the proposed framework and illustrates the results and discussion of the experiment. Finally, the benefits and restrictions of the method are concluded in Section 5.

## II. SOC ESTIMATION AND BATTERY DIGITAL TWIN

### A. State of Charge Estimation

As one of the most important values of batteries, SOC provides information about the charge level of the battery [13]. As the internal state of the battery cannot be measured directly, researchers use a state estimation mechanism to obtain the information.

To now, SOC estimation methods can be simply classified into three major types [8, 14, 15]: a) traditional feature and integral methods, such as ampere-time integration (Ah), open-circuit voltage method (OCV) and Electrochemical Impedance Spectroscopy (EIS); b) model-driven methods, such as Kalman filter class (KF), particle filter class and HIF filter; c) data-driven methods, such as random forest (RF), support vector machines (SVM) and neural networks (NN).

The Ah integration method only needs to integrate the battery current, but it requires a higher initial value [16]. It is simple and widely implemented in practice [17]. However, it is difficult to guarantee the accuracy and reliability of the estimated value as it relies heavily on the precision of the measurement noise and the initial value of the SOC. Open circuit voltage (OCV), is a nonlinear function of SOC of Li-ion battery [18]. However, it requires a long residence time and is easily affected by temperature, ageing, and current [19]. By collaboration with the Ah integration method and OCV method, the filter-driven methods are proposed and applied to estimate SOC with the support of offline built electric models [20]. Filtering algorithms are widely used in SOC estimation due to their fast response and high accuracy, but they do not consider the effect of battery ageing on SOC. Data-driven algorithms require large amounts of training data and long training times rather than exact mathematical models [21, 22].

### B. Battery Digital Twin

Digital twins exploit refined physical models, intelligent sensor data, and operation and maintenance history data and integrate multidisciplinary knowledge for a multi-physical quantity, multi-temporal scale, multi-probability simulation process. Digital twins realise the true mapping of smart local energy systems in a virtual space, which can be updated and

dynamically evolved in real-time, thereby reflecting the entire lifecycle process of the corresponding energy system.

Although battery research has become more extensive and sophisticated in recent years, there are still many issues that need to be addressed. State estimation of Li-ion batteries is not only the main basis for battery management systems and battery balance management but can also be used to prevent overcharging or overdischarging of the battery. However, accurately modelling lithium-ion batteries is still a particular challenge due to the highly non-linear and strong coupling of the internal battery relationships [23]. DT has made excellent performance in the aerospace field, especially in SOC estimation and RUL prediction and optimal control[4]. This indicates that DT could be used to solve battery management problems of state.

The application of DT technology in BMS started in the last two years, and BMS can be optimised by applying cloud computing and Internet of Things (IoT) technologies [24]. The current research on battery digital twin mainly focuses on the three major problematic issues of the current BMS: difficult data sharing and fusion from different BMS manufacturers, limited computational capacity of the embedded system, and limited data storage capacity. The battery management system applying digital twin technology and their functionality and reported methods in existing studies are summarised in Table I.

For instance, as the challenge of data sharing, Li [10] combined the DT technology and transferred all battery data to the cloud platform for building the DT of the battery management system. As the number of battery data increases, the amount of computation and data storage required by the BMS grows exponentially. Machine learning algorithms such as data starvation models are used to predict and optimise system states and will even change the understanding of battery ageing mechanisms. Reference [25] used a Health Indicator (HI) and Long short-term memory (LSTM) algorithm to effectively estimation of the battery discharge capacity. However, the above work still has room for improvement: the real-time and self-evolving characteristics of digital twins. In the next section, the methodology of digital twin-driven SOC estimation is illustrated.

TABLE I. BATTERY DIGITAL TWIN IN LITERATURE

The years of previous studies	The functionality of applying DT	Related methods and algorithms
2018 [26]	Monitoring cell voltage and temperature for decision making	Cloud-connected BMS; electric-thermal model and empirical ageing model
2019 [27]	Assessment of spacecraft lithium-ion battery pack degradation based on low-cost modules and software	ECM with SVM and filter algorithms; LabVIEW for visualisation
2019 [28]	Estimation of SOC	ECM and EFK algorithm
2020 [25]	Estimation of the battery discharge capacity	Health indicator and LSTM algorithm
2020 [10]	Estimation of SOC and SOH	AEHF-based SOC estimation algorithm and PSO-based SOH estimation algorithm
2021 [29]	Estimation of cell voltage, anode/cathode bulk SOC and surface SOC	Sparse-Proper Generalized Decomposition (s-PGD) and dynamic mode decomposition technique
2021 [30]	Estimation of SOC, capacity and internal resistance	ECM model parameter fitting, curve fitting and SOC-OCV curve
2021 [12]	Estimation of SOC and monitoring and visualisation of real-time voltage and current	ECM and joint HIF-PF online estimation of SOC

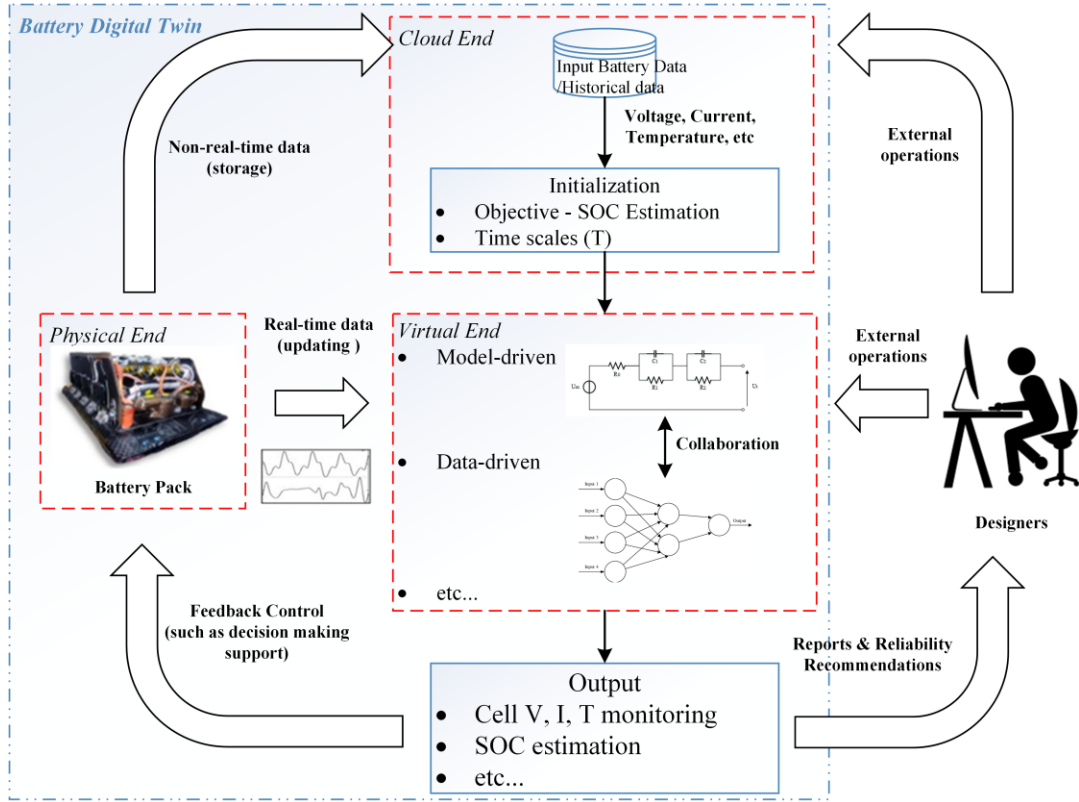


Fig. 1. The battery digital twin framework

### III. DIGITAL TWIN-DRIVEN SOC ESTIMATION

This section describes in detail the virtual end part of the framework, including the model-driven and data-driven algorithms and their interoperability. Also, a rolling learning method is incorporated for updating the model parameters when the battery capacity decreases to enable self-evolving of the digital twin.

#### A. The Battery Digital Twin Framework

The digital twin framework mainly contains three major features: hierarchical, bidirectional and self-evolving. Different models can be built for different purposes (e.g. state estimation, RUL prediction, energy management, etc.). In the meanwhile, data should be able to interact between different hierarchical structures even though it is multi-dimension.

The objective of this study is to utilise the digital twin to find the hidden transformation law between the SOC and the measured variables. As shown in Fig. 1, to attain a robust design, a battery digital twin framework is proposed which is the basis of the whole system. The specific elements of the digital twin system include six sections as follows:

- Physical End: entities of the system in the real world, including battery packs, motors, BMS systems and sensors. Parameters such as open-circuit voltage, current and temperature can be measured in real-time.
- Virtual End: the digital replica of real-world objects can reflect real-world systems to some extent depending on the set of objectives. The kernel consists of different algorithms, such as model-driven and data-driven algorithms, and works in conjunction with each

other for the integration of objectives at multiple hierarchies and different time scales.

- Cloud End: storage of system initialisation data and historical data; set up optimisation targets and time scales for the entire digital twin.
- Designers: external technicians who can perform operational tests on the virtual end and cloud end of the system
- Output: providing objectives such as cell status monitoring, SOC estimation and providing reliability recommendations with technicians for supporting decision making.
- Information flow: Communication among the three major parts of physical end, virtual end, cloud end. And the bidirectional data flow enables the digital twin self-evolving.

#### B. Battery Modelling

There are several model-driven methods: internal resistance model, n-RC model, PNGV model, GNL model [31, 32]. In this paper, the Thevenin model, also called the 2-RC model, is chosen as the battery equivalent circuit model, while it can better simulate the steady-state and transient characteristics of the battery [33]. In addition, it is unnecessary to select more complex models with an increase in the computational burden as the errors caused by model uncertainty will be offset by the LSTM [34].

Fig. 2 presents the 2-RC equivalent circuit model, where  $U_{oc}$  is the open-circuit voltage;  $R_0$  is the ohmic resistance;  $R_1$  and  $C_1$  circuits are electrochemical polarisation resistance and capacitance and used to simulate the process of the rapid rise of the discharge voltage;  $R_2$  and  $C_2$  circuits are concentration polarisation resistance and capacitance and used to simulate

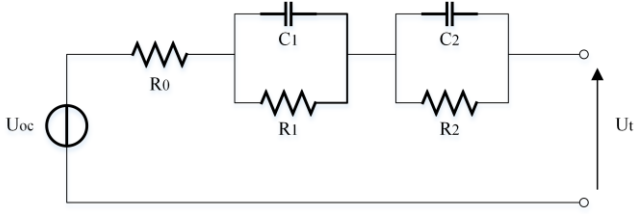


Fig. 2. The 2nd ECM structure

the process of slow stabilisation of the discharge voltage;  $R_1$ ,  $R_2$ ,  $C_1$  and  $C_2$  can reflect the polarisation of the battery.  $U_t$  is terminal voltage.

In theory, these parameters are changed dynamically by various factors, such as SOC state, temperature and ageing state, and these changes cause the estimation error. However, within the digital twin, these errors could be compensated by the LSTM neural network.

### C. Long Short-term Memory for SOC estimation

Long short-term memory (LSTM) is a special recurrent neural network (RNN) network. The RNN network structure differs from other neural networks in that it adds a ring that points to itself, passing the information processed at one time to the next in a self-perpetuating loop. This structure allows RNNs to have a memory function and to process sequential information better. The disadvantage is that when the time series is long, the gradient of the RNN will disappear. The LSTM uses hidden units as a gate to control the weights of the self-loop, which allows past data to be reflected in the current state decisions. In this case, the gradients form a path that can flow for a long time. In other words, the gradient does not vanish.

As shown in Fig. 2, the LSTM network mainly consists of cell states, forget, input and output gates. The forget gates decide which redundant information from the upper layer is discarded. Depending on the output of the last moment and the current input, a value from 0 to 1 is generated by the forget gate. The upper value 1 means the value should be retained totally; and on the contrary, the lower boundary 0 indicates discarding the information completely. Input gates are used to update the input information to the network, working in conjunction with the output information from the forget gates to update the cell state. The output gates are used to help process the network information to get the output of the cell structure.

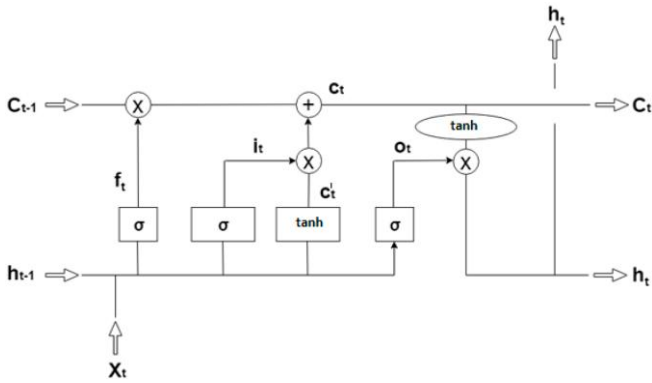


Fig. 3. Internal structure of the long short-term memory (LSTM) cell

### D. SOC Estimation with Collaborating EKF and LSTM

The traditional extended Kalman filter (EKF) SOC estimation method has the advantages of simplicity and fast response to meet the real-time requirements of digital twin systems [34]. Although the calculation time is short, its accuracy is very dependent on the initial SOC and impedance model. Therefore, there is a high demand for the correctness of the initial SOC level and the accuracy of the sensor. To alleviate this problem, the LSTM algorithm is incorporated to correct the initial SOC before the EKF estimation stages. The LSTM algorithm can accurately estimate the battery charge state even when the initial charge state is uncertain [7]. However, this comes at the cost of being computationally intensive and therefore too costly in terms of time.

The overall process of the virtual end for SOC estimation is shown in Fig. 3. An LSTM network is built to map the non-linear relationship between SOC and current, voltage and temperature, and to correct the initial SOC to provide support for online SOC estimation by the EKF. Also, to improve adaptation to the environment, a rolling learning approach [35] is used to adjust the model parameters of the LSTM so that the model can be updated.

Choosing the inputs to an estimation algorithm is not an easy task. However, current, temperature and voltage are directly measured parameters, and they have also been shown to play an important role in the estimation of the state of a battery [36]. Therefore, these three parameters are extracted as inputs for the ECM and LSTM in this study. To improve accuracy, the LSTM is initialised and pre-trained using the drive data from the first few operating cycles of the battery. Afterwards, the EKF is used for the final correction of the SOC. Compared to the traditional EKF estimation method, this method provides better SOC estimation performance and mitigates the uncertainty of the initial battery state data.

As a battery digital twin, real-time updating is necessary due to the significant impact of battery ageing on the estimation of the battery charge state. As a consequence, a rolling learning approach is introduced to update the model parameters of the LSTM to address the impact of ageing on SOC. Specifically, when the battery digital twin works, real-time data is continuously collected, and when the cumulative runtime  $t$  is greater than a preset length of time  $T$ , another LSTM network is used in the cloud for retraining and calibration, and the LSTM network on the virtual end is updated with the new layer parameters. Through a rolling learning mechanism, the battery digital twin is self-evolving and able to take into account historical influences.

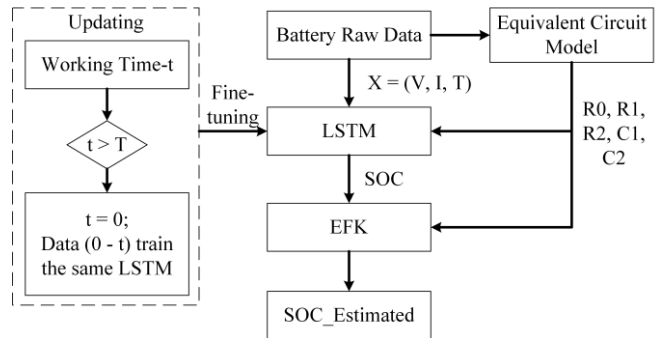


Fig. 4. Flowchart of the SOC estimation in Virtual End

### E. Validation of the Predictive Model

Root Mean Square Error (RMSE) is used as a reflection of the deviation between the predicted value and the actual value. RMSE is calculated as::

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (SOC_{ei} - SOC_{ti})^2} \quad (1)$$

where n denotes total the number of observation values,  $SOC_{pi}$  and  $SOC_{ti}$  are the  $i^{th}$  estimated SOC and true SOC, respectively.

## IV. EXPERIMENTAL VALIDATION AND DISCUSSION

In this section, experimental validations and discussions are conducted to validate the feasibility of the proposed framework.

### A. Data Preprocessing

In the case study, battery data collected on the Panasonic 18650PF Li-ion battery is used to validate the digital twin [37]. Due to an issue with the battery tester's logging, many drive cycles were saved in a single long file so that some drive cycle data was included twice. However, duplicates in the dataset may indicate data-logging errors and so should be removed from the dataset to ensure consistent and accurate results. As LSTM is supervised learning, the capacity loss is determined by Ah, and thus the reference SOC is inferred.

Based on the calibrated battery digital twin model described above, several highly accurate and robust state estimation algorithms can be deployed in the virtual end, as described in the previous section. Fig. 4 presents the estimation process. Firstly, the V, I and T are input, and then the ECM parameters  $R_0$ ,  $R_1$ ,  $R_2$ ,  $C_1$  and  $C_2$  are identified. Then the equation of state and the measurement equation of the equivalent circuit model are determined. In the next step, the LSTM algorithm is adopted for error correction, and then the final SOC is estimated by EKF. In the loop, the LSTM network will be retrained and updated with real-time data at every time interval T.

### B. Results and Discussion

This case study applied the Jupyter notebook with a deep learning environment. The LSTM network is constructed with an input layer consisting of one time series and three features (voltage, current and temperature), and the output layer for estimating the value of SOC and the hidden layer with 150 nodes. Mean absolute error (MAE) loss function and Adam optimiser are used with a batch size of 32. The role of the loss function and optimiser is to optimise the model by making the loss as close to 0 as possible. Fig. 5 shows the model loss of LSTM at training and test. It is clear that after 20 epochs, the loss in both training and testing stabilises to no more than 0.04, and the training set is below 0.005. This indicates that the model is robust. Indeed, the validation loss (test loss) is slightly greater than the training loss, which implies that overfitting occurs in the training process.

Fig. 6 shows the SOC estimated by the EKF after the final LSTM correction and the reference SOC. Three different coloured lines represent the reference value, the estimated value at training time and the estimated value at test time, respectively. It can be seen that the model fits the training data very well. However, it still has some errors in the SOC estimated for the fresh data. And the RMSE for training and

testing are 1.7% and 3.4%, respectively. The smaller the RMSE, the better the model's estimation of SOC.

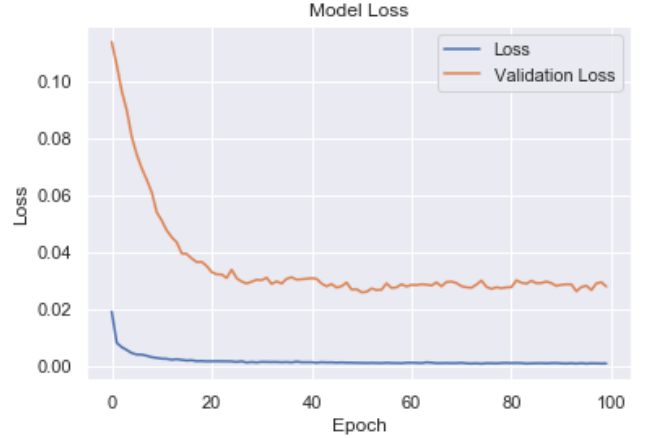


Fig. 5. The model loss of LSTM at training and test

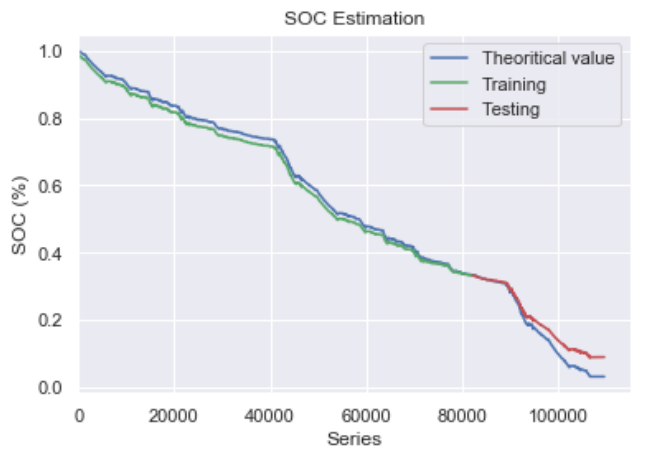


Fig. 6. The SOC estimation by EKF-LSTM

TABLE II. THE COMPARISON OF SOC ESTIMATION FOR DIFFERENT METHODS

Methods	RMSE
EKF	3.9%
SVM	3.2%
Neural Network	2.23%
EKF-LSTM	1.7%

The reason is due to a certain amount of overfitting of the model, which does not process some of the untrained data correctly. Therefore the RMSE for training is smaller than for testing. However, from the results of the comparison of the error analysis shown in Table II, it can be seen that the proposed algorithm has the smallest RMSE of the four algorithms. Thus its accuracy is still the highest, especially after solving the over-fitting problem.

## V. CONCLUSION

In light of the challenges, this paper has proposed an LSTM-EKF estimation approach of SOC in order to lower the EKF dependence on the initial value of SOC. Different from existing methods, the initial SOC is estimated by LSTM and then corrected by an EKF estimator. Furthermore, a battery digital twin and a rolling learning method are introduced for online model refinement. The structure of the proposed DT framework and the key steps established in learning have been

detailed. The experimental study has demonstrated the feasibility of the joint online SOC estimation approach. Simulation results have shown the applicability and merits of the algorithm for the SOC estimation of battery digital twin. Future work aims to maximise battery life by establishing a hierarchical structure of digital twin which will incorporate the prediction of RUL in conjunction with SOC estimation.

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