Lithium-Ion Battery Ageing Behavior Pattern Characterization and State-of-Health Estimation Using Data-Driven Method

ZHIYONG XIA, (Student Member, IEEE), AND JABER A. ABU QAHOUQ, (Senior Member, IEEE)
Department of Electrical and Computer Engineering, The University of Alabama, Tuscaloosa, AL 35487, USA
Corresponding author: Jaber A. Abu Qahouq (jaberq@eng.ua.edu)

This material is based upon work supported in part by the National Science Foundation under Grant No. 1509824. Any opinions, findings and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation.

ABSTRACT This paper presents a study on Lithium-ion battery aging behaviors/patterns and related State-of-Health (SOH) indicators before presenting the development of data-driven based SOH estimators. Battery charge/discharge cycling experiments are conducted in order to obtain needed data for this work. The battery ageing behavior patterns until the battery cell reaches highly deteriorated health conditions are investigated and characterized in this paper by analyzing the aggregated battery ageing data. The observed battery ageing behavior patterns include: (1) the rate at which the battery voltage decreases during discharging increases as the battery ages, (2) the speed at which the battery terminal voltage increases during Constant Current (CC) charging increases as the battery’s health deteriorates, (3) the time period for CC charging operation decreases as the battery ages, (4) the rate at which the battery current decreases during Constant Voltage (CV) charging increases as the battery ages, and (5) the speed at which the battery temperature drops during CV charging increases as the battery ages. Corresponding SOH indicators are developed to quantify these battery ageing behavior patterns for the development of SOH estimators. Deep Neural Network (DNN) is utilized to extract and model the nonlinear and complex correlation between the defined SOH indicators and SOH values of the Lithium-ion battery. Multiple DNN-based SOH estimators are developed in this paper. The SOH estimation results from different DNN-based SOH estimators indicate that the diversity of SOH indicators used for the development of SOH estimator can substantially improve the estimation performance.

INDEX TERMS Battery, battery capacity, battery management system, data-driven, lithium-ion, neural network, state of health.

NOMENCLATURE

A. ACRONYMS

AE Absolute error
ADC Analog-to-digital converter
BMS Battery management systems
CC Constant current
CV Constant voltage
DNN Deep neural network
ECM Equivalent circuit model
EKF Extended Kalman filter
EM Electrochemical model
EV Electric vehicle
GPR Gaussian process regression
GRA Grey relational analysis
GRU Gated recurrent unit
ICA Incremental capacity analysis
LSTM Long short-term memory
MAPE Mean absolute percentage error
MI Multiple SOH indicators
MSE Mean square error
PF Particle filter
RC Resistor-capacitor
RMSE Root mean square error
RPT Reference performance test
RUL Remaining useful lifetime
SEI Solid electrolyte interphase
SI Single SOH indicator
SOC State of charge
SOH State of health
SP Single particle
systems (BMS) is an important step toward meeting the increasing performance demands from the applications of battery systems [1]–[46].

State of health (SOH) estimation is one key function of BMS [11]–[16]. It can monitor the operation and health status of battery system, inform users when the health status of battery system is below a predefined threshold value, suggest better battery usage methods to prolong the lifespan of battery and lower the maintenance cost, and/or even can potentially help in taking protection actions against catastrophic battery failures [17]–[22]. Over the process of using the battery, an increase in solid electrolyte interphase (SEI) layer and a loss in the cyclable lithium and electrode active material occur, causing the battery performance and health conditions to deteriorate [20]–[22]. Two main phenomena associated with the deterioration of battery health are capacity fading and the increasing of internal impedance [20]–[22]. The battery health quantification is commonly defined in the references based on these two ageing phenomena [4]–[46]. The definition of SOH in this paper is based on the capacity fading phenomenon as given by Eq. (1).

\[
SOH = \frac{Q_{\text{cali}}}{Q_{\text{nominal}}} = 1 - \frac{Q_{\text{nominal}} - Q_{\text{cali}}}{Q_{\text{nominal}}} = 1 - \text{capacity fading}
\]  

where \(Q_{\text{cali}}\) is the calibrated capacity value obtained from Coulomb counting result at current ageing stage and \(Q_{\text{nominal}}\) is the nominal capacity value obtained from manufacturer’s document/datasheet, i.e., 2.6 Ah for the battery cells used in this paper for example. The range of the value of SOH is from 0 to 1 (or 0% to 100%). The lower the value of SOH is, the higher the deterioration of the health of the battery is.

Different types of SOH estimation methods are proposed in the literature [4]–[46]. These methods can be classified into two main categories: model based methods and data driven based methods.

A. MODEL BASED METHODS

A mathematical model or a state space model is usually first developed to characterize the electrochemical mechanisms or electrical behavior properties. A nonlinear state estimator or adaptive filter technique, such as extended Kalman filter (EKF) or particle filter (PF), is utilized to update the parameters of the developed model [4], [5], [23]–[33].

Model based methods can be further classified into two branches: electrochemical models (EMs) and equivalent circuit models (ECMs) [4], [5], [23]–[33]. EM based methods utilize complex differential equations to model the electrochemical reactions or processes occurring inside of the battery [23]–[26]. This can help in understanding the underlying ageing mechanisms of the battery. Ref. [23] develops a single particle (SP) based degradation model to reflect the SEI layer formation and crack propagation. This model can be utilized in estimating the capacity fading and voltage
profile changes as a function of ageing cycle number and temperature. Ref. [24] presents a reduced-order model to characterize the dynamic voltage response of a Lithium-ion battery cell using Padé approximation method. The electrochemical parameters that govern capacity fading are identified by systematic algorithm. Ref. [25] develops an adaptive partial differential equation observer to estimate state-of-charge (SOC) and SOH at the same time using the measurement results of battery voltage and battery current. Ref. [26] develops a model to calculate the differential capacity characteristics of LiFePO4/graphite battery for SOH estimation. The model is developed based on the deformed pseudo-Voigt peak function which is utilized to characterize the phase transition patterns of active LiFePO4 and graphite materials. For EM based methods, the computation cost is high which makes these EM based methods impractical for real-time online commercial applications. In addition, the adaptivity to new types of battery technologies is lower compared to other methods, such as ECM or data driven based methods, since significant experimental and analysis efforts have to be made to understand the complex underlying ageing mechanisms of a specific battery technology and then to develop the differential equations to model the extracted ageing mechanisms.

ECM based methods utilize the external electrical characteristics of battery to reflect the dynamic behaviors of battery cells [27]–[33]. Compared with EM based methods, ECM based methods have relatively low computation cost. They yield good tradeoff between complexity and accuracy. Ref. [27] develops a first-order resistor-capacitor (RC) ECM where battery capacity and internal ohmic resistance are utilized as model parameters. Two EKFs with different time scales are utilized to update the parameters of ECM and then to estimate SOC and SOH of battery. Ref. [28] utilizes EKF combined with a per-unit system to estimate and update the parameters of the adopted ECM. The diffusion resistance of the adopted ECM is utilized to estimate SOH. Ref. [29] develops a fusion method to combine capacity degradation model and resistance growth model. The SOH and remaining useful lifetime (RUL) are estimated using PF technique. Ref. [30] utilizes the charge transfer resistance of ECM to develop offline SOH estimation method for high power Lithium-ion batteries. An efficient three-point impedance extraction method is developed to update charge transfer resistance for SOH estimation. Ref. [31] utilizes three different active filters, which include EKF, PF, and least-squares-based filter, to update the parameters of ECM for SOH estimation. Ref. [32] and Ref. [33] estimate the resistance parameters of ECM to monitor battery operation status. Then the estimated SOC values together with battery current and battery temperature are utilized to estimate the capacity or SOH of battery cells. For the ECM based SOH estimation methods, their estimation accuracy or performance is affected by the assumptions which were used during the development of ECM.

**B. DATA DRIVEN BASED METHODS**

The data driven based methods extract and model the ageing patterns or characteristics from the historical data without needing to know the underlying ageing mechanisms of the battery [4], [5], [34]–[46]. Because of the recent advances in deep learning algorithms and computation capability of computers or microcomputers, the data-driven based methods are widely utilized to tackle and solve complex and challenging tasks. The data-driven based methods can also easily adapt to new battery technologies with different chemistries.

Ref. [34] utilizes a weighted least squares support vector machine (SVM) to estimate SOH of second-use Lithium-ion batteries. Ref. [35] develops a SVM based battery health diagnosis method using partial battery charging data. Ref. [36] extracts health indicators from the battery charging data. The extracted health indicators are used as the inputs of multiple Gaussian process regression (GPR) models which are utilized to predict the SOH values of battery cells. Ref. [37] utilizes GPR to develop incremental capacity analysis (ICA) based SOH estimation method. Ref. [38] utilizes Bayesian network which is one of indeterministic methods to model the degradation of battery for SOH estimation in EV applications. Ref. [39] proposes a fusion method which combines the SOH estimation results from the autoregressive moving average model and Elman neural network to improve the estimation accuracy. Ref. [40] integrates deep neural network (DNN) with autoencoder to predict RUL of battery. Ref. [41] proposes a SOH estimation method using prior knowledge-based neural network and Markov chain. Ref. [42] develops a recurrent neural network based SOH estimation method which utilizes the sequential data of battery voltage and battery current for SOH estimation. Ref. [43] develops a battery degradation assessment method for electric city transit buses by using the ICA and radial basis function neural network. The developed method takes several influencing factors into account, such as the mileage of vehicles and different charging operation conditions. Ref. [44] presents a temporal convolution network based SOH estimation method where causal convolution and dilated convolution are utilized to improve the stability of the estimation results. Ref. [45] utilizes long short-term memory (LSTM) with many-to-one structure to predict RUL of battery using battery voltage, battery current, and battery temperature during the charging process. Ref. [46] presents a gated recurrent unit (GRU) based SOH estimation method by extracting the spatial and temporal characteristics of battery data during charging and discharging processes.

For data driven based methods, the quality of data utilized to train the models affects the estimation performance [4]. In order to estimate SOH of battery cells under different operation conditions, the data utilized to train the models needs to cover the corresponding battery usage scenarios that the models plan to make the predictions under [34]–[46].

As a part of this work, Lithium-ion battery ageing experiments are conducted in the laboratory and the internal and external state information of batteries over the ageing
process is measured and collected. The reference performance test (RPT) of battery, such as capacity calibration, is conducted regularly after certain numbers of ageing cycles are completed. Several battery ageing behavior patterns are identified by analyzing the aggregated battery ageing data. To characterize these ageing behavior patterns, corresponding SOH indicators are defined and quantified/calculated. The correlation between SOH indicators and SOH values is extracted and modeled using deep neural network (DNN) algorithm (data-driven based method). Then the developed DNN based SOH estimators are used to estimate the health conditions of batteries. The main reason why DNN is selected to develop SOH estimators in this paper is because DNN has powerful nonlinear fitting capability and expressivity [6], which makes it a good candidate for modeling or extracting complex and nonlinear relationships or correlations between SOH indicators and SOH values of battery cells. DNN also has excellent scalability and upgradability, which makes it suitable for future obtained larger datasets and more complex relationship modelling.

The main contributions of this work/paper can be summarized as follows:

1. Battery ageing behavior patterns including those under highly aged conditions are investigated. The ageing experiment or aging process of the battery is carried out until the capacity fading value reaches ∼80% threshold (i.e., SOH ≤ ∼20%), which helps to understand the ageing characteristics or behavior patterns when the battery is highly deteriorated. The observed battery ageing behavior patterns include: (a) the rate at which the battery voltage decreases during discharging increases as the battery ages, (b) the speed at which the battery terminal voltage increases during Constant Current (CC) charging increases as the battery’s heath deteriorates, (c) the time period for CC charging operation decreases as the battery ages, (d) the rate at which the battery current decreases during Constant Voltage (CV) charging increases as the battery ages, and (e) the speed at which the battery temperature drops during CV charging increases as the battery ages.

2. The corresponding SOH indicators are defined and developed to characterize the aforementioned battery ageing behavior patterns. This helps in quantifying the ageing behavior patterns for the purpose of developing SOH estimators.

3. Different DNN-based SOH estimators are developed to estimate battery health conditions by extracting the correlation between the defined SOH indicators and SOH values. SOH estimation experimental results indicate that when there is a diversity in the types of SOH indicators (higher number of indicators) and input features used for the training or the development of SOH estimators, the SOH estimation performance can be substantially improved.

The remainder of this paper is organized as follows: Section II presents the battery ageing protocol and testing procedure used to age and test Lithium-ion battery in this paper. The observed battery ageing behavior patterns and corresponding SOH indicators are illustrated in

### TABLE 1. The main specifications of Tenergy ICR 18650-2600 Lithium-ion battery [47] used in this paper.

| Model         | 30005-0                     |
|---------------|-----------------------------|
| Nominal capacity | 2.6 Ah                     |
| Initial internal impedance | ≤ 65 mohm @ 1 kHz       |
| Cycle life     | 300th cycle ≥ 80% of 1th capacity (0.5 C/1.0 C at 25 °C) |
| Discharge end voltage | 2.7 V                    |
| Charging voltage  | 4.20 V ± 0.05 V           |
| Charge end current | 52 mA ± 5 mA            |

Section III. Section IV shows the details of the development of DNN-based SOH estimators and related SOH estimation results. The conclusion is drawn in Section V.

## II. BATTERY AGEING PROTOCOL AND TESTING PROCEDURE

The Tenergy ICR 18650-2600 Lithium-ion battery is selected for the battery ageing experiment in this paper. The main specifications of this type of battery are listed in Table 1 [47]. The ageing and performance testing procedure of the battery is given in Fig. 1.

The initial capacity of the battery cell is calibrated at the beginning before it goes through the ageing process. Then the battery is subjected to 30 ageing cycles using the ageing platform presented in [10]. The adopted ageing protocol is illustrated in Fig. 2. The capacity value of battery is calibrated every 30 ageing cycles using Coulomb counting method.

Compared with the conventional research and investigation [48] where battery cells are aged to 70% ∼ 80% SOH value, the battery cells are aged to ≤ 20% SOH value in this paper. This is in order to investigate and explore the characteristics and ageing behavior patterns of battery

![FIGURE 1. The ageing and performance testing procedure of battery cells in this paper.](image-url)
when it is highly deteriorated and evaluate the SOH estimation performance under low SOH values. There are applications where battery is used even after SOH is below 70% ~ 80%, such as second-use battery which is an emerging topic [34], [49], [50].

Fig. 2 illustrates the ageing process of the battery. At the beginning of each 30 ageing cycles, the cycle counter $n$ is reset to 0 to count how many ageing cycles the battery goes through. The CC discharging and CC-CV charging ageing cycling protocol is used. The rate for both CC discharging and CC charging is set to 1 C (i.e., 2.6 A). The cut-off voltage value for CC charging and cut-off current value for CV charging are 4.2 V and 0.05 A, respectively. After the charging process is completed, the battery is put into CC discharging operation. The cut-off voltage for discharging is set to 2.7 V.

During the ageing process, several battery states and ageing variables are monitored and recorded for battery health analysis and investigation. These variables include battery voltage, battery current, battery surface temperature, discharged coulombs, discharging time, charging time, and other related information. There are several protection features (battery over voltage protection, battery under voltage protection, battery over current protection, and battery over temperature protection) implemented in the developed autonomous battery ageing platform to ensure the safety of battery cells and ageing platform.

### III. Battery Ageing Behavior Patterns and Corresponding SOH Indicators

Three batteries (battery 1, battery 2, and battery 3) are aged in the laboratory according to the ageing protocol discussed in Section II and the related ageing data are recorded. By analyzing the aggregated battery ageing data, several battery ageing behavior patterns are observed. These ageing behavior patterns and the derived SOH indicators are presented in this section. In order to reduce the effects of measurement noise on the calculation of SOH indicators, the averaged values of instantaneously sampled battery voltage, current, and temperature are utilized to calculate the SOH indicators. The higher the analog-to-digital converter (ADC) sampling frequency for sensing battery voltage, current, and temperature, the better averaging results in order to reduce noise effect and obtain a more accurate SOH estimation result.

These three battery cells are aged up to about 630 cycles. The corresponding capacity fading values for battery 1, battery 2, and battery 3 after 630 aging cycles are 84.5%, 87.6%, and 82%, respectively. In other words, the SOH values of battery 1, battery 2, and battery 3 are 15.5%, 12.4%, and 18%, respectively. As listed in Table 1, the datasheet of the utilized battery cell indicates that after the first 300 ageing cycles the available capacity of the battery cell may decrease by up to 20% if the battery cell is aged using 0.5 C (i.e., 1.3 A) charging current and 1 C (i.e., 2.6 A) discharging current [47]. The degradation speed of the utilized three battery cells in this paper is faster mainly because higher CC charging current (1 C, i.e., 2.6 A) is utilized during the ageing process. Higher CC charging current results in faster degradation speed of battery cells [22]. The SOH values as a function of ageing cycle number of these three battery cells are plotted in Fig. 3.

The SOH values of these batteries decrease with the increase of ageing cycles. It can be observed that the capacity regenerative phenomenon [39] does not appear clearly in Fig. 3. This is mainly because large number of ageing cycles (ageing step) is utilized in the ageing process, i.e., for every 30 ageing cycles. The battery capacity is calibrated based on the Coulomb counting result during CC discharging operation.

The remainder of this section presents the ageing patterns of battery 1. Battery 2 and battery 3 exhibit similar ageing degradation of battery instead of per cycle local variation in battery health.
patterns. Therefore, in order to avoid repetition, the ageing pattern data of battery 2 and battery 3 is not presented here. However, battery 2 and battery 3 are used in this paper to evaluate the developed DNN-based SOH estimators that were trained using the data of battery 1.

A. VOLTAGE DECREASE RATE/SPEED (SLOPE) DURING DISCHARGING MODE

Based on the collected ageing data, the battery voltage during the CC discharging operation shows a distinctive ageing pattern as shown in Fig. 4. It can be observed that the voltage decrease rate becomes faster as the battery ages. It can also be observed that the time period for CC discharging operation decreases over the ageing process. This is expected and understandable because the battery capacity decreases gradually as the battery ages [14] and because the discharging current is constant here.

To quantify and utilize this ageing pattern for SOH estimation, the first SOH indicator SOH$_{I1}$ is defined by the absolute value of $\frac{dv}{dt}|_{\text{disch}}$ as given by Eq. (2).

$$SOH_{I1} = \left| \frac{dv}{dt}|_{\text{disch}} \right| = \frac{\Delta v}{\Delta t} = \frac{v_{t2} - v_{t1}}{t_{2} - t_{1}}$$

where $\Delta v$ is the battery voltage difference between the start point $t_1$ and the end point $t_2$ during the time interval $\Delta t = t_2 - t_1$, $v_{t1}$ is the battery voltage at $t_1$, and $v_{t2}$ is the battery voltage at $t_2$. The calculation result of SOH$_{I1}$ is a scalar. For each ageing cycle, there is only one single data point or calculation value for SOH$_{I1}$ as shown in Fig. 5.

From Fig. 4, battery 1 has shortest discharging time at cycle 630 which has a duration of less than 10 minutes. To be able to calculate $\left| \frac{dv}{dt}|_{\text{disch}} \right|$ for all of ageing cycles, the time interval $\Delta t$ is selected to be the time period from $t = 1$ minute to $t = 9$ minutes, i.e., $\Delta t$ is equal to 8 minutes. Another reason why $\Delta t$ is set to be this time period is because during this time period, the decreasing speed of battery voltage is relatively higher than that of other time intervals. The higher decreasing speed value can allow for relatively better noise immunity capability when calculating $\left| \frac{dv}{dt}|_{\text{disch}} \right|$.

The calculation results of $\left| \frac{dv}{dt}|_{\text{disch}} \right|$ over different ageing cycles and their correlation with SOH values are shown in Fig. 5 and Fig. 6, respectively.

From Fig. 4, battery 1 has shortest discharging time at cycle 630 which has a duration of less than 10 minutes. To be able to calculate $\left| \frac{dv}{dt}|_{\text{disch}} \right|$ for all of ageing cycles, the time interval $\Delta t$ is selected to be the time period from $t = 1$ minute to $t = 9$ minutes, i.e., $\Delta t$ is equal to 8 minutes. Another reason why $\Delta t$ is set to be this time period is because during this time period, the decreasing speed of battery voltage is relatively higher than that of other time intervals. The higher decreasing speed value can allow for relatively better noise immunity capability when calculating $\left| \frac{dv}{dt}|_{\text{disch}} \right|$.

The calculation results of $\left| \frac{dv}{dt}|_{\text{disch}} \right|$ over different ageing cycles and their correlation with SOH values are shown in Fig. 5 and Fig. 6, respectively.

From Fig. 5 and Fig. 6, it can be observed that the battery voltage decrease rate/speed (i.e., the absolute value of $\frac{dv}{dt}|_{\text{disch}}$) increases with the increase of the age of the battery (lower SOH). From Fig. 6, it can be observed that there is a strong correlation between $\left| \frac{dv}{dt}|_{\text{disch}} \right|$ and SOH values. However, this correlation exhibits complex and nonlinear characteristic. The DNN as powerful nonlinear fitting tool can be used to model this correlation or relationship to develop SOH estimator, which is the focus of Section IV in this paper. Compared with SOH estimators which utilize Coulomb counting method to count the discharged charges, the SOH estimators which utilize the SOH indicator $\left| \frac{dv}{dt}|_{\text{disch}} \right|$ as the input only need battery ageing data during 8 minutes to estimate battery health status, which can provide relatively
faster SOH estimation speed especially for the cases when the battery is slightly or moderately aged. For example, when the ageing cycle is 30, the Coulomb counting method needs ~57 minutes to count the charges and then to estimate SOH. However, the SOH estimators which utilize the SOH indicator \( \left| \frac{dv}{dt} \right|_{\text{disch}} \) as the input only need 8 minutes to estimate SOH, which yields ~86% improvement in SOH estimation speed.

SOH is extracted or identified by analyzing the battery ageing data collected from the developed autonomous battery ageing platform where the battery cells are aged using CC discharging method. In order to predict the SOH of battery cells in the applications with complicated and dynamic battery discharging usage, such as in electric vehicles, the SOH indicators can be extracted or identified by analyzing the battery data collected from the corresponding or similar applications under operation scenarios of interest.

### B. VOLTAGE INCREASE RATE/SPEED DURING CC CHARGING MODE

During the CC charging operation, the battery voltage increases over the charging process. When the battery’s SOH decreases, the battery reaches the end voltage of CC charging faster, i.e., reaches 4.2 V faster. This ageing characteristic can be observed from the measured results plotted in Fig. 7. To quantify this ageing pattern, SOH indicator SOH\(_{I2}\) is defined by the absolute value of \( \left| \frac{dv}{dt} \right|_{\text{CC-char}} \) as given by Eq. (3).

\[
SOH_{I2} = \left| \frac{dv}{dt} \right|_{\text{CC-char}} = \left| \frac{\Delta v}{\Delta t} \right| = \left| \frac{v_{t2} - v_{t1}}{\Delta t} \right| \tag{3}
\]

where \( \Delta v \) is the battery voltage difference between the start point \( t_1 \) and the end point \( t_2 \) during the time interval \( \Delta t = t_2 - t_1 \), \( v_{t1} \) is the battery voltage at \( t_1 \), and \( v_{t2} \) is the battery voltage at \( t_2 \). The calculation result of SOH\(_{I2}\) is a scalar. For each ageing cycle, there is only one single data point or calculation value for SOH\(_{I2}\) as shown in Fig. 8. The value of \( \Delta t \) is decided by the shortest CC charging time period, which is CC charging time of ageing cycle 630 here. This can be observed from Fig. 7. Therefore, \( \Delta t \) is selected to be the time interval from \( t = 0 \) to \( t = 0.612 \) minutes.

The calculation results of \( \left| \frac{dv}{dt} \right|_{\text{CC-char}} \) using the measured data at different ageing cycles are plotted in Fig. 8. The correlation between \( \left| \frac{dv}{dt} \right|_{\text{CC-char}} \) and SOH values is illustrated in Fig. 9. The value of \( \left| \frac{dv}{dt} \right|_{\text{CC-char}} \) shows a clear increasing trend over the ageing process. There is a negative correlation between \( \left| \frac{dv}{dt} \right|_{\text{CC-char}} \) and the SOH values.

### C. THE CC CHARGING TIME DURATION

From Fig. 7, it can be observed that the CC charging time decreases when the number of ageing cycle increases (lower SOH). The CC charging time values at different ageing cycles are shown in Fig. 10, and their correlation with corresponding SOH values is illustrated in Fig. 11. This correlation is strong and positive. The corresponding SOH indicator is defined as given by Eq. (4).

\[
SOH_{I3} = \Delta t_{\text{CC-char}} \tag{4}
\]
where $\Delta t_{CC-char}$ is the time period of CC charging process.

Compared with Coulomb counting method which requires counting the charges during the entire charging process (including CC charging and CV charging) to estimate SOH of battery, the SOH estimators which utilize the correlation between SOH$_{I3}$ and SOH values can provide a faster SOH estimation speed and a more practical one. The time period for CV charging is usually much longer than the time period for CC charging. However, for the SOH estimators based on the SOH$_{I3}$, only battery CC charging data is needed to estimate SOH, which is why SOH$_{I3}$ based SOH estimators can provide a faster estimation speed when compared with Coulomb counting method.

**D. CURRENT DECREASE RATE/SPEED DURING CV CHARGING MODE**

During CV charging operation, battery current decreases until it reaches the end CV charging current, i.e., 0.05 A [47] in this paper. From the collected ageing data plotted in Fig. 12, it can be observed that the battery current decrease rate/speed increases as the number of ageing cycle increases. To utilize this ageing pattern for SOH estimation, SOH\textsubscript{I4} is defined by the absolute value of $\frac{di}{dt}|_{CV-char}$ as given by Eq. (5).

$$SOH_{I4} = \frac{\Delta i}{\Delta t} = \frac{\Delta i}{\Delta t} = \frac{i_{t_1} - i_{t_2}}{t_2 - t_1}$$

where $\Delta i$ is the battery current change between the start point $t_1$ and the end point $t_2$ during the time interval $\Delta t = t_2 - t_1$, $i_{t_1}$ is the battery current at $t_1$, and $i_{t_2}$ is the battery current at $t_2$. The calculation result of SOH$_{I4}$ is a scalar. For each ageing cycle, there is only one single data point or calculation value for SOH$_{I4}$ as shown in Fig. 13. From Fig. 12, it can be observed that the largest current change for all ageing cycles occurs within the time period from $t = 0$ to $t = 20$ minutes. Therefore, $\Delta t$ is selected to be the time interval from $t = 0$ to $t = 20$ minutes.

The calculation results of $\frac{di}{dt}|_{CV-char}$ using the measured data at different ageing cycles and their correlation with corresponding SOH values are plotted in Fig. 13 and Fig. 14, respectively. The absolute value of $\frac{di}{dt}|_{CV-char}$ increases as the number of ageing cycles increases and has nonlinear correlation with corresponding SOH value.
FIGURE 13. The calculation results of $\frac{|d}{dt}|_{CV-char}$ using measured data at different ageing cycles.

FIGURE 14. The correlation/relationship between $\frac{|d}{dt}|_{CV-char}$ and SOH values over the ageing process.

E. TEMPERATURE DECREASE RATE/SPEED DURING CV CHARGING MODE

The surface temperature in the middle area of the battery cell is measured during the ageing process. It was observed that there is a distinctive ageing pattern related to the temperature specifically during the CV charging operation. This ageing behavior pattern is shown in Fig. 15.

From Fig. 15, it can be observed that the battery surface temperature decreases faster when the number of ageing cycle increases. This is mainly because during the CV charging operation, the battery current decreases faster with the increase of ageing cycle number as shown in Fig. 12. There is a strong correlation between battery surface temperature and the current flowing through the battery cell. The SOH$_{15}$ is defined by the absolute value of $\frac{|dT|}{dt}|_{CV-char}$ as given by Eq. (6).

$$SOH_{15} = \frac{|dT|}{dt}|_{CV-char} = \frac{\Delta T}{\Delta t} = \frac{T_{11} - T_{12}}{\Delta t}$$ (6)

where $\Delta T$ is the temperature change between the start point $t_1$ and the end point $t_2$ during the time interval $\Delta t = t_2 - t_1$.

FIGURE 15. Battery surface temperature during CV charging operation at different ageing cycles.

FIGURE 16. The calculation results of $\frac{|dT|}{dt}|_{CV-char}$ using measured data at different ageing cycles.
F. GREY RELATIONAL ANALYSIS

Grey relational analysis (GRA) is utilized to evaluate the correlation between SOH indicators and SOH values of battery cells. GRA is developed based on grey system theory, which is widely used to quantify or characterize the similarity and dissimilarity between reference sequence and comparison sequence [51], [52]. The calculation results of GRA between different SOH indicators and SOH values of battery cells are shown in the Table 2.

Based on the calculation results shown in Table 2, it can be observed that all of SOH indicators show strong correlation with SOH values of battery cells. SOH_{15}, i.e., $\frac{dT}{dt} |_{CV-char}$, has the smallest GRA calculation result for all of the three battery cells, which demonstrates its relatively weaker correlation with SOH values compared with other SOH indicators.

The outputs of feature extraction or SOH indicators are obtained from the calculation results of Eq. (2) through Eq. (6) by feeding battery raw ageing data to these equations. For instance, the outputs of feature extraction for battery 1 are the values of y-coordinates of data points shown in Fig. 5, Fig. 8, Fig. 10, Fig. 13, and Fig. 16.

IV. DNN BASED BATTERY SOH ESTIMATORS

Based on the results, analysis, and discussion in Section III, it can be concluded that there are strong correlations between the identified SOH indicators and the health status of the battery. These correlations can be used to develop SOH estimators. Each of these indicators has the potential to improve the accuracy of the SOH estimation. However, the correlations/relationships between these SOH indicators and the values of SOH are nonlinear and complex. Because of the powerful nonlinear fitting capability and expressivity of DNN, it is utilized to model the relationships between SOH indicators and SOH values to develop SOH estimators in this paper.

Fig. 18 shows the overall flowchart of the presented SOH estimators. The extracted SOH indicators presented in Section III are used as the inputs for the DNN. The SOH indicators are also referred to by input features of the DNN. The raw ageing data of battery 1, battery 2, and battery 3 are preprocessed before they are fed into the DNN. The data preprocessing includes three main steps: feature extraction, data cleansing, and normalization. For the feature extraction step, the SOH indicators or features are calculated or prepared based on the definitions presented in the previous section (Eq. (2) through Eq. (6)). Data cleansing step is mainly to remove some outliers that might exist in the data. Normalization is to eliminate the effect of the differences of data units and scales among different input features on the performance of data driven or machine learning based methods [44]. After normalization, the values of the input data/features are rescaled to the range of [0, 1]. The min-max normalization [45] is adopted in this paper, which can be calculated as given by Eq. (7).

$$x' = \frac{x - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}}$$

where $x'$ is the data after normalization, $x$ is the original sample data, $x_{\text{min}}$ is the minimum value of $x$, and $x_{\text{max}}$ is the maximum value of $x$.

After the data preprocessing, the ageing data of battery 1 is further split into training dataset and validation dataset, and the ageing data of battery 2 and battery 3 is used as test dataset. The training dataset and validation dataset are used to train DNN and tune the hyperparameters of DNN (such as the number of neurons in hidden layers). The test dataset is used to evaluate the estimation performance of the developed DNN based SOH estimators.

The structure of the adopted DNN for SOH estimation in this paper is illustrated in Fig. 19. The utilized DNN includes four different types of layers: input layer, hidden layer, dropout layer, and output layer. The number of neurons in the input layer (i.e., $N$) depends on the number of SOH indicators/features used for SOH estimation in the DNN. To investigate the effect of the number of the simultaneously used SOH indicators on the performance of SOH estimation, each single SOH indicator (SI) is taken separately as the input to the DNN and then multiple SOH indicators (MI) are integrated together to feed into the input of the DNN. For each SI SOH estimator, the number of neurons in the input layer is one. For the MI-DNN SOH estimators, a total of 4 different MI-DNN ($i=1, 2, 3, 4$) SOH estimators are developed and each of them uses a different number of SOH indicators. The performance results from the MI-DNN SOH estimator which uses all of the five SOH indicators as input features
FIGURE 18. The overall flowchart of the presented DNN based SOH estimators.

are compared with the performance results from each SI SOH estimator (with one of the five indicators used for each). The other Mi-DNN \((i = 1, 2, 3)\) SOH estimators are mainly used to illustrate the effect of the number of SOH indicators utilized to develop SOH estimators on the SOH estimation performance. Only some of the five SOH indicators are used as input features for these SOH estimators. There are no activation functions used in the neurons of the input layer.

There are two hidden layers in the adopted DNN. Each hidden layer has 128 neurons and the activation function for each neuron is ‘Relu’ [53]. Two dropout layers are added after each hidden layer and the dropout regulation rate is set to be 0.5 for the two dropout layers. The dropout layer is used to reduce the overfitting issue [45]. Only one neuron is utilized in the output layer with no activation function. The reason why activation function is not needed in the output layer is because the output of the output layer is just the linear combination of the outputs from each neuron of the last hidden layer [40].

The DNN based SOH estimators presented in this paper are implemented by using Keras [54] and Tensorflow [55] in Python (computer with 3.20 GHz Intel i7-8700 CPU and 64 GB RAM memory is used). The average training time for DNN based SOH estimators is less than 30 seconds. The \(k\)-cross validation technique [56] is utilized to guide the training with the value of \(k\) set to be 2. The training epochs and bitch size are set to be 400 and 1, respectively. There are two reasons why the batch size is selected to be 1 in this paper.

FIGURE 19. The structure of adopted DNN for SOH estimation in this paper. Note: \(N\) is the number of SOH indicators or features used as the input of DNN.
The first reason is that it can help to achieve fast learning speed and offer a regularizing effect [57], [58]. The second reason is that it can support online learning every time a data point becomes available [57], [58].

The loss function utilized in the DNN is mean square error (MSE) as given by Eq. (8).

$$MSE = \frac{1}{m} \sum_{i=1}^{m} (S_i - \tilde{S}_i)^2$$

where $m$ is the number of data samples used to train DNN, $S_i$ is the ground truth SOH value, and $\tilde{S}_i$ is the predicted SOH value by the DNN based SOH estimator. The unit of MSE is chosen to be $10^{-4}$ in this paper, which is the same as in [51].

The ‘Adam’ optimization algorithm [59] with the learning rate of 0.001 is utilized to find the optimum parameters of DNN (e.g., weight and bias) to have minimum value of defined loss function, i.e., MSE in this paper. To evaluate the estimation performance of the developed SI and MI DNN based SOH estimators, the root mean square error (RMSE) and mean absolute percentage error (MAPE) are calculated for comparison purposes as given by Eq. (9) and Eq. (10), respectively.

$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{m} \sum_{i=1}^{m} (S_i - \tilde{S}_i)^2}$$

$$MAPE = \frac{100}{m} \sum_{i=1}^{m} \left| \frac{S_i - \tilde{S}_i}{S_i} \right|$$

For the data-driven based methods such as DNN, it is always better to have more data which can be utilized to train and tune the model. The effectiveness and performance of data-driven based methods also depend on the model selection and on how to utilize limited and valuable data points to tune the parameters of the selected model.

There are five SI DNN based SOH estimators (i.e., SI-dvdtdisch, SI-dvdtCC, SI-CCtime, SI-didtCV, and SI-dTdtCV) and four MI-DNN ($i = 1, 2, 3, 4$) based SOH estimators developed in this work. For fair and better performance comparison among different SOH estimators, the same DNN structure is used for all of the developed DNN-based SOH estimators (Fig. 19) with the only difference being at the input layer. The difference at the input layer among different SOH estimators is discussed earlier this section.

In order to tune the hyperparameters of neural network such as the number of neurons in hidden layer, grid search method [60] is utilized to select the values of parameters which can allow for achieving the smallest cross validation error during the training of neural network. For instance, in order to tune the number of neurons in the hidden layer, the cross validation errors of MSE for the cases using different numbers of neurons in the hidden layer are calculated using grid search method. The calculation results during the training process of MI4-DNN are shown in Table 3. The ageing data of battery 1 is utilized as training data. From Table 3, it can be observed that the cross validation error is the lowest when the number of neurons is set to be 128. Therefore, the number of neurons in the hidden layer is set to be 128.

The SOH estimation results for battery 2 and battery 3 given by different SI DNN based SOH estimators and MI4-DNN SOH estimator are shown in Fig. 20 and Fig. 21, respectively. The calculation results of MSE, RMSE, and MAPE for these SOH estimators are summarized in Table 4, Table 5, Fig. 22, and Fig. 23. Based on the results shown in Table 4, Table 5, Fig. 22, and Fig. 23, it can be observed that the SOH estimation results given by SI DNN based SOH estimators and MI4-DNN SOH estimator match well with the

| The number of neurons in hidden layer | Cross validation error of MSE ($10^{-4}$) |
|--------------------------------------|------------------------------------------|
| 16                                   | 6.89                                     |
| 32                                   | 4.78                                     |
| 64                                   | 3.56                                     |
| 128                                  | 2.12                                     |
| 256                                  | 4.35                                     |
Based on the results shown in Table 4, Table 5, Fig. 22, and Fig. 23, the following observations can be made.

(1) All of MSE values are within $13 \times 10^{-4}$. The best/smallest MSE value is given by MI4-DNN SOH estimator, i.e., $2.483 \times 10^{-4}$ for battery 2 and $1.211 \times 10^{-4}$ for battery 3, and the worst/largest MSE value is given by the SI-dTdtCV SOH estimator, i.e., $12.753 \times 10^{-4}$ for battery 2 and $10.262 \times 10^{-4}$ for battery 3. RMSE calculation results have the same trend as MSE calculation results because of the relationship between these two variables as shown in Eq. (9).

(2) All of MAPE values are within 11%. The best/smallest MAPE value is given by MI4-DNN SOH estimator, i.e., 5.022% for battery 2 and 3.028% for battery 3, and the worst/largest MAPE value is given by the SI-dTdtCV SOH estimator, i.e., 9.287% for battery 2 and 10.797% for battery 3.

(3) Among the different SI DNN-based SOH estimators, SI-dvdtdisch SOH estimator has the best estimation performance for battery 2 with MSE, RMSE, and MAPE values of $4.172 \times 10^{-4}$, 2.042%, and 5.814%, respectively, and SI-didtCV SOH estimator has the best estimation performance for battery 3 with MSE, RMSE, and MAPE values of $2.483 \times 10^{-4}$, 1.156%, and 4.485%, respectively.
The SI-dTdtCV SOH estimator has the worst estimation performance for both battery 2 and battery 3. For battery 2, the values of MSE, RMSE, and MAPE for SI-dTdtCV SOH estimator are $12.753 \times 10^{-4}$, 3.571%, and 9.287%, respectively. For battery 3, the values of MSE, RMSE, and MAPE for SI-dTdtCV SOH estimator are $10.262 \times 10^{-4}$, 3.203%, and 10.797%, respectively.

Fig. 24 and Fig. 25 shows the absolute error (AE) of SOH estimation results of SI DNN based SOH estimators and MI4-DNN SOH estimator at different ageing cycles for battery 2 and battery 3, respectively. The AE of SOH estimation results is calculated by using Eq. (11).

$$AE = |S_i - \tilde{S}_i|$$  \hspace{1cm} (11)

From Fig. 24 and Fig. 25, it can be observed that the AE values of these developed DNN-based SOH estimators are within 9% for all ageing cycles. The highest AE value (8.85% for battery 2 and 8.82% for battery 3) comes from the estimation result given by SI-dTdtCV SOH estimator, which only occurs for the last ageing cycle. The SOH estimation results given by the MI4-DNN SOH estimator always have small AE values for most of the ageing cycles. Based on aforementioned analysis, it can be concluded that the MI4-DNN SOH estimator outperforms all of the SI DNN based SOH estimators.

To illustrate the effect of the number of SOH indicators used in DNN on the estimation performance/accuracy, different MI-DNN SOH estimators with different numbers of SOH indicators as input features are developed and evaluated, i.e., MI$i$-DNN ($i = 1, 2, 3, 4$) SOH estimators. The data of battery 2 is utilized here to investigate this effect. These four MI$i$-DNN ($i = 1, 2, 3, 4$) SOH estimators are developed by including different SOH indicators in a descending MSE value scheme, which is based on the MSE values of different SI DNN based SOH estimators as shown in Table 4. For example, dTdtCV and dvdtCC have the highest and second highest MSE value, respectively. Therefore, they are used as the two indicators for MI$1$-DNN in Table 6. The CCtime indicator has the third highest MSE value and therefore it is used as the third indicator for MI$2$-DNN in addition to the two indicators used for MI$1$-DNN. The same logic of the descending MSE value scheme is used to determine the indicators used for MI$3$-DNN and MI$4$-DNN. The details of which SOH indicators are utilized as input features in each MI-DNN SOH estimator are given in Table 6.

The SOH estimation results for battery 2 given by these MI-DNN SOH estimators are shown in Fig. 26. The MSE, RMSE, and MAPE calculation results for these MI DNN SOH estimators are listed in Table 7. From the results shown in Fig. 26 and Table 7, it can be observed that when the diversity of input features is increased, i.e., more different types of SOH indicators are utilized to train DNN, the SOH estimation performance is significantly improved.

While this paper has presented the utilization of multiple SOH indicators for SOH estimation, they do not have to be all used. The selection of SOH indicators and estimation method depends on the data availability. For example, if only battery CC charging data is available, SI-dvdtCC SOH estimator (the one uses SOH$1$, i.e., $|dv_{\text{CC}−\text{char}}|$, as its input) can be utilized to estimate SOH. If battery discharging data and CC charging data are both available, then SOH$1$ (i.e., $|dv_{\text{disch}}|$), SOH$2$ (i.e., $|dv_{\text{CC}−\text{char}}|$), and SOH$3$ (i.e., $\Delta t_{\text{CC}−\text{char}}$) can be utilized together to develop multi-indicators (MI) based SOH estimator which can achieve better estimation accuracy compared with single-indicator (SI) based SOH estimator.

To further evaluate the estimation performance of the developed DNN based SOH estimator, Bayesian regression method, Gaussian process regression (GPR) method, and support vector regression (SVR) method are utilized to compare with the presented DNN based SOH estimation method. For fair comparison, Bayesian regression based SOH estimator,
GPR based SOH estimator, and SVR based SOH estimator utilize the same set of SOH indicators as input features as MI4-DNN SOH estimator does, i.e., all of the five SOH indicators are utilized as input features. The ageing data of battery 1 is still utilized to train these SOH estimators. The performance of these SOH estimators is evaluated by using the ageing data of battery 2. The SOH estimation results of these different types of SOH estimators are shown in Fig. 27 and are compared in Table 8.

From Fig. 27 and Table 8, it can be observed that the developed MI4-DNN SOH estimator in this paper has better estimation performance or can provide more accurate SOH estimation results compared with other types of SOH estimators, which indicates the suitability of utilizing DNN to develop SOH estimators in this paper. For the GPR based SOH estimator, its 95% confidence interval calculation result is also shown in Fig. 27(b), which indicates a reliable SOH estimation given by GPR based SOH estimator. However, the estimation accuracy of the GPR based SOH estimator is less than that of the developed MI4-DNN SOH estimator as shown in Table 8.

In order to further evaluate the performance of the developed DNN-based SOH estimators, the ageing data of

| Estimator | MSE (10^-4) | RMSE (%) | MAPE (%) |
|-----------|-------------|----------|----------|
| SI-dTdtCV | 12.753      | 3.571    | 9.287    |
| MI1-DNN   | 6.637       | 2.576    | 6.685    |
| MI2-DNN   | 4.949       | 2.225    | 5.812    |
| MI3-DNN   | 2.855       | 1.690    | 5.653    |
| MI4-DNN   | 2.483       | 1.576    | 5.022    |
battery 3 is utilized as training dataset and the ageing data of battery 2 and battery 3 is used as test dataset. The training procedure and the structure of DNN are kept the same as the case when the ageing data of battery 1 is utilized as training dataset. The calculation results of performance evaluation metrics for different DNN-based SOH estimators which are trained using the ageing data of battery 3 are shown in Table 9 and Table 10. From Table 9 and Table 10, it can be observed that the RMSE values are within 4% for different estimators, which indicates that the developed SOH estimators can achieve fairly good estimation performance. MI4-DNN SOH estimator outperforms other SI DNN based SOH estimators, which is consistent with the case when the ageing data of battery 1 is utilized as training dataset.

V. CONCLUSION

Lithium-ion battery ageing behavior patterns or characteristics are extracted in this paper from the aggregated raw battery ageing data collected from the developed autonomous battery ageing platform. Several SOH indicators are defined based on these ageing patterns or characteristics to reflect the health status of battery. The nonlinear correlations between the SOH indicators and SOH values are extracted and modeled by DNN to develop different SI and MI DNN based SOH estimators. The SOH performance comparison among different SOH estimators indicates that MI DNN SOH estimator yields more accurate SOH estimation results when compared to SI DNN based SOH estimator. It is also observed that the diversity of input features or SOH indicators can substantially improve the estimation performance of DNN based SOH estimator. Future work includes but is not limited to conducting battery ageing experiments under dynamic and complex operation conditions (e.g., at different operation temperature, discharging current, and charging current) in order to investigate/study its effects on the battery ageing patterns or characteristics and utilize these effects in the development of SOH estimators.

ACKNOWLEDGMENT

This material is based upon work supported in part by the National Science Foundation under Grant No. 1509824. Any opinions, findings or conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation.

REFERENCES

[1] R. Xiong, Y. Zhang, J. Wang, H. He, S. Peng, and M. Pecht, “Lithium-ion battery health prognosis based on a real battery management system used in electric vehicles,” IEEE Trans. Veh. Technol., vol. 68, no. 5, pp. 4110–4121, May 2019.
[2] M. A. Hannan, M. M. Hoque, A. Hussain, Y. Yusof, and P. J. Ker, “State-of-the-art and energy management system of lithium-ion batteries in electric vehicle applications: Issues and recommendations,” IEEE Access, vol. 6, pp. 19362–19378, 2018.
[3] J. A. Abu Qahouq and Z. Xia, “Single-perturbation-cycle online battery impedance spectrum measurement method with closed-loop control of power converter,” IEEE Trans. Ind. Electron., vol. 64, no. 9, pp. 7019–7029, Sep. 2017.
[4] M. S. H. Lipu, M. A. Hannan, A. Hussain, M. M. Hoque, P. J. Ker, M. H. M. Saad, and A. Ayob, “A review of state of health and remaining useful life estimation methods for lithium-ion battery in electric vehicles: Challenges and recommendations,” J. Cleaner Prod., vol. 205, pp. 115–133, Dec. 2018.
[5] C. Vidal, P. Malyz, P. Kolmeyer, and A. Emadi, “Machine learning applied to electrified vehicle battery state of charge and state of health estimation: State-of-the-art,” IEEE Access, vol. 8, pp. 52796–52814, 2020.
[6] Z. Xia and J. A. Abu Qahouq, “State-of-charge balancing of lithium-ion batteries with state-of-health awareness capability,” IEEE Trans. Ind. Appl., vol. 57, no. 1, pp. 673–684, Jan. 2021.
[7] Z. Song, X. Wu, X. Li, J. Sun, H. F. Hofmann, and J. Hou, “Current profile optimization for combined state of charge and state of health estimation of lithium ion battery based on Cramer–Rao bound analysis,” IEEE Trans. Power Electron., vol. 34, no. 7, pp. 7097–7107, Jul. 2019.
[8] D. Ansean, V. M. Garcia, M. Gonzalez, C. Blanco-Viejo, J. C. Viera, Y. F. Pulido, and L. Sanchez, “Lithium-ion battery degradation indicators via incremental capacity analysis,” IEEE Trans. Ind. Appl., vol. 55, no. 3, pp. 2992–3002, May 2019.
[9] D.-I. Stroe and E. Schaltz, “Lithium-ion battery state-of-health estimation using the incremental capacity analysis technique,” IEEE Ind. Appl. Mag., vol. 36, no. 1, pp. 678–685, Jan. 2020.
[10] Z. Xia, J. A. Abu Qahouq, E. Phillips, and R. Gentry, “A simple and upgradable autonomous battery aging evaluation and test system with capacity fading and AC impedance spectroscopy measurement,” in Proc. APEC, Mar. 2017, pp. 951–958.
[11] A. El Mejroubi, H. Chaoui, H. Gualous, P. Van Den Bossche, N. Omar, and J. Van Mierlo, “Lithium-ion batteries health prognosis considering aging conditions,” IEEE Trans. Power Electron., vol. 34, no. 7, pp. 6834–6844, Jul. 2019.
[12] J. Lee, D. Kwon, and M. G. Pecht, “Reduction of li-ion battery qualification time based on prognostics and health management,” IEEE Trans. Ind. Electron., vol. 66, no. 9, pp. 7310–7315, Sep. 2019.
[13] C. Weng, J. Sun, and H. Peng, “Model parametrization and adaptation based on the invariance of support vectors with applications to battery state-of-health monitoring,” IEEE Trans. Veh. Technol., vol. 64, no. 9, pp. 3908–3917, Sep. 2015.
[14] J. Qu, F. Liu, Y. Ma, and J. Fan, “A neural-network-based method for RUL prediction and SOH monitoring of lithium-ion battery,” IEEE Access, vol. 7, pp. 87178–87191, 2019.

[15] J. Liu and Z. Chen, “Remaining useful life prediction of lithium-ion batteries based on health indicator and Gaussianas process regression model,” IEEE Access, vol. 9, pp. 39474–39484, 2019.

[16] C. Hametner, S. Jakubek, and W. Prochazka, “Data-driven design of a cascaded observer for battery state of health estimation,” IEEE Trans. Ind. Appl., vol. 54, no. 6, pp. 6258–6266, Nov. 2018.

[17] J. Kim, H. Chun, M. Kim, J. Yu, K. Kim, T. Kim, and S. Han, “Data-driven state of health estimation of li-ion batteries with RPT-reduced experimental data,” IEEE Access, vol. 7, pp. 106967–106997, 2019.

[18] J. Tang, Q. Liu, S. Liu, X. Xie, J. Zhou, and Z. Li, “A health monitoring method based on multiple indicators to eliminate influences of estimation dispersion for lithium-ion batteries,” IEEE Access, vol. 7, pp. 122302–122319, 2019.

[19] A. A. Hussein, “Capacity fade estimation in electric vehicle li-ion batteries using artificial neural networks,” IEEE Trans. Ind. Appl., vol. 51, no. 3, pp. 2321–2330, May 2015.

[20] A. Barré, B. Deguilhem, S. Grolloeu, M. Gérard, F. Suard, and D. Riu, “A review on lithium-ion battery ageing mechanisms and estimations for automotive applications,” J. Power Sources, vol. 241, pp. 680–689, Nov. 2013.

[21] 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, Apr. 2014.

[22] Y. Gao, J. Jiang, C. Zhang, W. Zhang, Z. Ma, and Y. Jiang, “Lithium-ion battery aging mechanisms and life model under different charging stresses,” J. Power Sources, vol. 356, pp. 103–114, Jul. 2017.

[23] J. Li, K. Adewuyi, N. Lotfi, R. G. Landers, and J. Park, “A single particle model with chemical/mechanical degradation physics for lithium ion battery state of health (SOH) estimation,” Appl. Energy, vol. 212, pp. 1178–1190, Feb. 2018.

[24] J. Marcicki, M. Canova, A. T. Conlisk, and G. Rizzoni, “Design and parametrization analysis of a reduced-order electrochemical model of graphite/LiFePO₄ cells for SOC/SOH estimation,” J. Power Sources, vol. 237, pp. 310–324, Sep. 2013.

[25] S. J. Moura, N. A. Chaturvedi, and M. Krstic, “Adaptive partial differential equation observer for battery state-of-charge/state-of-health estimation via an electrochemical model,” J. Dyn. Syst., Meas., Control, vol. 136, no. 1, pp. 1–11, Jan. 2014.

[26] S. Torai, M. Nakagomi, S. Yoshitake, S. Yamaguchi, and N. Oyama, “State-of-health estimation of LiFePO₄/graphite batteries based on a model using differential capacity,” J. Power Sources, vol. 306, pp. 62–69, Feb. 2016.

[27] Y. Zou, X. Hu, H. Ma, and S. E. Li, “Combined state of charge and state of health estimation over lithium-ion battery cell cycle lifespan for electric vehicles,” J. Power Sources, vol. 273, pp. 793–803, Jan. 2015.

[28] J. Kim and B. H. Cho, “State-of-charge estimation and state-of-health prediction of a li-ion degraded battery based on an EKF combined with a per-unit-system,” IEEE Trans. Veh. Technol., vol. 60, no. 9, pp. 4249–4260, Nov. 2011.

[29] A. Guha and A. Patra, “State of health estimation of lithium-ion batteries using capacity fade and internal resistance growth models,” IEEE Trans. Transport. Electrific., vol. 4, no. 1, pp. 135–146, Mar. 2018.

[30] H.-F. Yuan and L.-R. Dung, “Offline state-of-health estimation for high-power lithium-ion batteries using three-point impedance extraction method,” IEEE Trans. Veh. Technol., vol. 66, no. 3, pp. 2019–2032, Mar. 2017.

[31] S. Li, S. Pischinger, C. He, L. Liang, and M. Stapelbroek, “A comparative study of model-based capacity estimation algorithms in dual estimation frameworks for lithium-ion batteries under an accelerated aging test,” Appl. Energy, vol. 212, pp. 1522–1536, Feb. 2018.

[32] T. Kim, A. Adhikaree, R. Pandey, D.-W. Kang, M. Kim, C.-Y. Oh, and J.-W. Baek, “An on-board model-based condition monitoring for lithium-ion batteries,” IEEE Trans. Ind. Appl., vol. 55, no. 2, pp. 1855–1843, Mar. 2019.

[33] X. Tan, Y. Tan, D. Zhan, Z. Yu, Y. Fan, J. Qiu, and J. Li, “Real-time state-of-health estimation of lithium-ion batteries based on the equivalent internal resistance,” IEEE Access, vol. 8, pp. 56811–56822, 2020.

[34] W. Xiong, Y. Mo, and C. Yan, “Online state-of-health estimation for second-use lithium-ion batteries based on weighted least squares support vector machine,” IEEE Access, vol. 9, pp. 1870–1881, 2021.

[35] X. Feng, C. Weng, X. He, X. Han, L. Lu, D. Ren, and M. Ouyang, “Online state-of-health estimation for li-ion battery using partial charging segment based on support vector machine,” IEEE Trans. Veh. Technol., vol. 68, no. 9, pp. 8583–8592, Sep. 2019.

[36] X. Zheng and X. Deng, “State-of-health prediction for lithium-ion batteries with multiple Gaussian process regression model,” IEEE Access, vol. 7, pp. 150383–150394, 2019.

[37] Z. Wang, J. Ma, and L. Zhang, “State-of-health estimation for lithium-ion batteries based on the multi-island genetic algorithm and the Gaussian process regression,” IEEE Access, vol. 5, pp. 21286–21295, 2017.

[38] Z. Chen, Q. Xue, R. Xiao, Y. Liu, and J. Shen, “State of health estimation for lithium-ion batteries based on fusion of autoregressive moving average model and emlan neural network,” IEEE Access, vol. 7, pp. 102662–102678, 2019.

[39] L. Ren, L. Zhao, S. Hong, S. Zhao, H. Wang, and L. Zhang, “Remaining useful life prediction for lithium-ion battery: A deep learning approach,” IEEE Access, vol. 6, pp. 50587–50598, 2018.

[40] H. Dai, Q. Zhao, M. Lin, J. Wu, and G. Zheng, “A novel estimation method for the state of health of lithium-ion battery using prior knowledge-based neural network and Markov chain,” IEEE Trans. Ind. Electron., vol. 66, no. 10, pp. 7706–7716, Oct. 2019.

[41] F. Wu, Y. You, S. Park, and D. Oh, “Diagnosis of electric vehicle batteries using recurrent neural networks,” IEEE Trans. Ind. Electron., vol. 64, no. 6, pp. 4885–4893, Jun. 2017.

[42] L. Dai, Z. Li, J. Zhu, H. Zhang, and L. Hou, “State of health monitoring and remaining useful life prediction of lithium-ion batteries based on temporal convolutional network,” IEEE Access, vol. 8, pp. 53307–53320, 2020.

[43] K. Park, Y. Choi, W. J. Choi, H.-Y. Ryu, and H. Kim, “LSTM-based battery remaining useful life prediction with multi-channel charging profiles,” IEEE Access, vol. 8, pp. 20786–20798, 2020.

[44] S. Cui and I. Joe, “A dynamic spatial-temporal attention-based GRU model with healthy features for state-of-health estimation of lithium-ion batteries,” IEEE Access, vol. 9, pp. 27374–27388, 2021.

[45] G.-W. You, J. Lei, “Cross-validation with confidence,” Deep Learning With Keras, Birmingham, U.K.: Packt Publishing Ltd, 2017.

[46] V. Nair and G. E. Hinton, “Rectified linear units improve restricted Boltzmann machines,” J. Mach. Learn. Res., vol. 33, pp. 2321–2324, 2014.

[47] A. Gulli and S. Pal, Deep Learning With Keras. Birmingham, U.K.: Packt Publishing Ltd, 2017.

[48] M. Abadi, P. Barham, J. Chen, Z. Chen, A. Davis, J. Dean, M. Devin, S. Ghemawat, G. Irving, M. Isard, and M. Kudlur, “TensorFlow: A system for large-scale machine learning,” in Proc. OSDI, vol. 16, 2016, pp. 265–283.

[49] J. Lei, “Cross-validation with confidence,” J. Amer. Stat. Assoc., vol. 115, no. 532, pp. 1978–1997, Oct. 2019.
ZHIYONG XIA (Student Member, IEEE) received the bachelor’s degree in automation and the master’s degree in control engineering from Central South University, Changsha, China, in 2012 and 2015, respectively. He is currently pursuing the Ph.D. degree with the Department of Electrical and Computer Engineering, The University of Alabama, Tuscaloosa, AL, USA.

His research interests include power electronic systems, modeling and control of power converters, battery management systems, embedded systems, and data science. He was a recipient of the Graduate Council Fellowship Award from The University of Alabama, in 2015.

JABER A. ABU QAHOUQ (Senior Member, IEEE) received the B.Sc. degree (Hons.) from the Princess Sumaya University for Technology/Royal Scientific Society (RSS), Amman, Jordan, in 1998, and the M.S. and Ph.D. degrees from the University of Central Florida (UCF), Orlando, FL, USA, in 2000 and 2003, respectively, all in electrical engineering/electronics. He is currently an Associate Professor with the Department of Electrical and Computer Engineering, College of Engineering, The University of Alabama, Tuscaloosa, AL, USA. He received promotion to Professor effective August 16, 2021. Before that, he was with Intel Corporation, Hillsboro, OR, USA; UCF; and RSS. He is the author or coauthor of more than 100 refereed publications and two book chapters, and holds 31 U.S. patents, as of September 2020. He was elected a Senior Member of the National Academy of Inventors (NAI), in 2020. He was a recipient of the King of Jordan Royal Watch, in 1998; the IEEE Outstanding Graduate Student Award, in 2002; the Division Recognition Award from Intel Corporation, in 2006; and the Institution of Engineering Technology Premium Award, in 2009. He served as the Chair/Co-Chair for the Technical Program Committee of the IEEE CPERE 2019 Conference and an IEEE Conference Technical Program Committee Member for several other conferences, such as the IEEE APEC Conference, from 2013 to 2021.