Key Technologies on New Energy Vehicles

Zhongbao Wei

# Smart Battery Management for Enhanced Safety

Springer

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# Foreword by Prof. King Jet Tseng

The rapid development of electric vehicles underscores the pressing need for sustainable energy solutions in our society, as well as the growing demand for eco-friendly modes of transportation. As the core component of electric vehicles, batteries, especially the lithium-ion batteries (LIBs), are considered key to promoting transportation electrification. Nevertheless, the performance and longevity of LIBs have persistently posed a significant challenge, impeding the further evolution of the electric vehicle industry. The solution to these challenges, to a great extent, lies in the innovation of battery management system (BMS). BMS is at the kernel of the battery system due to users' ever-increasing concerns over the safety, efficiency, and longevity of user-end products. With the widespread adoption of electric vehicles, the significance of BMSs will continue to rise.

As components of electrochemical energy conversion and storage, LIBs involve complex electrochemical reactions that are often intricate to elucidate accurately. Traditional BMSs predominantly rely on simplified electrochemical models and empirical guidelines. However, this approach exhibits limitations, particularly when confronted with the intricate and ever-changing battery working conditions, as well as dynamic charging and discharging behaviors. With the continuous advancement of sensing and artificial intelligence technologies, we now possess more effective tools and methodologies to address these challenges in battery management. The incorporation of AI technologies, such as deep learning, reinforcement learning, and data-driven modeling, empowers battery management systems to gain a deeper understanding of battery status, health, and predict future battery performance. Consequently, this leads to elevated levels of battery control and optimization.

I take pleasure in introducing the latest monograph in the field of BMS titled Battery Management and Smart Battery. Dr. Wei has meticulously compiled the most recent advancements in BMS and smart batteries within this monograph. Special focuses are given to the fundamental principles of BMSs and their profound integration with AI methods. This synergy aims to enhance the performance of battery systems, prolong the life of batteries, and ensure a more dependable electric vehicle travel experience.

This ultimate objective of this book is to amalgamate the finest practices from Dr. Wei' previous works, furnishing readers with state-of-the-art knowledge in battery management and future smart batteries. This book summarizes the key findings from Dr. Wei over these years regarding the battery management, with special emphasis given to the fusion of mechanism and AI-based approaches for enhanced management of LIBs. This book firstly overviews of the research progresses and future trends of battery management. Following this endeavor, some underlying theories and techniques of BMS have been discussed in detail. These involve some critical algorithms and methodologies targeted for the modeling, state estimation, diagnostic and prognostic, and charging control of batteries. As a significant extension to the traditional batteries and the associated management strategies, this book further discusses the emerging techniques like embedded multi-dimensional sensing, reconfigurable battery system, to illustrate the future smart battery design and its associated management.

With this book, readers will acquire insights into the important topics regarding battery management, like battery modeling, parameter/state estimation, health prognostic, fault diagnostic, optimal charging, and the future smart battery. Furthermore, the book explores how advanced intelligent technologies can enhance the performance of batteries. It also provides an in-depth exploration of emerging embedded sensing technologies and their potential utilization in the field of battery management. I firmly believe that this book will emerge as a seminal reference material in the realm of battery management, imparting valuable knowledge to researchers and engineers. This book will also contribute significantly to the sustainable development and ongoing innovation of batteries and energy storage.

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# Foreword by Prof. Jun Shen

Modern transportation is on the verge of transition in response to the climate change and resource scarcity, witnessed by the readily proactive deployment of electrical vehicles, vessels, and aircrafts, with strong growth foreseeable in the coming decades. In particular, electric vehicle industry in China is in a vigorous development stage, with the strong support of national policies and people's increasing awareness of environmental protection. Along with this, the number of electric vehicles in China is expected to continue growing in the near future.

The quick development of electrified transportation is enabled by the far-going advances in energy storage techniques toward higher volumetric and gravimetric energy densities. With the rapid growth of the number of EVs, the lithium-ion battery (LIB), as the main energy storage of NEVs, has also entered a period of vigorous development. However, the pursuit of utmost user experience can risk violating important physical limitations, which is accompanied by unexpected side reactions within the ESS. This will result in several unfavorable consequences like efficiency reduction, quick degradation, and even catastrophic safety hazards in the most severe case. Particularly, onboard battery systems have been identified as one of the major contributors to recent-reported fire accidents of EVs. Moreover, risks can accumulate over the life cycle and eventually spread to the second-life use. In practical applications, a reliable battery management system (BMS) is critical to fulfill the expectations on the reliability, efficiency, and longevity of LIB systems.

This book focuses on the rapidly growing field of battery management and new concept of smart batteries. This book summarizes the key findings from Dr. Wei over these years regarding the battery management, with special emphasis given to the fusion of mechanism and AI-based approaches for enhanced management of LIBs. This book starts with a systematic overview of state-of-the-art techniques and future trends of battery management and smart battery. It continues with several key topics of modern battery management system, including the modeling, state estimation, health prognostic, life prediction, and optimal charging. Finally, this book introduces the emerging techniques on smart battery design and its associated management.

Dr. Wei's expertise and contributions lay in the promotion of battery management system toward enhanced safety and longevity of battery utilization in both electric vehicles and energy storage. He was a research fellow with Nanyang Technological University from 2016 to 2018. He came back to China with Beijing Institute of Technology as an associate professor in 2018. In 2019, he was promoted to a full professor due to his excellent contributions to the agenda of energy storage and EVs. During years of investigation, Dr. Wei held several projects as the principal investigator regarding well-focused topics of environment-adaptive BMS, embedded sensing and smart battery, and battery big data management. His research outcomes are witnessed by 100+ research articles widely cited by scholars over the world.

This is a book that leads the audiences into the profound world of advanced battery management and future smart batteries. With this book in hand, the readers can receive key knowledge necessary for understanding the basic principles and mechanisms of LIBs and the associated battery management technologies. Moreover, recent progresses in control theory and artificial intelligence are also investigated for the practical utilization on the management system of LIBs.

I highly recommend this book to students, scholars, and engineers who are working in the fields of battery management. The state-of-the-art overviews, systematic introduction, detailed theories, and methodologies, and cautiously designed case studies promise the book with great significance and insights to the diversified groups of audiences with different majors and research experiences, from graduates to experienced engineers. By deeply understanding the mechanism and operation of BMSs, as well as how to improve them through modeling and AI technology, the audiences are expected to gain necessary knowledge and to promote the progress of electric transportation in the near future.

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# Preface

The emerging concerns over resource depletion, climate change, and environmental pollution have led to a major transformation of energy system, witnessed by the proactive penetration of renewable energies such as wind and solar, which, unfortunately, are highly intermittent and difficult to match with users' demands. Within this context, energy storage system (ESS) has been recognized as a key technology to address such intermittency and facilitate the future penetration of renewables in a stable and sustainable manner. ESSs are also at the forefront of applications for the end-user sector electrification such as electrified transportation to pursuit an efficient and low-carbon society.

Among the available energy storage technologies, lithium-ion battery (LIB) is recognized as the most promising, attributed to the superiority of high power and energy density and low self-discharge rate. Aligned with this trend, the LIB has entered a period of vigorous development, evidenced by the rapidly rising global installation capacity of LIB. In spite of the quick development, the safety and longevity of LIBs are still major barriers in practical applications. This is rooted in the intrinsic complicated electrochemical nature of LIBs. It is well known that either the abusive operation from the users or the hostile application environment can risk violating the physical limits of LIBs, which further triggers a series and even uncontrollable side reactions. The occurrence of unwanted side reactions further induces a rapid drop of overall performance, like the efficiency reduction, quick depletion, and even safety hazards. Motivated by this, new structural design and reliable management techniques are essential for enhancing the performance of LIB system in both electrified transportation and stational energy storage.

The battery management boils down to multiple tasks of state monitoring, balancing, thermal management, fault warning, and life prognostic, relying on onboard measured current, terminal voltage, and temperature. The development of high-fidelity, high environmental-adaptive, and fault-tolerant battery management algorithms is viewed as the most demanding technique to enhance the LIB performance in the future. Moreover, emerging sensing techniques allowing the internal measurement of LIB parameters have also been viewed as promising solution for the future enhanced battery system. This is rooted in the fact that the LIB performance is dominated by the inner physics linked more closely to the inner status. This vision also motivates the development of “smart battery,” which can promise enhanced safety with the embedded sensing and cell-level diagnostic function.

This book consolidates studies in the rapidly and foreseeably growing field of battery management and smart battery. The primary focus is to overview the management of batteries with the fusion of mechanism and AI-based approaches and also the emerging design of new battery structures. The book is broken down into six chapters. The key features are described in this book as:

- The state-of-the-art techniques and future trends of battery management and smart battery with embedded sensing are systematically analyzed.
- The modeling of LIB is securitized, including the electrochemical, electrical, artificial intelligence, and hybrid approaches.
- The estimation of multiple battery states which serves as the prerequisite of advance battery management is discussed.
- The data-driven approaches on health prognostic and future life prediction of LIB are elaborated and discussed.
- The model-based and artificial intelligence-based approaches for battery fast charging and cold charging are discussed.
- Emerging techniques on smart battery design and its associated management are introduced.

This book is meant to add new knowledge to the paradigm and attract the attention from academics, scientists, engineers, and practitioners. It is useful as a reference book for researchers and engineers working in related fields. The step-by-step guidance, comprehensive introduction, and case studies make it accessible to audiences of different levels, from graduates to experienced engineers.

Beijing, China Zhongbao Wei

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# Contents

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# Abbreviations

| | |
|---|---|
| AEKF | Adaptive extended Kalman filter |
| ANN | Artificial neural network |
| BDP | Big data platform |
| BMS | Battery management system |
| BPNN | Back propagation neural network |
| BTMS | Battery thermal management system |
| BV | Bulter-Volmer |
| CC | Constant current |
| CCCV | Current-constant voltage |
| CI | Confidence interval |
| CL | Conductivity loss |
| CNN | Convolutional neural network |
| CPE | Constant-phase element |
| CV | Constant voltage |
| DDPG | Deep deterministic policy gradient |
| DEKF | Dual extended Kalman filter |
| DKF | Dual Kalman filter |
| DNN | Deep neural network |
| DP | Dynamic programming |
| DRL | Deep reinforcement learning |
| DST | Dynamic stress test |
| DUKF | Dual unscented Kalman filter |
| DVA | Differential voltage analysis |
| ECM | Equivalent circuit model |
| EIS | Electrochemical impedance spectroscopy |
| EIV | Error-in-variables |
| EKF | Extended Kalman filter |
| EM | Electrochemical model |
| EOL | End of life |
| ESC | External short circuit |
| ETNN | Electrochemical-thermal-neural-network |

| | |
|---|---|
| EV | Electric vehicle |
| FBG | Fiber Bragg grating |
| FE | Fuzzy entropy |
| FEM | Finite element method |
| FP | Fabry-Perot |
| FUDS | Federal urban driving schedule |
| FVM | Finite volume method |
| GMM | Gaussian mixture model |
| GPR | Gaussian process regression |
| HF | Hydrofluoric acid |
| HPPC | Hybrid pulse power characterization |
| ICA | Incremental capacity analysis |
| IE | Information entropy |
| ISC | Internal short circuit |
| KF | Kalman filter |
| LAM | Loss of active material |
| LIB | Lithium-ion battery |
| LLI | Loss of lithium inventory |
| LSTM | Long short-term memory neural network |
| MAE | Mean absolute error |
| MHE | Moving heroization estimation |
| MPC | Model predictive control |
| MR | Metal resistance |
| MSD | Mean square error |
| NDT | Nondestructive testing |
| NEDC | New European driving cycle |
| NN | Neural networks |
| OCV | Open-circuit voltage |
| PF | Particle filter |
| PSO | Particle swarm optimization |
| PTC | Positive temperature coefficient |
| QP | Quadratic program |
| RBF | Radial basis function |
| RC | Resistance-capacitance |
| RF | Random forest |
| RL | Reinforcement learning |
| RLS | Recursive least squares |
| RMSE | Root mean square error |
| RNN | Recurrent neural network |
| RQ | Rayleigh quotient |
| RTD | Resistance temperature detector |
| RUL | Remaining useful life |
| RVM | Relevance vector machine |
| SAC | Sinusoidal alternating current |
| SEI | Solid electrolyte interface |

| | |
|---|---|
| SHLB | Self-heating lithium-ion battery |
| SNR | Signal noise ration |
| SOC | State of charge |
| SOH | State of health |
| SQP | Sequential quadratic programming |
| SVD | Singular value decomposition |
| SVM | Support vector machine |
| SVR | Support vector regression |
| TLS | Total least squares |
| UKF | Unscented Kalman filter |
| UT | Unscented transformation |

# Chapter 1
# Overview of Battery Management

Energy storage systems (ESSs) are playing a crucial role in future energy systems with high requirements for power quality and resilience. As a key component of the future carbon–neutral and smart society, ESSs are the kernel of electrified transportation, smart grid, industrial cyber-physical-social systems, and residential communities. This dispensability has been witnessed by the rapid growth of global energy storage and electric vehicle (EV) deployments, especially for the proliferation of high-density batteries over the past decade.

Amongst others, lithium-ion battery (LIB) is recogniz ed as one of the most promising energy storage technology, attributed to the superiority of high power/energy density and low self-discharge rate. Aligned with this trend, the LIB has entered a period of vigorous development. According to recent data, the global installed capacity of LIB continues to rise rapidly, reaching 137 GWh in 2020. Moreover, the global demand is expected to reach 1156 GWh by 2026 with the world-wide rapid growth of EVs and the stationary energy storage market (Li et al. 2022a).

However, the safety and longevity of LIBs are still difficult to ensure, considering their intrinsic complicated electrochemical nature. Both the hostile environmental condition and the abusive operation can risk violating the physical limits of LIBs, leading to a chain of detrimental side reactions. Direct consequences of this include efficiency reduction, quick depletion, and even safety hazards. Therefore, a reliable battery management system (BMS) is indispensable for the practical use of LIB systems.

A general architecture of the presently-used BMS can be referred to Fig. 1.1. Relying on onboard measured current, terminal voltage and temperature, the BMS is expected to complete the tasks of state monitoring, balancing, fault warning and life prognostic. Each of the mentioned tasks has been widely studied over the years, giving rise to many reviews regarding the state of the art, e.g., state estimation, fault diagnostic, lifetime prognostic, thermal management, cell balancing, and charging management.

 
Z. Wei, *Smart Battery Management for Enhanced Safety*, Key Technologies on New Energy Vehicles, https://doi.org/10.1007/978-981-97-4639-2_1

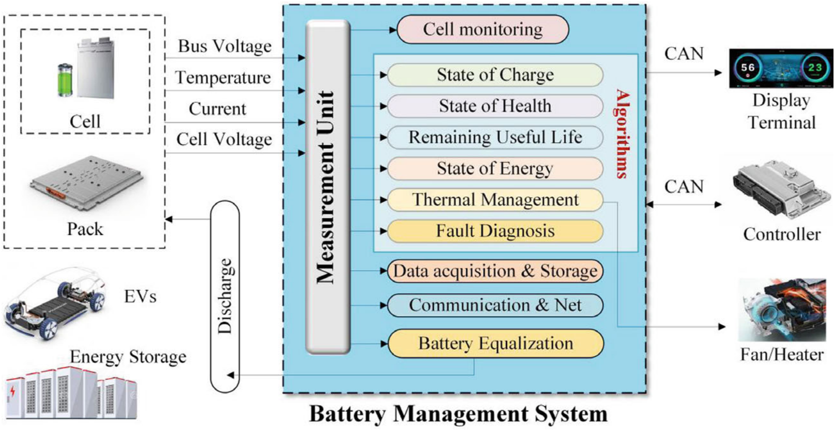


**Fig. 1.1** Architecture of commonly-used BMS, reprinted from Wei et al. (2023), with permission from IEEE

## 1.1 State Estimation

Due to the complex electrochemical dynamics and strong electrical-thermal-physical coupling, direct monitoring of battery states using different sensing technology such as current, voltage and temperature sensors is not enough for high-performance battery management. In this context, how to effectively estimate and capture states within a battery becomes crucial in all real battery applications.

A variety of model-based and data-driven methods have been explored to estimate various types of battery internal states in the literature. In specific, the key battery internal states generally consist of state of charge (SoC), state of energy (SoE), state of power (SoP), temperature, and state of health (SoH).

To be specific, SoC is a key and fundamental state to reflect the remaining amount of charge inside the battery during operation. Generally, SoC stands for the available capacity defined as the percentage of battery nominal capacity. Such information can provide the prior knowledge to guide battery charging or discharging, and further ensure battery is able to work in a safe condition. By similar definition, SoE is another key state to reflect the residual energy that a battery can provide during its operations. In real transportation applications, SoE could be used to reflect the driving mileage of EVs. In order to reflect the available power that a battery could supply or absorb, SoP is utilized. In general, SoP can be seen as the product of threshold current and relevant voltage, while different hard constraints during battery operations need to be carefully considered. During battery operation, temperature is a key factor to affect battery safety, efficiency, and performance. For battery SoH, this state is utilized to quantify battery health level with a definition of battery current capacity or internal resistance. In real applications, it is difficult to directly measure battery capacity or internal resistance by commercial sensors. As a 20% degradation of capacity or a 100% increase of internal resistance are defined as the end-of-life (EoL) of battery in transportation electrification applications, it is crucial to estimate SoH for ensuring safe and reliable operations of LIB.

It is noted that several states, such as SoC, SoE, and SoP, vary in a short-term timescale level due to the rapid-changing electrochemical parameters. In contrast, due to intermediate heat transfer and thermal characteristics of LIB, the battery temperature changes much more slowly with a middle-term timescale level. Furthermore, as the capacity degradation and the resistance increase occur slowly in the whole life of LIB, the SoH presents a long-term timescale property.

### *1.1.1 State Estimation Within Short-Term Timescale*

For battery SoC estimation, machine learning methods such as deep neural network (DNN), support vector regressor (SVR), and XGBoost have been adopted to derive suitable data-driven models for effective battery SoC estimation (Li et al. 2021a). Meanwhile, some data-driven methods are also developed to estimate battery SoE. For instance, based on the wavelet NN-based model and particle filter estimator, battery SoE is estimated rapidly with good accuracy in Dong et al. (2015). After quantifying the relationship between battery SoC and SoE, a dual forgetting factor-based adaptive extended Kalman filter (AEKF) is developed to effectively estimate battery SoC and SoE jointly under dynamic operating conditions for different batteries (Shrivastava et al. 2021). Ma et al. (2021) propose a long short-term memory (LSTM) DNN-based data-driven method to achieve joint estimation of battery SoC and SoE, where its accuracy and robustness outperform the SVR, random forest (RF) and simple recurrent NN.

The SoP estimation is mostly realized with a model-based architecture. In spite of this, recent works have also seen the use of data-driven methods for SoP estimation. A typical study on data-driven based SoP estimation is referred to Tang et al. (2021a). A softmax NN-based strategy is proposed to estimate the SoP for the intervals between pulse tests. The AI methods like deep reinforcement learning (DRL) have also been used for the maximum power estimation of LIB. In particular, Wei et al. (2022a) proposed a multi-constrained maximum power estimation method based on an electrical-thermal-ageing model for data generation and the deep deterministic policy gradient (DDPG) algorithm for problem solution. A general framework of the DRL-based maximum power estimation is shown schematically in Fig. 1.2. It is worth noting that battery models are involved in these methods acting as an environment for the DRL-based optimization. However, the DRL-based estimator can also be model-free and purely data-driven, provided that sufficient battery data are available in real-world applications. In the case, the data pool containing massive battery data acts as a "real-world environment", so that the effort for modeling can be mitigated.

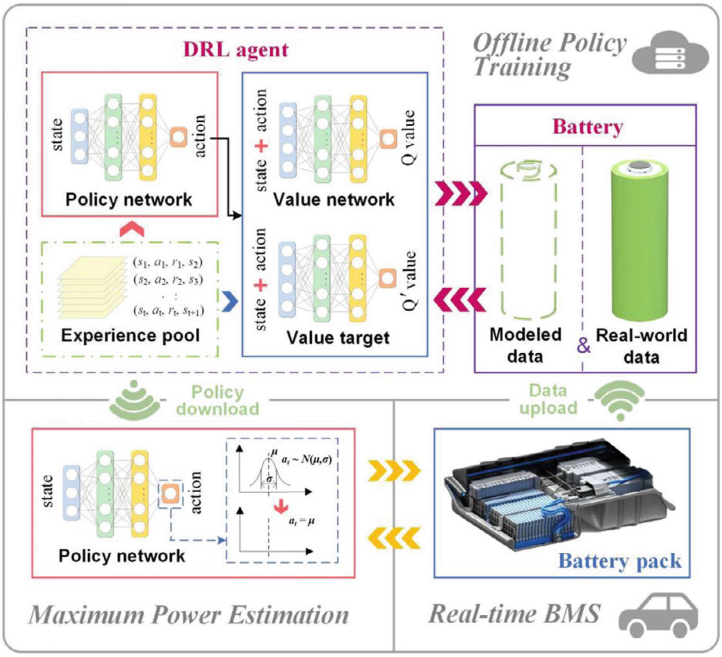


**Fig. 1.2** General framework of the DRL-based maximum power estimation methods, reprinted from Wei et al. (2023), with permission from IEEE

### *1.1.2 State Estimation Within Middle-Term Timescale*

The state belonging to the middle-term timescale is generally referred to the temperature of LIB. The model-based internal temperature estimation has been well studied in the literature, as will be discussed in the following sections. In comparison, the data-driven strategies to benefit battery temperature estimation are still in the nascent stage. An electrochemical-thermal-NN model, as illustrated in Fig. 1.3, is combined with the unscented Kalman filter to jointly estimate the SoC and inner temperature in Feng et al. (2020). A data-driven method combining the Radial Basis Function (RBF)-based NN and the filtering method is used to estimate the inner temperature with higher robustness than the linear NN model (Liu et al. 2018). A data-driven method combining long short term memory (LSTM) NN and transfer learning is proposed to estimate the inner temperature of LIB under various current profiles in Wang et al. (2021). Overviewing the existing works, machine learning techniques have been increasingly used for temperature estimation due to their independence to complicated thermal characterization. At the same time, their combination with model-based approaches can be a trend to improve the estimation performance.

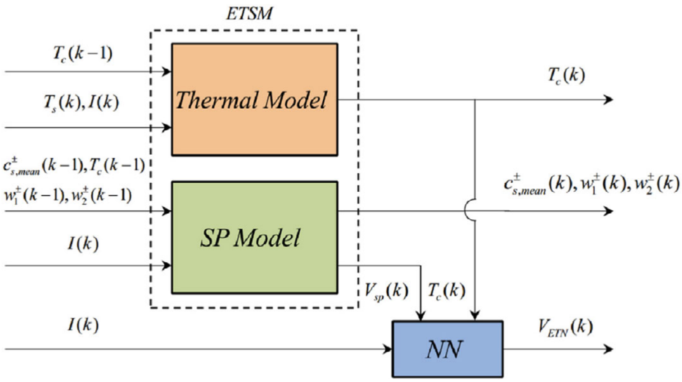


**Fig. 1.3** Framework of electrochemical-thermal-NN model for joint estimation of battery SoC and inner temperature, reprinted from Wei et al. (2023), with permission from IEEE

### *1.1.3 State Estimation Within Long-Term Timescale*

The SoH belongs to a slow-varying state and is influenced by many ageing factors. Since the association between these factors and battery SoH is highly nonlinear and difficult for quantification, data-driven solutions have become an even more powerful tool for SoH estimation with limited information of ageing factors. Estimation methods with direct use of BMS measurements are appealing without tedious data pre-processing. Roman et al. (2021) developed a machine-learning pipeline for SoH estimation by combining parametric and non-parametric algorithms. Thirty feature points are extracted from the current and voltage to estimate the SoH. Tang et al. (2021b) established a balancing current ratio-based data-driven solution to estimate the SoH, which reduced the dependence on cell-level models and thus provided stronger robustness. To tackle the risk of low data quality and quantity, Bamati et al. (2022) developed a nonlinear autoregressive with exogenous inputs recurrent NN for SoH estimation. The estimation accuracy was well ensured with randomly- missed observation data points.

Incremental capacity analysis (ICA) and differential voltage analysis (DVA) have also been widely employed for the ageing analysis and SoH estimation of LIB. One challenge of DVA is that the peaks and valleys in DV curves cannot be easily identified. Moreover, the DV trajectory is referred to the capacity of LIB, which however fades over time. By comparison, the ICA approach transfers the voltage plateaus into observable peaks. Specifically, the mitigation of IC peaks and valleys over time can efficiently reflect the ageing mechanisms of LIB, such as the loss of lithium inventory (LLI) and the loss of active material (LAM). Therefore, the peak position, amplitude, and envelope area of the IC curve can be utilized as informative health indicators (HIs) to estimate the battery SoH. This can be realized by mapping the HIs directly to the capacity or applying fusion algorithms like Gaussian process regression (GPR) and the Bayesian model (Hu et al. 2015).