Multi-level Data-driven Battery Management: From Internal Sensing to Big Data Utilization

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***Abstract*—Battery management system (BMS) is essential for the safety and longevity of lithium-ion battery (LIB) utilization. With the rapid development of new sensing techniques, artificial intelligence and the availability of huge amounts of battery operational data, data-driven battery management has attracted ever-widening attention as a promising solution. This review article overviews the recent progress and future trend of data-driven battery management from a multi-level perspective. The widely-explored data-driven methods relying on routine measurements of current, voltage, and surface temperature are reviewed first. Within a deeper understanding and at the microscopic level, emerging management strategies with multi-dimensional battery data assisted by new sensing techniques have been reviewed. Enabled by the fast growth of big data technologies and platforms, the efficient use of battery big data for enhanced battery management is further overviewed. This belongs to the upper and the macroscopic level of the data-driven BMS framework. With this endeavor, we aim to motivate new insights into the future development of next-generation data-driven battery management.**

***Index Terms*—Battery management system, data-driven, battery sensing, battery big data, lithium-ion battery**

I. Introduction

Energy storage systems (ESSs) are playing a crucial role in future energy systems with high requirements for power quality and resilience. ESSs are the kernel of electrified transportation, smart grid, industrial cyber-physical-social systems, and residential communities. This has been witnessed by the rapid growth of global energy storage and electric vehicle (EV) deployments.

Amongst others, lithium-ion battery (LIB) is promising attributed to the high power/energy density and low self-discharge rate [1]. The global demand is expected to reach 1156 GWh by 2026 with the world-wide growth of EVs and the stationary energy storage [2]. However, the performance of LIBs are difficult to ensure, considering their 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 quick depletion and even safety hazards in the most severe cases. Therefore, a reliable battery management system (BMS) is indispensable for the practical use of LIB systems.

BMS has been a vast area of intensive studies, incubating a myriad of algorithms and system design methodologies. A general architecture of the presently-used BMS can be referred to Fig. . 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 review works regarding the state of the art, e.g., state estimation [3], fault diagnostic [4], lifetime prognostic [5], thermal management [6], cell balancing [7], and charging management [8].

The existing BMS algorithms can be generally classified into mechanism-based and data-driven approaches. The former emphasizes the modeling of complicated physical processes of LIB [9], which are further used to design the management algorithms. The major challenge of mechanism-based methods is rooted in the high complexity, along with the enhanced ability to explain the multi-physical processes in LIB. In contrast, the latter category focuses primarily on the optimal mining of the measurable signals from the LIB systems [10]. The data-driven management is foreseeably promising, with the increased availability of huge amounts of operational data and emerging artificial intelligence (AI) techniques. To this end, this review article focuses primarily on the present progresses and future trend of data-driven battery management technologies.

The data-driven battery management methods, especially for those used for battery state estimation and health prognostic, have been reviewed in recent works [11-13]. However, almost all the works lay their summaries within the commonly-used BMS architecture as shown in Fig. 1. However, several key technical bottlenecks exist for the present battery management technologies. First, the data available for management is confined to the battery current, cell voltage and surface temperature. Unfortunately, the performance, safety and longevity of LIB are

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determined by the inner coupled physics. These are further linked closely to the inner parameters and statues, like the inner temperature, potential, pressure, strain, gas, etc. The lack of inner information barriers the accurate judgement of the status of inner active components. This is recognized as a primary challenge for the present BMS technologies. Second, the battery big data is available nowadays along with the rapid growth of EV and grid-tied energy storage markets. The big data covering the whole lifetime under various application scenarios are quite valuable for the future battery management. Nevertheless, relevant experience is extremely rare in the present stage. Several challenging technologies should be addressed for the big data-driven management, like the improvement of data quality, transmission of huge amount of data, data mining methods, cyber-security, and platform technology. Focusing on the aforementioned barriers, new possibilities have been opened for future battery management along with the extensive investigations of LIB.

First, the sensing of LIB has been moving from the external signals to the internal ones. This is essential since the LIB performance is dominated by the inner physics linked closely to the inner statues. The internal sensing can therefore provide insightful information for more efficient battery management. The LIB sensing from traditional approaches towards internal measurement has been reviewed by Wei et al. [14]. The specific review emphasizes the sensing techniques, while their potential contribution to enhancing battery management has not been sufficiently disclosed and discussed.

Second, the fast growth of big data and machine learning techniques has opened new paradigms for future data-driven management. The spring-up of big data platforms and the associated infrastructures enable the acquisition and storage of huge amounts of battery data for deep learning and analysis. With the availability of LIB big data, future data-driven management can be quite different from the traditional module- or pack-level management. To date, the data-driven management techniques within the emerging big data environment have not been systematically reviewed.

To bridge the aforementioned gaps, this review aims to motivate new insights into the future data-driven management, which incorporates multi-level data utilization from the internal sensing to the cell/module/pack-level measurements, and finally towards the battery big data, as illustrated in Fig. 2.

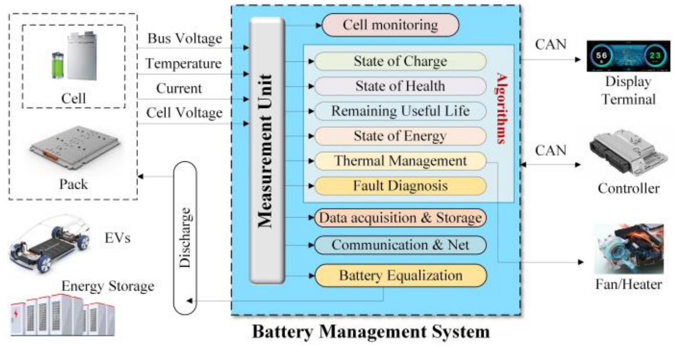

Fig. 1. Architecture of commonly-used BMS

II. Data-Driven Battery Management

A. State Estimation

Direct monitoring of battery states using different sensing technology such as current, voltage and temperature sensors is not enough for high-performance battery management [15]. In this context, how to effectively estimate the states within a battery becomes crucial in real applications. With the rapid development of machine learning and computing technology, data-driven methods have been explored to estimate various battery states in the literature [16]. 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), as illustrated in Fig. 3 [17].

It is noted that SoC, SoE, and SoP vary in a short-term timescale level due to the rapid-changing electrochemical parameters [18]. 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.

a) State estimation within the short-term timescale

With the advantages of being flexible and mechanism-free, data-driven methods have been widely adopted to estimate battery states within the short-term timescale level, including SoC, SoE, and SoP [19]. For battery SoC estimation, machine

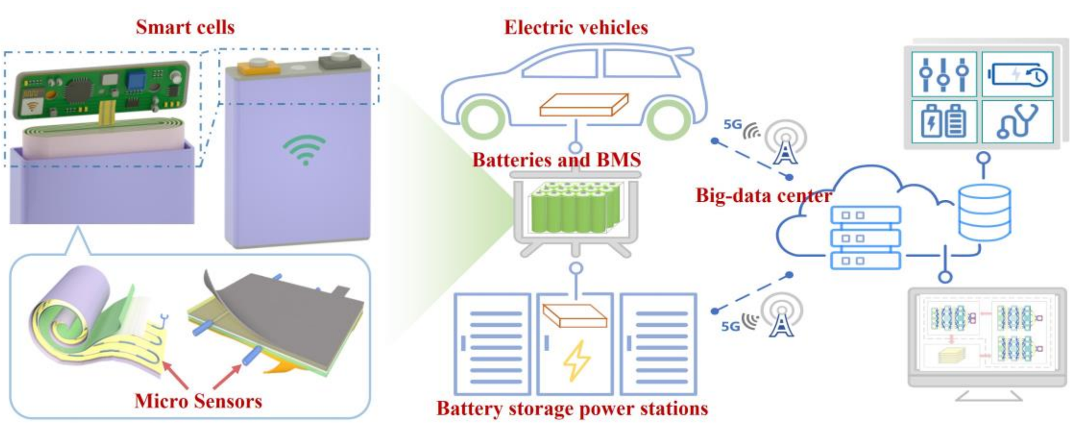

Fig. 2. Data-driven management with multi-level data utilization: from the internal sensing to the battery big data.

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learning methods such as deep neural network (DNN) [20], support vector regressor (SVR) [21], and XGBoost [22] have been adopted to derive suitable data-driven models for effective battery SoC estimation. 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 [23]. 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 [24]. Ma et al. [25] 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.

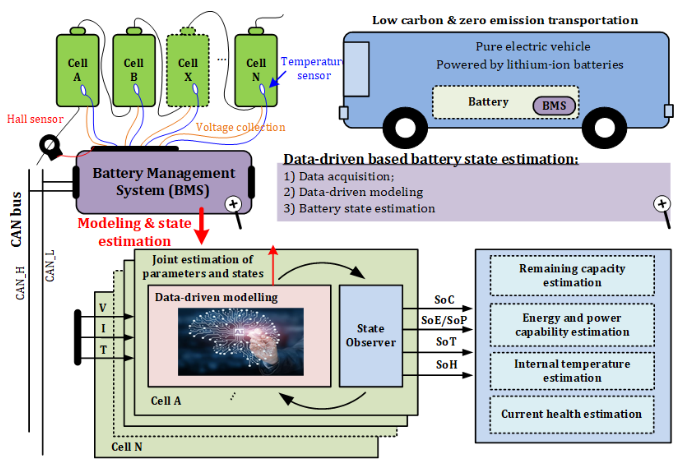

Fig. 3. Diagram of data-driven-based battery state estimation.

The data-driven method for SoP estimation is still limited [26]. The SoP estimation boils down to determine the maximum power of battery under certain physical constraints [27-29]. Therefore, the SoP estimation can be used directly for the fast charging of LIB [30, 31]. A typical study on data-driven SoP estimation is referred to [32]. A softmax NN-based strategy is proposed to estimate the SoP. The AI methods like dynamic programming [33] and deep reinforcement learning (DRL) [34-36] have also been used for the maximum power determination of LIB. Wei et al. [37] 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 solution. Within a similar framework, Yang *et al.* [38] proposed an soft actor-critic (SAC)-Lagrange algorithm to obtain the maximum charging current that satisfies the physical constraints. Furthermore, the side reactions of LIB were taken into account, and the maximum power estimation was realized with the SAC algorithm. A general framework of the DRL-based maximum power estimation is shown schematically in Fig. 4. It is worth noting that the models are involved as an environment for the DRL-based optimization [39]. However, the DRL-based estimator can be purely data-driven, provided that sufficient battery data are available. 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.

b) State estimation within the middle-term timescale

The data-driven strategies to benefit battery temperature estimation have been studied in the literature [40]. An electrochemical-thermal-NN model, as illustrated in Fig. 5, is combined with the unscented Kalman filter to jointly estimate the SoC and inner temperature in [41]. A data-driven method combining the RBF NN and the filtering method is used to estimate the inner temperature with higher robustness than the linear NN model [42]. A data-driven method combining LSTM and transfer learning is proposed to estimate the inner temperature of LIB under various current profiles in [43]. 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 [40].

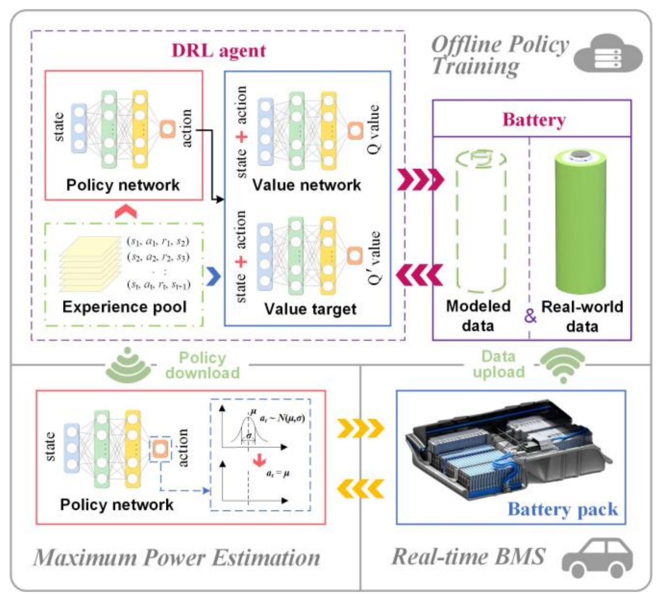

Fig. 4. General framework of the DRL-based maximum power estimation methods.

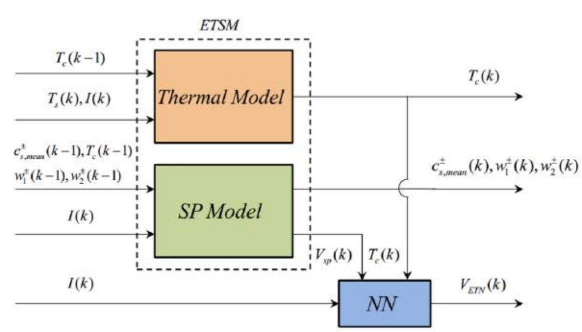

Fig. 5. Framework of electrochemical-thermal-NN model for joint estimation of battery SoC and inner temperature [32].

c) State estimation within the long-term timescale

The SoH belongs to a slow-varying state and is influenced by many ageing factors [44, 45]. Typically, the SOH can be

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characterized by both the capacity and the internal resistance, depending on the specific utilization scenario [46]. Since the association between these factors and SoH is highly nonlinear, data-driven solutions have become a powerful tool for SoH estimation. Estimation methods with direct use of BMS measurements are appealing without tedious data pre-processing. Roman et al. [47] developed a machine-learning pipeline for SoH estimation by combining parametric and non-parametric algorithms. Tang et al. [48] established a balancing current ratio-based data-driven solution to estimate the SoH, which reduced the dependence on cell-level models. To tackle the risk of low data quality and quantity, Bamati et al. [49] 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 method is that the peaks and valleys in DV curves cannot be easily identified [50]. Moreover, the DV trajectory is referred to the capacity, 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 reflect the ageing mechanisms of LIB, such as the loss of lithium inventory (LLI) and the loss of active material (LAM). Therefore, the features of IC curve can be utilized as health indicators (HIs) to estimate the battery SoH. This can be realized by mapping the HIs directly to the capacity [51, 52] or using fusion algorithms like Gaussian process regression (GPR) [53] and the Bayesian model [54].

A major challenge of the ICA method is the need of complete constant-current (CC) charging which is hardly available in a real-world environment. This is because the LIB systems, regardless of EV or storage application, are typically recharged before being depleted to a very low SoC. To mitigate this barrier, Wei *et al.* proposed a series of estimation methods relying on heavily-partial charging data applicable to wide scenarios. The methods promised high accuracy with easily-available data from the CC charging within narrow SoC ranges [55], CC-CV transient stage [56], and early CV charging data [57]. Moreover, the transfer learning has also been exploited in the literature to improve the estimation performance in practical complicated environment [58].

d) Future trend: rapid estimation for large-scale utilization

In typical battery storage applications, hundreds or thousands of cells are connected in parallel and series to meet the requirement of high power and energy. The cell inconsistency in large-scale applications becomes apparent and poses a big challenge for data-driven state estimation. For example, when the battery pack in an EV has reached its EoL during the first-life application, the cells within the pack need to be sorted and regrouped for further second-life applications. A major challenge for second-life applications is to estimate the states of hundreds/thousands of cells rapidly and accurately, since the cells present remarkable inconsistencies. It should be noted that the second-life application of batteries is becoming increasingly important as the number of retired batteries is increased significantly. Reports show that the volume of retired LIBs from EV will reach more than 12 million tons by 2030 [59]. In this context, it is essential to develop appropriate data-driven solutions that can extract the information of state inconsistency among cells, and estimate the battery states accurately and rapidly using limited measurements.

B. Life prognostic

The prognostics of battery future ageing information such as future capacity trend or battery lifetime is also of extreme importance to ensure high-performance battery operation, as illustrated in Fig. 6. Given the importance and necessity, there have been extensive works on developing data-driven methods for reasonably predicting the future aging of batteries in terms of capacity trend and lifetime [60]. Herein the battery future capacity trend refers to the future trajectory in which the battery capacity fades, while the battery lifetime stands for the time a battery reaches its EoL under a specific operating condition. Capturing the future capacity trajectory can help to better understand the ageing of LIB and benefit an efficient operation at the early stage [61]. Meanwhile, the accurate lifetime prediction can save testing resources after the manufacturing stage, and relieve utilization anxiety during the service stage.

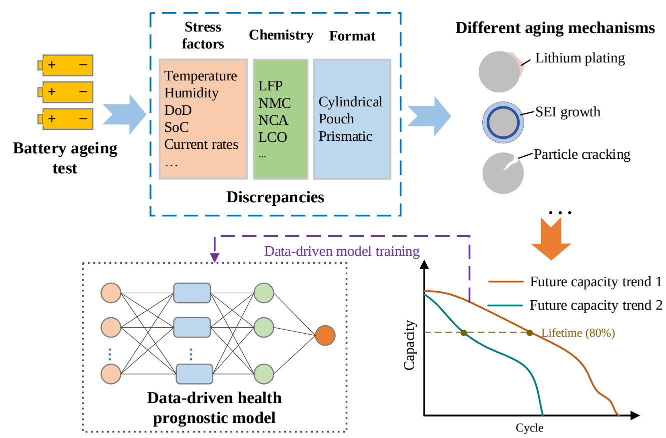

Fig. 6. Diagram of data-driven based battery ageing trend prediction

a) Prediction of future aging trend

There are a growing number of literature that adopt machine learning technologies to predict the future capacity trajectory of LIB based on the data collected both in the laboratory and in real operating conditions. A transferred recurrent NN-based method is presented in [62] to predict the future calendar capacity under both witnessed and unwitnessed storage conditions. In [63], a data-driven model is developed for the calendar health prognostics of LIB, realizing a satisfactory combination of complementary domain knowledge and data. Also, after integrating battery's electrochemical knowledge, such as the Arrhenius law, into machine learning, a modified GPR-based model is proposed in [53]. This model can predict the ageing trajectory of batteries under various operational temperatures and depth-of-discharge (DoD) conditions with satisfactory results for both one-step and multistep predictions. As the aging trajectory has strong time-series characteristics and great uncertainty, machine-learning methods that are capable of storing time-sequence information and providing probabilistic capabilities are preferred [64].

b) Prediction of battery lifetime

According to recent reports [65], the prediction of battery lifetime depends on the analysis of ageing mechanisms to extract useful features related to the battery lifetime [66]. To achieve this, characterization technologies have been adopted to obtain useful measurements such as impedance spectroscopy [67] and coulombic efficiency [68] for extracting valuable features. After that, machine learning and statistical methods are adopted to derive appropriate data-driven models that capture the relationship between the extracted features and battery lifetime. In [69], a probabilistic data-driven approach was developed to diagnose battery health. In [70], a machine learning method was developed for LIB lifetime prediction based on symbolic regression. This framework is capable of inferring physically interpretable models from cell ageing data without requiring domain knowledge. In [71], a unified LSTM-based method was designed to predict the battery lifetime. Consistent evaluation of different datasets shows strong scalability of the proposed model with less than 10 cycles of lifetime prediction. In [72], a data-driven model combining LSTM and GPR, as illustrated in Fig. 7, was proposed for lifetime prediction. The model can capture the long-term dependence of capacity and uncertainty caused by capacity regenerations, and thus appeals for both multistep ahead prediction and lifetime prediction at the early stage.

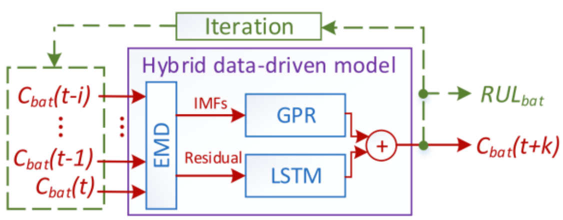

Fig. 7. Hybrid data-driven model combining GPR and LSTM to predict LIB future capacities and lifetime with uncertainty quantification [73].

c) Future trend

In spite of the successful use of data-driven approaches for predicting the future ageing trend and lifetime of LIBs, there are still many aspects that need to be explored to improve the performance of the data-driven solutions.

***Early battery lifetime prediction*:** The early lifetime prediction aims to predict the future lifetime of LIB using data from only the early operating cycles, where obviously-less ageing happens. Although obtaining battery lifetime in the early stage is crucial for forecasting the LIB performance and benefiting battery design, early lifetime prediction is challenging as the information involved in the early cycles is quite limited. The early lifetime prediction of the battery is rooted in analysing the electrochemical mechanisms in the start-up cycles and then extracting informative features closely linked to the lifetime of LIB. It was reported that the battery life could be predicted with a compact linear regression model after extracting appropriate features based on the data from the first 100 cycles [74]. Inspired by this, future efforts can be drawn to extracting more informative features from less cycling data, and developing advanced data-driven solutions. Moreover, combining the first principle elements [75] or physical models [76] with the data-driven approaches is also promising to reduce the complexity of lifetime prediction model.

***Battery knee point prediction*:** The LIB presents more non-linear aging paths in a form of two-stage capacity reduction if cycled extensively after the capacity drops below 80% (second-life applications). In particular, the capacity degrades initially in an approximately linear fashion, followed by a strongly-enhanced ageing rate. The point at which the capacity degradation rate before and after shows a clear difference is named the “knee point”. It is critical to predicting the knee point of LIB ageing since the battery performance after the knee point deteriorates rapidly. However, the works on developing data-driven solutions to predict the knee point of ageing at the early stage are still sparse. Some limited attempts have been reported [77]. The lack of knee point prediction would heavily hinder the cascading use of LIBs. In this context, it is worthwhile to explore feature engineering [78] or deliberate data generation solutions [79] to extract appropriate features from early cycling data. Effective data-driven solutions are also critical to capture the information on the knee point at the initial degradation stage. Such information is valuable to better understand the dynamics of battery aging in two stages and then design proper solutions to extend battery service life.

***Manufacturing information-based lifetime prediction*:** The current data-driven future ageing prediction focuses mainly on extracting features in the operation phase to predict battery lifetime. Although many advantages have been shown by using features from the operation phase, there are still obvious limitations especially considering the lack of research into the impact of battery manufacturing elements on battery lifetime. It should be known that battery manufacturing plays a critical role in determining battery health performance, further significantly affecting the lifetime of battery. As the battery manufacturing line is complex with many intermediate stages (e.g., mixing, coating, drying, etc.) and multidisciplinary operations, the features and parameters at each stage of manufacturing have a significant impact on the lifetime of the battery products [80]. Therefore, it is crucial to analyse the parameters within the manufacturing line and capture the battery lifetime at the key manufacturing stages. In this context, it becomes meaningful to develop appropriate data-driven solutions using information from the manufacturing stage to predict the battery lifetime. This can also be paramount to explaining the effects of manufacturing parameters involved. Moreover, with reliable manufacturing information-based lifetime prediction, the battery manufacturing line can be optimized to help the development of long-lifetime battery products.

C. Cell Balancing

Cell balancing is an essential and beyond-neglect aspect of battery management. Previous studies have shown that cell imbalances are common in both series and parallel cell connections. The capacity difference between series-connected

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cells will always be maintained due to the same discharge current in the string. The spontaneous-balancing effect between parallel connected cells cannot compensate for the uneven discharge pressure when continuous discharges [81]. Along with the repetitive charging-discharging cycles, the cell imbalance becomes increasingly severe because of the inconsistent cell aging rate without effective equalization measures [82]. In this regard, the aforementioned data-driven approaches can provide necessary input for detecting the cell imbalance. Specifically, the data-driven SOC estimation can provide real-time feedback on the degree of cell imbalance. Meanwhile, the SOH estimation and life prognostic can provide an essential reference for the adaptive update of critical parameters in the equalization strategies. State-of-the-art balancing methods can be found in recent works [83].

D. Fault diagnostic and safety warning

The abusive utilization of LIB may trigger a chain of side reactions that lead to irreversible damage and even catastrophic thermal runaway. Motivated by this urgent need, data-driven LIB fault diagnostic and safety warnings have been extensively investigated in recent years [84]. Some works are devoted to the detection of abnormal cells for coarse screening instead of diagnosing the specific type of fault. For example, Qiao et al. [85] investigated the anomaly detection of battery packs based on the statistical distribution, where the K-means clustering algorithm, Z-score method, and 3σ screening method were used to detect and find abnormal cells. From the perspective of fault category, the overheating, short circuit, and over-charge/discharge are typical faults associated with many reported data-driven diagnostic methods. Moreover, fault-tolerant estimation and control methods have also been investigated to enhance the performance of BMS with the faults of auxillary devices [86-88].

a) Overheating diagnostic

Overheating can be directly diagnosed if the temperature and local hotspot can be measured. However, the temperature sensing resolution in typical BMS is low due to the constraint of system complexity and cost. Therefore, the overheating diagnostic is dedicated to the accurate estimation of battery temperature with BMS measurements [89]. Hussein et al. [90] proposed an artificial neural network (ANN) model with reduced complexity for sensor-less temperature estimation of LIB. Zhang et al. [91] developed a data-driven multi-mode thermal propagation forecasting neural network fusion model for early over-temperature warning using thermal images and discrete BMS data. Li et al. [92] proposed a convolutional and long short-term memory neural network (CNN-LSTM) model, to predict the temperature of EV batteries accurately. Ojo et al. [93] presented an improved LSTM to estimate the battery surface temperature. Li et al. [94] proposed a convolution recursive diagnostic network for LIB temperature estimation by using an adaptive thinning algorithm combined with LSTM and time convolution network. Ding et al. [95] developed a meta-thermal runaway forecasting neural network for LIB. The thermal distributions were captured with thermal images and low-dimensional temperature and voltage features.

Generally, the reported data-driven overheating diagnostic is realized by accurate surface, or internal temperature estimation combined with the machine learning approaches [96, 97]. Such methods are favorable for single-cell diagnostic. However, the feasibility should be declined for pack-level application, taking into account the non-ignorable cell inconsistency and abundant parameters for calibration. Diagnostic based on thermal images, albeit limited, can be promising for large-scale applications. A potential challenge is the elevated cost and space occupancy due to the need of thermal image acquisition. The effective extraction of thermal features is also challenging due to the low resolution of typical thermal imaging techniques.

b) Short circuit diagnostic

Short circuit faults are destructive due to the large amount of energy loss and the potential to trigger unwanted thermal events rapidly. As described in [98], the external short circuit (ESC) can cause abnormal heat generation due to uncontrollable electrical and thermal dynamics, which can risk triggering dangerous thermal runaway. In the case of an internal short circuit (ISC), regardless of the cause, an internal current path is established between the active materials of the cathode and the anode. This further promotes the local current, which leads to a quick temperature build-up [99]. To date, the works on short circuit diagnostic are relatively limited. Hu et al. estimated the current passing the short-circuit path with real-time current and cell voltage [100]. With the aid of adaptive filtering techniques, the equivalent short circuit resistance can be determined to reflect the severity of the short circuit accurately. An ANN-based diagnostic method was developed to estimate the short-circuit current and further predict the temperature rise and temperature distribution of an ESC cell [101].

It is worth noting that the ISC remains a major challenge for LIB safety management for many years and will remain in the future. This is rooted in the fact that the ISC can be formed from different sources, including manufacturing defects, abusive utilization from the mechanical/thermal/electrical perspective, and self-triggering during long-term degradation. In addition, the external performance can be highly diverse and uncertain for different routes or even a single pattern of ISC. Therefore, the diagnostic in a practical LIB pack can be much more complicated than the results in laboratory conditions.

c) Over-charge/discharge diagnostic

Cells are integrated into a battery pack to achieve the desired capacity and power, which easily leads to remarkable cell inconsistency and the over-charge/discharge problem [102]. This can further induce unfavorable consequences like the irreversible capacity loss and safety issues. Based on an improved Gaussian mixture model (GMM) and feature fusion, Tian et al. [103] proposed a pack inconsistency evaluation method to assess the battery characteristics accurately. Relying on the spatial-temporal images converted from the LIB electrical characteristics, a multi-fault joint diagnosis method was proposed for packs using the texture analysis [104]. Zhang *et al.* [105] present a 2-Dimensional Gaussian filter to improve the pseudo random sequence method, which contributes to measuring the battery impedance accurately for fault diagnosis. To date, the diagnostic methods of over-charge/discharge using electrical signals are relatively limited. One major difficulty is the outer similarity and cross-interference of multiple faults during the diagnostic.

III. Multi-Dimensional Sensing-Enhanced Management

As overviewed in Section II, the data-driven approaches have been widely developed for the state estimation, life prognostic, and fault diagnostic of LIB. However, the data available for use is mostly confined to the battery current, voltage and surface temperature. As known, the performance of LIB is dominated by the physics linked closely to the inner parameters and statues. The lack of inner information is a primary challenge for the further improvement of BMS. Motivated by this, new sensing techniques applicable to LIB have been focused on in recent years to obtain more signals of value to the battery management. Moreover, the efficient use of multi-dimensional data to enhance the management performance has also been studied. This will be an important supplement to the methods reviewed in Section II, and push the existing management system to a microscopic level. This section summarizes the progress of emerging sensing techniques for battery use and the potential of new information utilization in future BMS.

A. New sensing techniques for lithium-ion batteries

The present sensing systems in BMS can only collect macro information like current, terminal voltage and surface temperature. It is difficult to obtain the inner or micro information, such as the strain, pressure, and expansion related to the variation of battery states. However, this inner or micro information is essential for evaluating the battery’s working status. In specific, the inner temperature of LIB is more insightful than the surface one, since it reflects better the condition of inner active components. The volumetric change in cell level is relevant to many important electrochemical processes [106]. Considering the potential benefits of improving the current BMS, new sensing protocols have been studied in recent years to acquire more insightful information of LIB for more efficient management.

To date, the sensing techniques reported for LIB utilization can be generally classified into five categories, including the electrical, thermal, mechanical, chemical and gaseous types, depending on the physical detection objective. The categories and some representative sensors are summarized in Fig. 8, while more detailed use for battery management will be elaborated in the following subsections. It is worth noting that the primary focus of this review is the use of new sensing data to enhance the battery management. A comprehensive review of the battery-oriented sensing techniques will not be elaborated herein but the reader can refer to the existing review works [14].

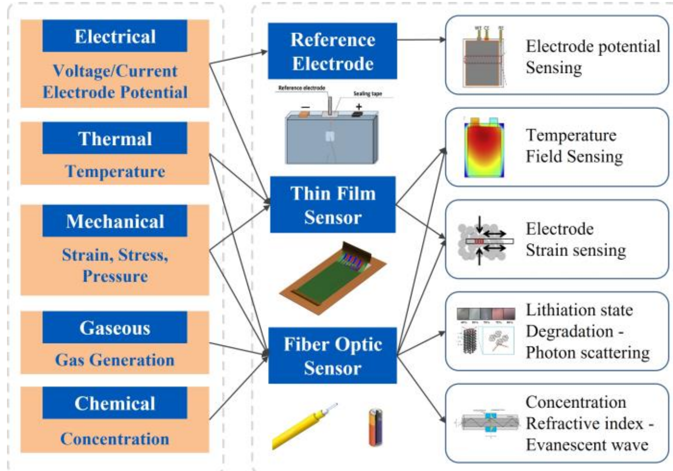

Fig. 8. Categories and representative sensors for battery monitoring

B. New sensing techniques-enabled state estimation

Commonly-used state estimation methods rely on sensors equipped with the BMS. The availability of new sensing techniques and the associated signals is promising to provide new solutions for high-fidelity state estimation.

***a) Strain sensing-based state estimation*:** The structural change of microscopic lattice induced by lithium intercalation and deintercalation will be transformed into the periodic expansion and contraction of the cell or electrode, which are related strongly to SoC at the macroscopic scale. Therefore, the strain signal can be used to provide a new solution and potentially improve the existing SoC estimation techniques relying on pure electrical signals. This has been a hot topic recently, even though relevant studies are still quite limited. Based on the strain measured by the FBG sensor, a semi-empirical model was developed and further incorporated with the filtering techniques to estimate the SoC in real time [107]. Subsequently, real-time SoC estimation with FBG-based strain signals was realized using a dynamic time warping algorithm [108]. A model-free SoC estimation method was reported using the non-electrical signals in a data-driven fashion. In particular, the FBG-measured strain and battery temperature were used as the inputs of DNN for accurate SoC estimation [109]. The encouraging results observed in these works further validate the strong correlation of the strain to the SoC of LIB.

The long-term timescale battery SoH can also be estimated by using the strain change of LIB. This is rooted in the fact that the capacity loss and strain divergence show a strong correlation during the ageing of LIB. Illustratively, cycling experiments suggested that the capacity of LIB dropped to 93.7% after 400 cycles, while the strain difference between the fully-charged and discharged states rose from 40 μm/m to 120 μm/m at the same time [110]. Therefore, the strain can be an informative signal to estimate the SoH of LIB with data-driven approaches. There have been some initial studies regarding this point in the literature. Enabled by the FBG sensing, the strain signals at the end of each charging cycle were collected and used to estimate the battery SoH in [107]. It was shown that the strain-based new estimator was able to predict battery capacity

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accurately 10 cycles in advance. The variation of peak strain during charging was used to correlate with the capacity fade and further to estimate the SoH of LIB in [111].

It is worth noting that different battery states are coupled and interact with each other. Therefore, joint state estimation utilizing multidimensional data becomes a promising research direction. A machine learning framework for SoC and SoH joint estimation is proposed in [112]. In particular, the FBG-measured wavelengths that contain both strain and temperature information were input directly to a GPR model to estimate the SoC and update the SoH subsequently.

***b) Thermal sensing-based state estimation*:** The inner temperature is essential reflecting the thermal condition of LIB and underlies other battery management tasks. As discussed in Section II-A, the inner temperature of LIB is commonly estimated indirectly with various algorithms using the directly-measured surface temperature [113-115]. With the availability of new thermal sensing techniques, especially for the embedded micro-sensors, the inner temperature is possible to be monitored directly without complicated algorithms. To date, different types of thermal micro-sensors have been used to measure the internal temperature of LIB in the literature. Illustratively, the inner temperature of LIB was measured with embedded micro-thermocouples, and a remarkable temperature gradient over 10 °C was observed in [116]. Under the overcharge condition, the internal temperature of the coin cell battery is up to 48.4 °C, while the highest external temperature is only 27.9 °C.

Moreover, the inner temperature sensing can also benefit the estimation of other important battery states. A typical work can be referred to [117], where the thermal impedance, heat generation rate, SoC, and maximum capacity were estimated simultaneously based on the data acquired by an embedded and distributed temperature sensor. Furthermore, the distributed temperature sensor also enables the efficient calibration of thermal impedances and accurate thermal state estimation [118]. These works also inspire the design of future smart batteries for efficient self-state monitoring.

***c) Optical signal-based state estimation*:** Optical signals obtained from the inner environment of LIB also demonstrate a strong correlation with the electrochemical and degradation states of battery [119]. To date, optical signal-based battery management is still less explored in the literature. For the short-term scale estimation, the graphite lithiation process was measured by optical fiber sensors, and the obtained optical signals were used as effective indicators to infer the SoC of LIB [120]. In a longer timescale, the slope of the optical transmittance was observed to be highly relevant to the capacity fade of LIB [119]. This demonstrated the feasibility of using the optical signals to predict the capacity fade of LIB. Moreover, the *in-situ* fiber optic evanescent wave sensors were embedded into the LIB cell to directly measure the metal deposition on electrodes [121]. This measurement can also facilitate the early warning of lithium dendrites of LIB.

C. New sensing techniques-enabled fault diagnostic

The use of new sensors can provide valuable information to improve the performance of fault diagnostic. This has been witnessed by the initial attempts to use various types of micro sensors for the early warning of LIB faults.

***a) Thermal micro sensor-based diagnostic*:** The temperature inhomogeneity can be utilized for timely fault diagnostic with embedded thermal micro-sensors. This necessity is rooted in the temperature inhomogeneity between the surface and the inner temperatures, especially with the occurrence of undesirable thermal events. With the occurrence of external short circuit, the measured inner temperature rose to 82 °C within 6 s, ~30 °C higher and 3 times faster than the surface temperature variation [116]. A similar phenomenon can be found in [122]. The observed pronounced temperature build-up has been used to diagnose the short circuit events more efficiently [116]. Under the overcharge condition, the internal temperature of battery is up to 48.4 °C, while the external temperature is only 27.9 °C. In this case, the internal RTD detected 90% of the maximum temperature rise in 7.45 s on average, ~10 times faster than the external RTD [123]. This also suggests the possibility of using internal thermal sensors for overcharge warning.

Moreover, the inner temperature has been suggested to be several hundreds of degrees Celsius higher than the surface during the triggering of thermal runaway events [124]. The fast temperature rise is hardly detectable with surface temperature sensors within a timescale that allows to shut off the cell before the occurrence of serious consequences. Therefore, implanting the thermal micro-sensors into the cell is promising for the timely warning and protection of thermal runaway. Illustratively, the embedded RTDs detected the onset temperature of solid-electrolyte interface decomposition 10 s earlier than the surface sensors during the overcharge-triggered thermal runaway [125]. This suggested that the RTDs were effective for the early warning of thermal runaway of LIB.

***b) Reference electrode potential sensor-based diagnostic*:** Lithium plating leads to irreversible capacity fade and even the formation of lithium dendrites that pierce the separator and cause internal short-circuit, which could lead to thermal runaway in severe cases. In this regard, the reference electrode method has been frequently used to measure real-time anode potential, indicating the occurrence of lithium plating. A three-electrode LIB with metallic lithium as the reference electrode was fabricated to measure the anode and cathode potential in [126]. Results showed that the lithium precipitation occurred during charging and was exacerbated by high currents or low temperatures. Therefore, lithium plating detection method is further used to guide the development of fast charging strategy. The microprobe Li/Cu reference electrodes were used to characterize graphite anodes in [127]. With 6C fast charging, the anodic potential dropped to negative, measured by the reference electrode. The occurrence of lithium plating was verified by post-mortem analyses. A lithium plating-free fast charging method was proposed using lithium metal as a reference electrode on three-electrode pouch cells [128]. This was realized by maintaining the anode potential at a level slightly above 0 V vs. Li/Li^+. Similarly, a fast-charging strategy without lithium precipitation was proposed for a 120Ah large-format LIB, with the reference electrode used for potential

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measurement [129]. The capacity decay after 100 cycles was similar to that with slow charging. In spite of the successful use of reference electrode for strategy development, its use in commercial LIBs is challenging due to the quick failure and loss of accuracy in LIB inner environment.

***c) Deformation sensor-based diagnostic*:** With the presence of lithium plating, an additional increase in cell thickness can be expected for the LIB. Therefore, it is theoretically practical to use the space deformation signal to detect the lithium plating. The thickness measurement was proposed to detect lithium plating for the first time in [130], where a dial indicator was installed on the top surface of the pouch cell to measure the thickness. During −5 °C charging, the thickness was observed to increase progressively due to the lithium plating. Subsequently, laser scanning was used to detect the change of local cell thickness at multiple locations, which was further used to indicate the local lithium plating [131]. The thickness variation of LIB was found to correlate strongly with the severity of lithium plating. Furthermore, the reversible deformation heterogeneity derived from mechanistic information was found to be relevant to lithium plating [132]. Therefore, the deformation sensing method also shows the ability to characterize local degradation inside the battery.

***d) Pressure, strain and gas sensor-based diagnostic*:** The inner pressure is another essential indicator for battery safety. The electrolyte of LIB decomposes into gas and causes pressure build-up during abusive operations. Motivated by this, the pressure sensors have been reported to diagnose the thermal runaway more timely than the widely-used thermal sensors [133]. In another practice, the internal pressure measured by the embedded optical fiber sensor was used to trigger the current interruption device [134]. Once the internal pressure reached a specific threshold, the current was cut off automatically to prevent the LIB from venting and firing. The strain information is also useful for fault diagnosis. By employing the FBG sensors, the strain was monitored to increase 45μm/m during overcharge [110]. Due to the dual sensitivity of FBG to strain and temperature, the temperature was also monitored to increase by 750 K during the thermal runaway [110].

Moreover, the growth of lithium dendrite generates hydrogen gas. Therefore, the hydrogen sensor can be sensitively used to warn the growth of lithium dendrites of LIB. From another perspective, CO_2 is the main gaseous component of the electrolyte decomposition reaction. Motivated by this, the fiber optic colorimetric sensor has been utilized to achieve the *in-situ* measurement of the gaseous CO_2 inside pouch cells, and this contributes to providing a timely warning for the risk of LIB overcharging [135].

D. Future trend

The acquisition of multi-dimensional sensing data, especially for the inner data, is highly valuable for circumventing the current challenges encountered by the traditional BMS. This is reflected by the following two aspects that can well represent the future trend in this field.

***a) Future self-sensing smart battery*:** With the availability of new sensing techniques, the integration of self-sensing smart battery can be a future trend. This is mentioned initially in BATTERY 2030+ Roadmap of Europe, where the goal of smart battery is defined as integrating multi-dimensional sensing into each single cell [136]. A conceptional design of the future smart battery is shown in Fig. 9. Within this framework, the data collected by cell-level sensors are used for self-monitoring and management. A wireless communication unit is also demanded to transmit the information to the upper-layer controller [81]. In this way, the important inner physical parameters can be perceived and used for more-refined battery management. A smarter and distributed management system can foreseeably promise the benefits of enhanced safety and longevity.

Despite the far-reaching goal of the ultimate smart battery, this trend has to be pushed forward by addressing several key challenges. Generally, the sensor integration of smart battery should meet several prerequisites, i.e., high tolerance to the inner battery environment, effective insulation, less impart to cell performance and long-term stability. These tasks eventually cause a rise of cell manufacturing costs, which barriers the quick commercialization of the smart battery.

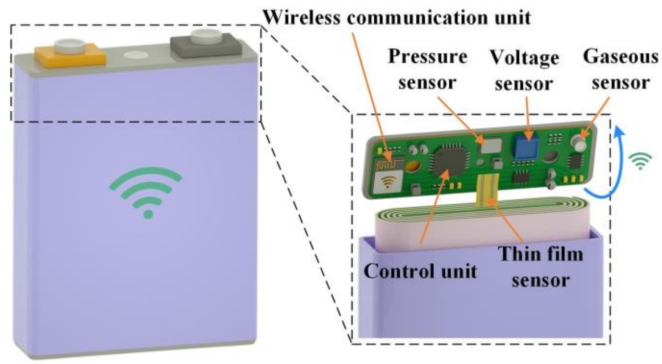

Fig. 9. A conceptual design of future self-sensing smart battery

***b) Digital twin-based enhanced management*:** Considering the difficulty of quick commercialization of smart battery, an alternative approach easier to implement is to deploy the digital twin-based management system leveraging the multi-dimensional data provided by the new sensors. The basic idea is to build refined multi-physical battery models with the mechanical, electrical and thermal data given by the outer/embedded sensors. The built multi-physical models will serve as "virtual cells" within the digital twin framework, which can support improved real-time management of LIB. Actually, this trend has been reflected in recently-reported works, where multi-dimensional sensing data were used to build physical models, which were further used for either the inner parameter estimation [117] or microscopic state-conscious active control of the LIB.

Nowadays, various technologies related to the digital twin such as cloud collaboration could be applied to enrich data-driven management solutions [137]. Therefore, it is technically feasible to build a digital twin-based enhanced battery management system fully exploiting the value of multi-dimensional sensing of battery.

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IV. Big data Battery Management

With the development of the Internet of Things and cloud platform technology, it is possible to record the operating data of large-scale batteries for the whole lifetime. The efficient mining and analysis of battery big data can be expected to provide valuable information for future battery management than the data-driven solutions discussed in Section II. Moreover, the exploitation of more multi-dimensional data from the cell level, as discussed in Section III, will also increase the data volume useful for battery management remarkably. Taking the two aspects into account, the big data technique can play a critical role in the future management systems of LIB. Therefore, this section overviews the current progresses and future trends of big data battery management.

A. Big data health diagnostic

As shown in Fig. 10, both the microscopic ageing mechanism analysis and the macroscopic health assessment have the potential to be realized with big data-driven battery diagnosis.

***a) Ageing mechanism analysis*:** For the former, the effect of capacity fade to the voltage characteristics is typically viewed as a critical clue to explain the ageing mechanism. In this case, the availability of battery big data can facilitate exploring relevant ageing mechanisms. Dubarry et al. [138] analyzed the ageing mechanism of $LiFePO_4$, Nickel Aluminum Cobalt Oxide and Nickel Manganese Cobalt Oxide 811 batteries using big data, where the law of battery ageing was explored through ICA. With this method, the individual contributions of LLI and LAM to the overall capacity drop were revealed explicitly. Moreover, it is known that the loss of electrode material leads to a change of the open circuit potential of the electrode. Consequently, Tian et al. [139] investigated the law of LLI and LAM-induced battery ageing using an empirical OCV model with massive OCV data.

***b) Big data health prognostic*:** In terms of big data battery health evaluation, most of the existing methods are oriented to the laboratory environment, unable to learn the unpredictable driving behavior and complex road/weather conditions in actual vehicle applications. The same problems exist considering the applications in grid and household energy storage, where the load and environmental conditions are also highly uncertain. To remedy this deficiency, recently-reported big data diagnostic methods incorporate the historical data of both battery operation and environmental conditions [140]. Hong et al. [141] established a real-world degradation model by fitting the degradation factors to the vehicle operating parameters, such as the ambient temperature and accumulated mileage. Considering the significant effect of temperature on battery life decay, an empirical capacity attenuation model was developed with temperature offset compensation [142]. Wang et al. [143] proposed a data-driven method based on a large amount of real EV performance data to diagnose battery charging capacity, where a statistics-based approach is used to diagnose battery charging capacity anomalies by analyzing the error distribution of a large dataset. He et al. [144] proposed a method for estimating SoH based on actual data on the behavior of EV users, where a locally weighted linear regression algorithm based on historical charging data was used to qualitatively characterize the capacity decline trend.

Compared to the empirical methods, the closed-loop estimation methods have also been widely explored attributed to their high robustness. The associated challenge is the high computing complexity due to the involvement of mechanism models and high-dimensional computation. Fortunately, the development of cloud technology makes it possible to implement the battery digital twins, which allow the use of complex algorithms within the end-to-cloud framework. Li et al. [137] proposed an SoH estimation method based on particle swarm optimization to monitor the capacity and power attenuation in the cloud server. It is worth noting that the data acquisition of BMS is subjected to remarkable noise corruption, which can decline the accuracy of estimation. To address this problem, a Kalman Filter modified by fuzzy logic was proposed to mitigate the impact of noises [145]. As a matter of fact, the unknown OCV-SoC relationship challenges the model-based capacity estimation algorithms in practical applications. To mitigate this barrier, the unknown OCV-SoC function coefficients were combined into the state vector and observed jointly in [103].

Recently, the development of AI has opened the possibility of intelligent battery health diagnosis. Song et al. [146] analyzed the one-year data of a hybrid electric vehicle, and an SoH estimation method based on the feedforward neural network was established. Most recently, an SoH estimation method based on multi-model fusion was proposed for a plug-in hybrid vehicle by combining the support vector machine, Gaussian process regression, and ANN [147]. A clustering multisource fusion-based feature extraction method was proposed to enrich the feasible health features, and the XGBoost algorithm was used to estimate the SoH with improved accuracy [148]. Leveraging the radial basis function neural network model, She et al. [149] established an estimation method which described the mapping between the IC peak and SoH. Evidently, AI techniques are intrinsically powerful for analyzing the inner mechanisms hidden behind the large amount of battery operating data [150]. The appropriate combination of AI techniques and the battery big data can potentially boost the performance of battery health diagnostic in the near future.

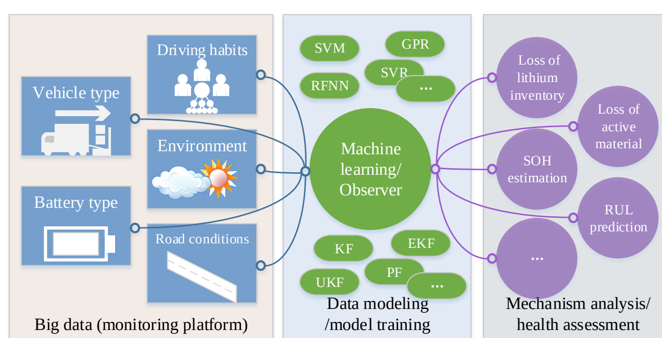

Fig. 10. Battery health diagnosis based on big data

B. Big data fault diagnostic and safety warning

The existing big data battery safety warning methods can be classified according to the used algorithm and data dimension, as summarized in TABLE I. As can be seen, the traditional statistical methods generally include the entropy and correlation analysis. They are efficient but preferable to be utilized for one-dimension data analysis. By comparison, the machine learning methods, including both supervised and unsupervised learning, are superior for multi-dimension data processing, even though the algorithmic complexity elevates in accordance.

a) Statical analysis**:** Battery voltage has always been an important signal that conveys abundant fault information, albeit inexplicit. It is typically hard to distinguish the subtle voltage abnormity during the early incubation stage of battery fault. Therefore, statistical analysis was applied to improve the usability of voltage measurements. In particular, the entropy analysis is widely used. The Shannon entropies of voltage were calculated and the Z-scores of Shannon entropy were evaluated to detect and predict the battery fault in [6]. With an improved relative entropy-based data-driven approach, Sun et al. [151] developed a short-circuit detection method for LIB pack. Hong et al. [84] applied a modified multiscale entropy to calibrate the sensitivity factor and abnormal coefficient, which were further utilized to diagnose the thermal runaway of LIB.

Alternatively, the abnormal detection can also be realized by correlation analysis. To be specific, a voltage correlation coefficient-based method was proposed in [152] to detect the battery fault. The voltage correlation coefficient of every adjacent cell pair was calculated and used for fault diagnostic with a pre-defined threshold. Furthermore, Lai et al. [153] reported an SoC correlation coefficient-based method to diagnose the early-stage ISC fault. The estimated SoC and the correlation coefficient were calculated in a moving window to ensure reasonable real-time performance.

Other methods belonging to the scope of statistical analysis have also been studied for LIB fault diagnostic. Illustratively, based on the interleaved measurement, Zhang et al. [154] proposed a multi-fault detection method, where the calculated voltage and temperature residuals were evaluated by cumulative sum test, and the entropy method was used to capture the battery fault. Wang et al. [155] proposed a statistical method to evaluate cell inconsistencies based on a large amount of real-world EV deployment data. Liu et al. [156] assessed the voltage consistency of EV batteries, where a web-based method for assessment of battery pack compliance status based on big data is developed based on the statistical method of outlier values. Chang et al. [157] proposed a micro-fault diagnostic method based on the consistency of the evolution of the relative battery position over several charging segments.

b) Machine learning approaches**:** Compared to the statistical analysis, machine learning approaches are promising for big data LIB fault diagnostic attributed to the superiority in multi-dimension data processing [158]. Unsupervised learning has been attempted for this purpose in the literature. The 3σ multi-level screening strategy and the local outlier factor algorithm are proposed in [159] for voltage abnormity detection and clustering. In [160], the discrete Fréchet distance of temperature measurements and the standard deviation of voltage measurements are calculated in a real-time manner. Hence, the local outlier factor is utilized to realize fault clustering and early warning of battery thermal runaway.

Supervised learning has also been studied and validated in the literature for the big data LIB diagnostic. Hong et al. [161] proposed a machine learning-based fault diagnosis method by using the LSTM NN to prognose the voltage abnormity. Furthermore, a battery fault diagnosis method based on the combination of a neural network and an equivalent circuit model was proposed in [162], which uses a pre-selected model to reduce the calculation time. In [92], a long short-term memory neural network is combined with a coevolutionary neural network to predict battery temperature and detect battery abnormal heat generation with multi-dimension inputs of vehicle state, driving behavior, and local weather.

c) Hybrid approaches**:** In addition to the statistical and machine learning methods, hybrid approaches have also been studied and proved with expected performance for fault diagnostic. A three-layer statistical fault detection method was proposed in [163]. The cells with the highest and lowest voltage in a pack were distinguished in the first layer. The 3σ criterion was used in the second layer to screen the risky cells and calculate the cluster center, which was used in the third layer to identify faulty cells by the K-means method. By combining multi kinds of kernel function, a kernel principal components analysis-based method was proposed in [164] to detect the ISC fault of LIB. The kernel principal components analysis was adopted to calculate the fault indicator with voltage measurements of LIB. Jiang et al. [165] developed a state representation-based method for fault diagnosis and thermal runway warning of LIB pack using the normalized battery voltages. The state representations contributed to easing the fault detection by enlarging the voltage abnormity.

It is hard to figure out which category of methods is better for the big data fault diagnostic of LIB. However, with the rapid development of big data platform, cloud computation, and machine learning techniques, the big data-driven diagnostic of LIB is clearly recognized as a promising solution, since the demand for massive data storage and fast processing can be expected to be fulfilled in the near future.

The big data-based management of battery packs has also shown a great potential and possibilities for regional electric vehicle networks and power systems. This has been reported in the recent works, although quite limited. By implementing the big data-based management, vehicle operations can be better coordinated, power distribution can be optimized, and energy waste can be reduced [166, 167].

It is worth noting that the cybersecurity is vital to the big data-based battery management. A two-step process is generally required to defend against the cyberattacks. The first step is characterized by the quick detection of the fake data, while the subsequent step entails implementing corrective measures to mitigate the impact of the attack. Dey et al. [168] proposed a filter-based approach for the detecting the abnormal data dynamically. A multi-objective criterion was employed and validated with the superiority in terms of attack detectability. Guo et al. [169] designed a physics-guided machine learning method to detect the cyberattacks imposed to EVs, which demonstrated a high accuracy for detection under various driving scenarios. Kim et al. [170] analyzed the potential threats of BMS from cyber and physical attacks. On this premise, attack-defensive strategies were developed with the adoption of the blockchain technology. Generally, the cybersecurity problems involved in EVs and BMSs have been emergingly studied in recent years, giving rise to a variety of approaches

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for detecting the injection of fake data so that the corrective actions can be implemented to mitigate the impact of the attacks.

TABLE I
BIG DATA SAFETY WARNING CATEGORIES

		1-Dimension	Multi-Dimension
Traditional statistical Method	Entropy	[6, 84, 151]	-
	Correlation Coefficient	[152, 153]	-
	Other	[154-157]	-
Machine-learning Method	Supervised	-	[92, 161, 162]
	Unsupervised	-	[159, 160]
Hybrid Method		-	[163-165]

C. Big data platform

Big data platform (BDP) is a kind of network platform that provides services in the form of massive data storage and resource sharing. BDP is the fundamental element of the future big data battery management systems. Generally, there are five components of BDP, i.e., data source, data transceiver system, big data infrastructure system, big data analysis system, and data visualization, which are shown schematically in Fig. 11. In recent years, BDP has received more and more attention from both the academic community and industry attributed to their unique advantages of huge data volume, high timeliness, and fast service request response.

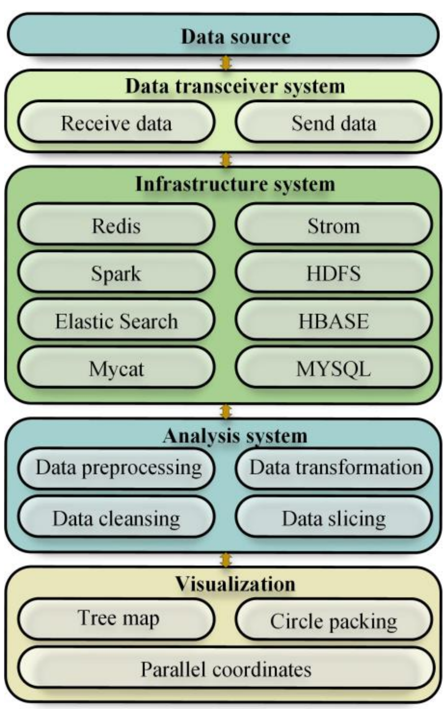

Fig. 11. General components and structure of BDP.

Data source underlies the big data-driven battery management, and thus serves as the kernel of BDP. It is well recognized that the data sharing and big data utilization has been a trend over the world for more efficient and intelligent industrial application. Narrowing the focus to the battery management, China government has set up the National Monitoring and Management Center for New-Energy Vehicles. Massive battery operating data are collected from the new-energy vehicles and stored in the data center. Another example can be refered to the big-data platform established by the Mitsubishi heavy industries group, which can realize the operating data collection, data analysis, demand prediction, and operation optimization for the large-scale LIB application [171].

Data transceiver system aims to present the information from the data source to the big data-base system, which can be viewed as the intermediaries of BDP. Furthermore, the big data infrastructure can transfer the data from one endpoint to another. Apache Map Reduce is a typical framework for distributed processing [172]. Meanwhile, Apache Spark is an open-source distributed framework for big data processing with good adaptivity to machine learning solutions [173].

To achieve the efficient data utilization, the big data analysis system provides a variety of interfaces for data exchange. The system is oriented toward the de-privatization, normalization, filtering, and consolidation of the imported big data. Technically, it also works on the tasks of data preprocessing, data cleaning, data remedy and slicing [174]. Based on the CHAIN framework, Yang et al. [175] presented a cloud-based battery management system, where the battery data were collected and analyzed for fault diagnostic and failure warning.

Visualization is mostly a graphical display of data, which can help to integrate multiple data points together. This component facilitates the quick understanding of data relationships, and more-easily identification of events not easily perceived [176]. Generally, big data visualization is realized with different construction methods according to different data types. As described in [177], there are three common methods for data visualization, i.e., tree map, circle packing, and parallel coordinates. Chen et al. [178] presented a VizLinter framework to help users detect flaws and rectify already-built but defective visualizations. It consists of two components: a visualization linter to inspect the legitimacy of rendered visualizations, and a visualization fixer to automatically correct the detected violations according to the linter. Chou et al. [179] developed a modern PRS data replication solution to achieve efficient data aggregation for heterogeneous storage structures.

The cloud computing and IoT technology can be used to ensure the data transmission and real-time sharing [180]. By storing data in the cloud and using IoT technology to collect and transmit data, real-time sharing and transmission of data can be achieved. Moreover, the use of blockchain technology can ensure the security and integrity of data. At the same time, 5G technology can provide faster and reliable data transmission with lower latency [181]. Furthermore, digital twin technology can create a virtual model of the battery pack in the cloud [182]. By simulating and analyzing the operation status of the battery pack, the lifetime and performance of the battery pack can be predicted, and thus better maintenance plans can be developed. It is worth noting that the data privacy is critical to the big data-based management. In this regard, the encryption and access control technology have been used in practical applications [183]. By encrypting the data or adopting the access control mechanisms, only authorized users can get access to the battery big data so that the data security can be enhanced.

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D. Future trend

The battery management-oriented BDP has been widely focused in recent years. Illustratively, a full-function big data platform has been successfully launched and operated for the purpose of battery management. The Contemporary Amperex Technology Co., Limited (CATL) company has established an enterprise-level battery BDP. The system collects and stores the full-lifetime data of battery R&D, testing, production, operation and failure analysis. Based on the collected data, the BDP supports intelligent battery data analysis, state monitoring, and safety assessment via data mining and AI techniques. It is foreseeable that the deployment of BDP for enhanced battery management will be a major trend in the future.

However, it is worth noting that the battery system generates massive data in a short period under the large-power energy storage scenarios such as EVs and energy storage plants. This requires the BDP with the capabilities of fast data storage and processing, i.e., the high-speed BDP [184]. The key technologies of high-speed BDP are summarized in Fig. 12. Existing works have exhibited the realization of high-speed database management using distributed storage, clustered processing, and intelligent data management. Furthermore, combined with the data management methods like big data warehouse and service sharing, a high-speed data storage framework is expected to be realized with efficient "storage-generalization-usage" coordination. In terms of fast data processing, the available AI approaches can realize the intelligent software platform and distributed hardware platform for big data based on multi-intelligence collaboration [185]. The combination of software and hardware platforms constitutes an AI-analysis platform for big data with the potential for exponential data processing in seconds.

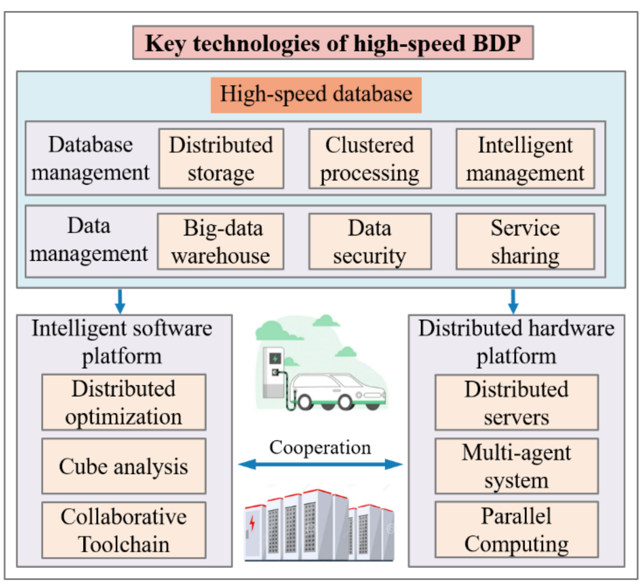

Fig. 12. Key technologies towards a high-speed BDP

V. DISCUSSIONS

The data-driven battery management have been extensively explored for many years. Existing methods generally rely on the current, voltage and surface temperature for management within the cell or pack level. Challenging this mindset, the big data-driven technology can be a promising direction for the future battery management with enhanced performance. With battery big data covering the whole lifetime and various working scenarios, a variety of management tasks can see new solutions, especially for the challenging health evaluation, lifetime prediction, abnormal diagnostic and risk pre-warning.

A potential challenge of the big data-driven management is still the lack of battery inner information. To this end, the embedded sensing technology can be a good supplement to remedy this deficiency. The smart cell with embedded sensors may have a long way for commercialization. However, the lab-scale embedded sensing tests and data can provide important support for building refined battery models or management strategies. These models and strategies can be combined with the battery big data tehnique, for instance within a digital twin framework, for more efficient performance analysis, life prediction and fault diagnostic.

In summary, based on the present management technologies, big data-driven management is highly prospective for the future enhanced management of LIBs. Within this scope, the emerging battery-embedded sensing techniques can provide important models and data support to extend the value of big data, and in accordance improve the performance of future battery management.

VI. CONCLUSION

This review article overviews the recent progress and future trend of data-driven battery management from a multi-level fashion. The primary conclusions are drawn as follows:

1) The data-driven battery management has been extensively studied over the past decade, giving rise to myriads of methods regarding multi-timescale state estimation, life prognostic, fault diagnostic and fast charging. However, some critical challenges exist for future investigation, like the rapid state estimation for large-scale batteries, early-stage lifetime prediction, knee point prediction of quick degradation, and manufacturing information-incorporated lifetime prediction.

2) The emerging sensing techniques open new paradigms for the future data-driven battery management. To date, electrical, thermal, mechanical, chemical and gaseous sensors have been reported for use in LIBs. Enabled by this, alternative data-driven methods for state estimation, life prognostic, and fault diagnostic have been developed. Following these progresses, the development of smart battery and digitial twin smart management system are viewed as the future trend.

3) Big data-driven battery management is promising due to the fast advances of big data technologies. To date, statistical and machine learning approaches have been developed for battery big data-driven management, but relevant works are still in the nascent stage. Moreover, some critical challenges for big data deployment still exist, like the development of high-speed BDP and more efficient data mining methods.

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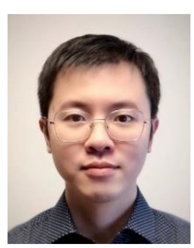

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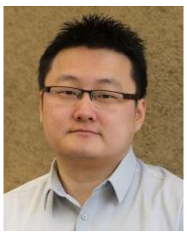

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