© April 2022 | IJIRT | Volume 8 Issue 11 | ISSN: 2349-6002

Study of varies methods on the estimation of state of charge and state of health for lithium_ion batteries in electric vehicles

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Abstract:With electric vehicles (EVs) being extensively accepted as a clean technology to break carbon emigrations in ultramodern transportation, lithium-ion batteries (LIBs) have surfaced as the dominant energy storehouse medium in EVs due to their superior parcels, like high energy density, long lifetime, and low tone- discharge. Performing real-time condition monitoring of LIBs, especially directly estimating the state of charge (SOC) and state of health (SOH), is pivotal to keep the LIBs work under safe state and maximize their performance. Still, due to thenon-linear dynamics caused by the electrochemical characteristics in LIBs, the accurate estimations of SOC and SOH are still gruelling and numerous technologies have been developed to break this challenge. This paper reviews and discusses the state-of-the- art online SOC and SOH evaluation technologies published within the recent five times in view of their advantages and limitations. As SOC and SOH are explosively identified, the common estimation styles are specifically reviewed and bandied. Grounded on the disquisition, this study ultimately summarizes the crucial issues and suggests unborn work in the real- time battery operation technology. It's believed that this review will give precious support for unborn academic exploration and marketable operations.

***Index Terms*: State-of-charge, state-of-health, lithium-ion battery, fractional-order model, dual Kalman filter.**

I. INTRODUCTION

Dealing with the pressure from environmental damage and energy extremity has been one important task for all countries (Akinlabi and Solyali, 2020). Electric vehicles (EVs) have been extensively accepted as a clean transportation technology to reduce the reliance on fossil energies, and play an important part in decelerating down global warming rate thanks to the exploitation of the sustainable energy (Wang etal., 2020d; Al-Ghussain etal., 2021), and the development of energy operation technologies (Gong etal., 2020; Lan etal., 2021). As the energy power for the EVs, batteries are the most critical part in the performance and safe handling of EVs. A variety of rechargeable batteries are developed as energy storehouse for EVs in which lithium-ion batteries (LIBs) became the dominant power storehouse result, owing to their unique graces similar as high viscosity and long lifetime (Guo etal., 2021). For illustration, the battery systems not only serve to drive the electric motor, but also supply power to other electronic systems. EVs frequently work in complex working conditions, similar as frequent acceleration and the charging geste from humans is frequently arbitrary. Likewise, the battery is an electrochemical system so that the high nonlinearity and time- varying characteristics make the state estimation veritably gruelling (Eeetal., 2021). Thus, developing accurate and dependable technologies in BMS is still a demanding task to insure batteries and the affiliated energy systems work in a safe state and maximize their performance.

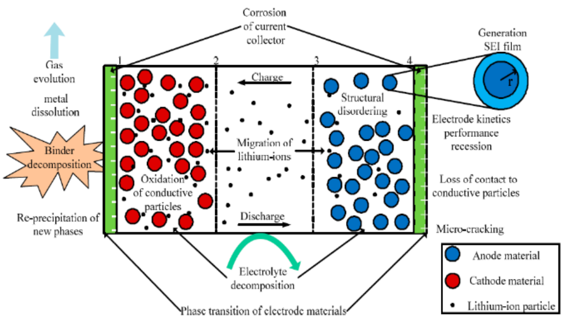

Fig:1Basic schematic of lithium_ion battery aging

Battery Operation technologies involve various types of estimations, similar as the state of charge (SOC), state of health (SOH), state of energy (SOE), state of power (SOP), state of temperature (SOT), and state of safety (SOS). Generally, the explosively identified SOC and SOH monitoring are the main enterprises and the base to ameliorate trustability and insure safety (Hu etal., 2018b). The SOC estimation of LIBs aims to check the remaining capacity of a battery during a charge – discharge cycle, which can avoid the overcharging and over discharging of the battery. In particular, the battery SOC changes with time when charging/ discharging and it's an important factor for farther SOH prediction. The open- circuit voltage (OCV) system is performed grounded on the functional OCV – SOC relationship.

In terms of SOH estimation, the online estimation styles are distributed into the differential analysis (DA) system, model based method, and data-driven method. The offline styles correspond of capacity measurement and internal resistance measurement in which capacity and internal resistance are the two main declination parameters of the battery. These two declination characteristics can be measured through specific tests to reflect the SOH status of the battery. For illustration, the capacity measurement needs to be discharged at a small discharge rate until reaching the cut-off voltage of the battery To bridge the exploration gap, this paper exhaustively discusses the stateof-the- art progress in SOC and SOH estimation of LIBs. Science Direct and IEEE are the main sources to search for applicable papers according to the keywords similar as electric vehicles, lithium ion battery, state of charge, and state of health. Compared with former exploration work, the benefactions of this review work are given as follows

(1) The SOC/ SOH estimation styles are divided into two orders, i.e. online and offline ones. The promising online estimation styles are specially discussed. The model basedmethod and data-driven method are substantially introduced for online SOC estimation. And the online SOH estimation includes (DA) styles, model- based methods, and data- driven methods.

(2) The being online co-estimation strategies of both SOC and SOH are originally bandied in this paper to fill the gaps in the exploration area of common estimation. Also, it's reviewed from the aspects of the model- based methods, data- driven methods and advanced sensing- basedmethods.

(3) Grounded on the bracket of state estimation, the rearmost exploration styles in recent times are named and reviewed considering their strengths and downsides in practical operations.

(4) A list of crucial issues and unborn work are suggested for the advancement of online SOC and SOH estimation of LIBs.

Definition of SOC and SOH:

1. Definition of SOC:

SOC is defined as the percentage of the remaining capacity tothe maximum available capacity of the battery (Kim, 2008), andit can be given by

$$SOC\ (t) = \frac{C_r}{C_m} \times 100\%$$

where Cr stands for the remaining capacity that can be powered to electric devices. Cm specifically presents the maximum available capacity that the cell can store, which is determined by the electrochemical characteristics of the battery. The value of SOC ranges from 0 to 100. A SOC of 0 denotes the battery is completely discharged, while a SOC of 100 means the battery is completely charged. In practice, the battery generally works under the SOC range from 20 – 80 to avoid over-discharging (Wang etal., 2019a). In another way, SOC can be expressed by the Eq. (2) due to the relationship between the charging/ discharging current and the battery capacity (Haisch etal., 2020).

$$SOC\ (t) = SOC\ (t_0) - \int_{t_0}^{t} \frac{I(t)\eta}{C_m} dt$$

where SOC (t0) and SOC (t) represent the SOC at the initial time t0 and time t, respectively. η denotes the coulombic efficiency that presents the rate of the battery discharge capacity to the charge capacity during the same cycle. The current I (t) varies with time in which it's negative in charging state and positive in discharging state. And a separate form of Eq. (2) can be described as

$$SOC_k = SOC_{k-1} - \frac{\eta \Delta T}{C_m} \cdot I_k$$

where ΔT is the sampling time, and Ik is the loading current. SOCk and SOCk − 1 represent the battery SOC at time step k and k − 1, respectively.

In fact, the SOC values can be directly calculated when determining the initial SOC value according to Eq. (2) or Eq. (3). Still, the inaccurate intial SOC value and the accretive errors due to the dimension system can lead to significant estimation error in practical operations (Khan etal., 2021). Thus, growing attention has been attracted to exploring the advanced styles for further dependable real-time SOC estimation.

2. Description of SOH

Lithium-ion battery inescapably degrades with the increase of cycling and it consists of mechanical and chemical declination. Mechanical declination is substantially caused by the volume expansion or loss due to the lithium de/-intercalation during the process of charging or discharging. Chemical declination is substantially caused by electrolyte reduction and corruption, solid electrolyte interphase (SEI) formation and so on since these processes can lead to the loss of lithium-ion and indeed the increase of the electrical resistance (Kabir and Demirocak, 2017; Xu etal., 2017). The declination process of LIBs can be reflected by variousphenomena such as the attenuation of the maximum remaining capacity and the increase of the internal resistance. This means batteries need to be replaced by new ones. Thus, the SOH of the battery can be quantified by the ratio between the state value and the original value of the capacity or internal resistance (Li etal., 2021b; Ge etal., 2021). They can be expressed as

$$SOH = \frac{C_a}{C_{rated}} \times 100\%$$

$$SOH = \frac{R_{EOL} - R_{cur}}{R_{EOL} - R_{new}} \times 100\%$$

where Ca and Crated are the actual and rated capacity, respectively. Rcur presents the current internal resistance through charging – discharging cycles. REOL and Rnew are the ohmic internal resistance of a new battery and an EOL battery. Although the SOH monitoring needs to be tested and analysed in a long- life period, developing accurate and effective SOH evaluation strategies is vital for replacement plans and fault discovery of LIBs. Presently, neither capacity nor internal resistance is directly measurable with commercially available detectors, and they tend to be indicated and estimated through other measured variables similar as the voltage, current and temperature. As a result, a variety of sweats are contributed to the effective SOH estimation of LIBs under different working conditions.

II. SOC AND SOH ESTIMATION METHODS

1.SOC estimation methods:

In recent times, a number of advanced ways grounded on collected current and voltage parameters have been designed for real- time SOC estimation of LIBs. As bandied preliminarily, the model- based and data- driven approaches for online SOC estimation are bandied in this section.

2. Model- based SOC estimation methods:

As illustrated in Fig, the model- based SOC estimation is generally carried out by four procedures battery model selection, battery testing, model parameter recognition, and estimation algorithms performance.

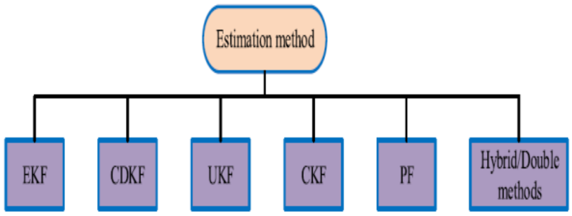

Fig. 2. Different EECM for modelling LIBs

3. Battery model selection:

The first stage is to select an applicable model to pretend the electrochemical dynamics ofLIBs.Four common models, including empirical model (EM) (Meng etal., 2018), electrochemical model (ECM) (Li etal., 2020e), electrical equivalent circuit model (EECM) (Mousavi and Nikdel, 2014), and electrochemical impedance model (ECIM) (Mu etal., 2017) were employed to replicate battery characteristics for SOC estimation. EM is used for SOC estimation by the empirical data fitting, which presents low accuracy to depict the dynamics of battery. Both ECM and ECIM bear significant computational loads to solve the partial differential equations. The EECM is the simplest model that captures the largely dynamic behaviour of LIBs through specific factors similar as voltage source, capacitors and resistors. By comparison, the EECM can achieve a better trade-off between estimation accuracy and computational efficiency. Thus, the EECM for SOC estimation is especially bandied in this section.

4. Battery testing.

After opting an applicable battery model, various types of tests can be carried out to gain measurement data for model parameter recognition, similar as Hybrid pulse power characterization(HPPC) (Xu etal., 2020a), constant

current discharge (CCD), Federal urban driving schedule (FUDS),
Dynamic stress test (DST) (Hunt, 1996), Urban dynamometer driving schedule (UDDS) (Duong etal., 2017), and Beijing driving cycle (BJDC) (He etal., 2013b).

5. Model parameters recognition.
Latterly, the model parameters are honored using specific identification styles grounded on the battery tests mentioned over. The model accuracy greatly relies on the perfection of linked parameters, in which various parameter identification methods(PIMs) play an essential part in guaranteeing the estimation delicacy (Yang etal., 2018c). A variety of identification algorithms were put forward for accurate parameter recognition. Still, these two styles can only be used offline for model parameter identification due to their iterative process. RLS system is the generally used system for real- time parameter identification due to the fast computation, while it needs to further
confirm the least places so that it's unfit to effectively identify the model parameters. FFRLS (Yang etal., 2018a) was proposed to overcome this weakness and it improves the speed of confluence.
Also, Zhu etal. (2020) presented RLS encounters the issue of identification impulses due to measurement errors of current and voltage. Thus, the recursive restricted total least squares (RRTLS) was proposed to reduce the identification impulses, hence enhancing the identification delicacy of model parameters.
An advanced unscented Kalman filter (IUKF) was operating temperatures. In order to improve the convergence capability and estimation robustness, Ye etal. (2018) employed the dual PF for the model parameter identification and dependable SOC estimation. Xu etal. (2020b) applied the Dual Kalman Filter (DKF) to SOC estimation, and the comparison results presented that SOC estimation error was within the range of} 1% under utmost test conditions. Either, considering the influence of measurement noise on battery SOC estimation delicacy, the Dual extended Kalman filter (DEKF) algorithm was proposed to reduce system noise and handed accurate SOC estimation (Lipu etal., 2020; Wang etal., 2019a). Liu etal. (2019a) designed a common strategy combined with ACKF and singular value corruption to reduce the observation error and nonlinear approximation error. Likewise.

6. Data-driven SOC estimation methods:Compared with the model- based SOC estimation approaches, the data- driven styles are intelligent tools, free of considering the electrochemical dynamics of LIBs. Multitudinous data- driven strategies that concentrate on the relationship between input and affair have been proposed for the SOC estimation due to the implicit graces of high rigidity, nonlinear mapping, and inflexibility (Dong etal., 2018). As shown inFig. 9, the data- driven SOC estimation methods involve three major procedures data collection, model training, and SOC estimation. They substantially concentrate on the discharging process based on the training features similar as current, voltage and temperature. Some popular intelligent methods, similar as artificial neural network (ANN) (Ragone etal., 2021), support vector machine (SVM) (Meng etal., 2015), support vector regression (SVR) (Farmann etal., 2015), fuzzy logic (Ma etal., 2018), Gaussian process regression (GPR) (Deng etal., 2020) and GA methods (Chen etal., 2017), have been validated for SOC prediction.
The traditional operation of GA (Lu etal., 2018) cannot effectively estimate the SOC, because it has slow confluence speed and cannot insure clustering to global optimization. Hence, the Chaos genetic algorithm (CGA) combining the global search ability was proposed to address the weakness of GA (El-Shorbagy etal., 2016). Also, an Improved chaos genetic algorithm (IGGA) was also designed for reducing the computation quantum (Shen, 2018b).
In addition, some advanced literacy tools have lately been introduced for SOC estimation Chemali etal. (2018) applied the deep feedforward neural networks (DNN) that tone- learn their weights for SOC discovery and offered better estimation performance. In Zhao etal. (2019), Zhao etal. introduced the combination of recursive neural network and convolutional neural network (RNN – CNN) with advanced delicacy and briskly confluence speed, in which RNN aimed to prize LIB status information that was seen as the input of CNN. Yang etal. (2019a) used the recurrent neural network with the Gated recurrent unit (GRU – RNN) and received satisfactory estimation results under varying temperature conditions. Likewise, Jiao et al.

SOH Methods:
1. Model-Based Method:

The model- basedmethod is grounded on the declination and the failure mechanism of lithium-ion batteries to realize the estimation and vaticination of SOH. The delicacy of the estimation depends on the decay law of the model's key parameters representing the internal aging degree (4 – 14). This method is fairly mature, substantially including several forms, similar as the electrochemical impedance spectroscopy (EIS) model (5 – 7), the thermoelectric coupling model (4 – 5), the Thevenin model (1 – 3), and the shunt of themulti-stage resistor- circuit (RC) model (4 – 6). According to the difference between the proposition of model construction and the principle of algorithm in state prediction, it can be divided into two orders electrochemical models and equivalent circuit models.

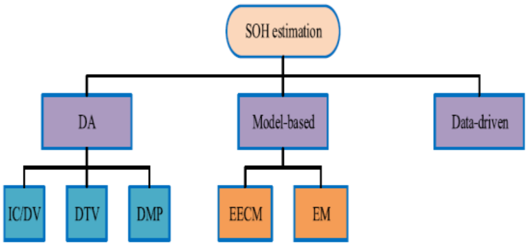

Fig. 3. Popular methods for online SOC estimation

2. Electrochemical Model Method

The electrochemical model is substantially based on the electrochemical response medium inside the lithium-ion battery. The porous electrode theory and kinetic knowledge are espoused to establish a physical model by rooting internal parameters representing the battery's dynamic aging and failure process, which can be used for SOH estimation and

Prediction (7 – 9). Zhang etal. (6) anatomized the impedance characteristics through a pseudo 2-dimensional (P2D) model based on the variation of battery impedance characteristics.

They found that the low frequency band's impedance characteristics were harmonious with the actual battery impedance characteristics. On this base, the original model was revised and compared with the EIS model, so that the prediction error was reduced by half compared with the original model. Improved reliability is more suitable for SOH estimation under actual operating conditions. The electrochemical model method has a strong theoretical support, which can determine the detailed internal electrochemical reaction process and reaction intensity in the battery's aging process. It can directly characterize lithium-ions' movement law and the change trend of active substances in positive and negative electrodes at different SOH locales. Still, the lithium-ion battery electrochemistry system is more complex, having numerous side goods in real time. As the working condition is different, the intensity is different (varies), which describes the aging condition of the model as being fairly complex, having characteristic parameters coupled with each other, leading to poor generality, the method to use single range, dynamic prediction delicacy is poor, and doesn't favor online real- time SOH estimation and prediction.

3. Equivalent Circuit Model Method

The Equivalent circuit model as a modeling method, is based substantially from the perspective of electrotechnics; the battery as a black box, according to the working system of input- output corresponding relations to the structure of electrical factors, it's basically the structure of a mathematical model to represent a lithium-ion battery, which has become a circuit model to describe the lithium battery capacity decline characteristics. The equation of state was named based on Kirchhoff's current equation and Kirchhoff's voltage equation. Combined with known amounts that could be measured, parameters related to SOH estimation were decided to eventually achieve the purpose of estimating SOH (2 – 5). Common equivalent circuit models substantially include Rint model, Thevenin model, Partnership for a new generation of vehicles (PNGV) model, andmulti-stage RC model. The Rint model is shown in Figure 3a. This model linearizes the battery characteristics and is easy to operate. Still, due to theover-idealization of modeling, the error is large. Wei (6) etal., considered the strong capacitance characteristics of the battery, added a resemblant module of resistor and capacitor, and named the first- order Thevenin model, as shown in Figure 3b. The grey neural network was introduced for offline training, and the health index (HI) was taken as the input parameter, battery capacity declination was taken as the output parameter of the grey neural network model, and eventually, battery SOH was estimated by online construction of battery HI. Panchal (7) used driving cycle data from the factual operation of the electric vehicle. These data include the battery application environment of roadways and metropolises at different temperatures. The Thevenin battery

4. Data-Driven Method:

The delicacy of model- basedmethods generally depends on the complexity of the model and the delicacy of parameter identification. Combined with the characteristics of delicate dimension of SOH and strong time variation, this method's anti-interference ability is weak in practical operation, and the trustability and high situations of delicacy are delicate to reach (2 – 4). With data mining and big data analysis technology development, the data-driven method has come a hot content for further experimenters at this stage (5 – 7). The data- driven system doesn't need to consider the complex electrochemical changes and the oscillations of affiliated active substances inside the lithium-ion battery. By extracting the characteristic values of parameters measured directly or laterally and combined with the data mining algorithm, the relationship between characteristic parameters and state of health is established from the data's overall position (7 – 8).

Due to the lithium-ion battery systems generally conforming of a large number of monomer battery in series/ parallel mode, characteristic parameters don't only reflect different monomer battery working terrain goods on the exploration object and hindrance, but can also characterize the monomer battery charged state and aging between comparison with the model law, it isn't sensitive to some characteristic data, good antiinterference capability, strong universality, and high dynamic delicacy. According to the difference in data mining styles, the main data- driven styles at the present stage are divided into four orders statistical filtering system, neural network system, vector machine system, and statistical data system.

5. Statistical Filtering Method:

Statistical filtering is a method to extract and reproduce effective signals and waveforms from data containing numerous noise signals. Generally used statistical filtering methods are substantially divided into Kalman filtering (KF) and particle filtering (PF).

KF is a level-by- level recursive direct data processing algorithm that automatically calculates and determines the best weighting factor. Contemporaneously, the weighted factor can be automatically acclimated to keep the result in the best state all the time, therefore having a strong target following capability (81 – 83). Due to the largely nonlinear characteristics of lithium-ion batteries during operation, it's delicate for a single KF algorithm to meet the system's conditions (84), which limits the applications of KF in the factual operation scripts of lithium-ion batteries. In order to meet the conditions of high accuracy and reliability of SOH estimation and prediction for lithium-ion batteries, several bettered KF algorithms similar as unscented Kalman filtering (UKF) (5) and extended Kalman filter (EKF) (6) have been proposed successfully. A double extended Kalman filter (DEKF) joint which is applicable for lithium-ion battery application scripts by comparison with a single KF. They introduced optimization parameters of bettered Kalman filtering, and the accuracy and prediction results was significantly bettered. Still, it requires a large quantum of computation. In the case of battery trial data (9), PF was applied to an empirical model of power decline to prognosticate the life endpoints of each phase of the battery, and the prediction results were verified by using power attenuation data. The results showed that the delicacy of SOH prediction was continuously bettered with the increase in the number of samples. Still, with the increase of the terrain's complexity, a large number of sample parameters are demanded to make the PF vaticination results near to the posterior probability viscosity, which greatly increases the complexity and quantum of computation by the algorithm, performing in poor punctuality of the online vaticination algorithm.

III. CO-ESTIMATION METHODS OF SOC AND SOH

Apart from the pure SOC or SOH estimation, it's technically gruelling for the contemporaneous estimation of these two crucial state variables. The variation of some important factors can indicate SOC in a short timescale and reflect SOH in a long timescale. Grounded on the close correlations between SOC and SOH, the common estimation is likely to be achieved. Theco-estimation strategy has the advantage to improved prediction accuracy because it focuses on the collective goods from different battery countries. A lot of exploration workshop have been devoted to dependableco-estimation of SOC and SOH. This system offers a good perspective on common estimation and the maximum estimation crimes of SOC and SOH were limited to 2 and2.8, independently.

Also, colourful styles grounded on EECM have been employed for theco-estimation of both battery SOC and SOH. Because the model- grounded system is an effective path for SOC estimation and the linked model parameters present a high relationship with battery life span. For illustration, Topan etal. (2016) carried out the common estimation combined with the 1RC model and KF algorithm, while the mean relative error was as important as5.26 as the direct estimator KF fluently introduces large system crimes. In order to avoid the uncertain factors similar as modelling, parameter error, and dimension noise, Afsharid et al.

IV. KEYISSUES IN BOVE METHODS

According to the comprehensive review in Section 3, a variety of techniques have been proven effective in estimating the SOC or SOH state of LIBs. Still, substantial progress is still needed to ameliorate estimation accuracy and computationefficiency for online operations. As a dynamic coupling system, numerous factors circumscribe the effective monitoring of SOC and SOH in practice directions
in online SOC and SOH estimation are outlined from five perspectives as illustrated.

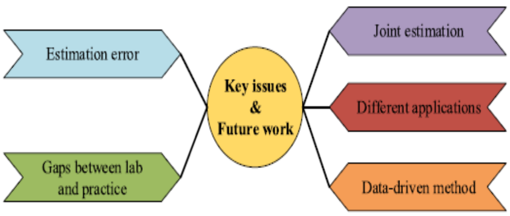

Fig. 4. Key issues and future work for online SOC and SOH estimation

1. Estimation errors:
Several error sources can impact the state estimation process of LIBs, which can come from the battery model, measurement system, estimation algorithms and so forth. These errors aren't negligible as the accumulation of these errors will ultimately beget significant estimation errors. Originally, it's insolvable for any model to entirely replicate the nonlinear geste of LIBs. Secondly, in the case of model parameter identification, inaccurate parameters can vitiate the state estimation performance.

2. Gaps between lab and practice
Presently, utmost of the exploration work for the battery SOC and SOH estimation is still in the laboratory stage. Some impacting factors similar as changing ambient temperature and computational effectiveness greatly impact the battery SOC and SOH estimation in practice. The LIBs in EV or charging systems work under complex operation conditions where the ambient temperature varies constantly. Due to the electrochemical dynamics of LIBs are fluently affected by the temperature, it produces a significant gap between laboratory exploration and practical operation.

3. Joint estimation
A variety of advanced ways have been proposed for individual SOC or SOH estimation. Still, limited workshop have concentrated on the effective common estimation of SOC and SOH. The fairly accurate results can be only achieved if estimating one of them independently and not considering another bone. Because the battery is a dynamic system in which multiple countries are coupled
with each other like the relationship between SOC and SOH. Specifically, accurate SOC vaticination should be associated with the variation of SOH as the capacity declination also influences the parameters in the model- grounded styles for SOC estimation. In addition, the dependable SOH estimation can give an accurate original value for SOC monitoring.

4. Different Applications
Presently, the LIBs are extensively applied to EVs and EV charging systems retaining to their high energy viscosity and trust ability. Although a number of styles are specifically developed for the state estimation of LIBs, utmost of the advanced ways parade poor generality if they're applied to different use of LIBs. On the one hand, the being styles pay further attention to the cell battery rather of the battery packs or battery module. Addressing the inconsistency of the batteries and furnishing accurate battery pack or module state estimation have realistic meanings in practice.

5. Data- driven method
With the advancement of pall computing technology and the vacuity of large quantities of monitoring data, data- driven ways have entered adding attention for the state estimation of LIBs. Compared to the model- grounded system, the data driven approaches can more collude the

nonlinearity grounded on self learning characteristics. To achieve good performance in practical operations, two critical directions including point selection and algorithm enhancement must be enhanced to ameliorate the robustness and trustability. On the one hand, intelligent pall calculating technologies predicated on the real- world battery data collected from the big data platform can be developed to achieve real-time and effective monitoring of a large number of batteries in practice. Pall- grounded machine literacy approaches can break the problem that limited data is deduced from a single vehicle or battery module.

V CONCLUSION

In this paper, the promising online SOC and SOH estimation technologies for EV batteries are reviewed with a focus on the development in recent five years. Model- based and data- driven method are specifically reviewed for online SOC estimation.

The DA, model- based, and data- driven methods for real- time SOH estimation are delved, independently. In addition, the coestimation of SOC and SOH based on model- based, data-driven, and advanced sensing- based method are reviewed. These methods are bandied and estimated by fastening on their strengths and downsides. Eventually, the crucial issues and unborn work are proposed for the guidance of online SOC and SOH estimation of LIBs in practice.

The current online estimation methods still face significant challenges when applied to practice. On the one hand, large errors from the battery model and measurement systems have significant influences on the state estimation of the battery. Also, these methods are generally developed based on laboratory data, therefore causing a large gap between lab and practical applications. The battery is a time- varying and nonlinear electrochemical system so that its status can be fluently affected by various factors similar as ambient temperature and charge – discharge rate, which increases the difficulty of state estimation in practice. Likewise, model- based and data- driven methods suffer from complex calculations, which really increases the computation load, especially when applied to battery packs.

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