A Review on Battery Management system and its Application in Electric vehicle

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***Abstract*—Presently electric vehicles (EVs) are considered as most propitious solution for the replacement of internal combustion (IC) engine-based vehicle. The development of EV technologies is growing rapidly and the battery technology is an important concept for development of the electric vehicles. The EV performance mainly relies on the battery performance and battery management system (BMS). Recently, the Lithium-ion (Li-ion) battery is mainly used as a battery in EVs due to smaller weight, high energy density and capability of fast charging and discharging. Considering the dynamic performance, economy, safety friendliness to the environment of the EVs, the BMS is designed such a way to meet the challenges like the energy management of battery, reduction of heating-time at low temperature and enhancing remaining-useful life (RUL) with accuracy of prediction. The battery is managed and controlled by BMS and it is mainly focused to maintain the reliability and safety. The state estimation of the battery is essential for vehicle control and management of energy. The paper gives review on the strategies like battery modeling, state estimation and prediction. The state estimation for State of charge (SOC), State of power (SOP), State of health (SOH) and prediction of RUL are overviewed.**

Keywords—battery management system, electric vehicle, state of health, state of charge, battery state estimation

I. INTRODUCTION

The vehicle industry is dominated for a long time by the conventional vehicles, which are run by the internal combustion engine. Due to the fuel energy crises along with the market requirement and opportunity, there is a competition among all the countries over the world for the development of EV technology. The investment and expansion of the new energy vehicle industry is actively promoted [1]. The EV performance depends on the battery performance and BMS. Considering the requirements of the economy, dynamic performance, safety and environmental friendliness of the EVs, the battery system must be strengthened to meet the high specific power, high specific energy, long service life time, high safety, high reliability, excellent low or high temperature performance, low self discharge rate, low cost [2].

Presently, according to the capacity of battery and power output, the EV commercialized batteries can be categorised into three types: the power type batteries, the energy type batteries and the energy/power type batteries. In power type battery, the capacity is less and the high instantaneous power can be supplied that is used in light HEVs [3-8]. In energy type battery, the capacity is more and energy can be supplied continuously which is mainly used in battery electric vehicle (BEVs) and Hybrid electric vehicle (HEVs). In the energy/power type, energy density, output capability in a low SOC range and acceptability of power in a high SOC range are high. The plug-in hybrid vehicles (PHEVs) are under this category [9].

The BEV is presently used as energy vehicle that relies solely on battery for energy storage. Through the battery, electrical energy is provided to the motor, which drives motor and propels the vehicle. The range of a BEV is entirely determined by its battery capacity. The larger the battery capacity, the greater the vehicle driving range, whereas the smaller the battery capacity, the shorter the vehicle range [14].

The main battery control system of BMS is ensuring that the battery used must be in safety and the major states of the battery system such as its State of Charge (SOC), State of Power (SOP) and State of Health (SOH) should be estimated accurately. The existing amount of stored energy information in the battery is provided by SOC [5-6]. The SOP gives indications about the capability of battery for supplying the required power [9-12]. The SOH is a figure of merit which gives indications level of degradation of battery. As the behavior of the battery is nonlinear complex, it can be very challenging estimating battery SOC, SOP and SOH. For automotive applications, estimating the real time battery SOH is critical [4]. It enables for the detection of battery faults and aids in the prevention of potentially dangerous situations. It gives precise information on battery performance, which can be used for better management of energy distribution in HEVs and increase their consumption and lifespan. It gives knowledge about the battery performance accurately which can be helpful for managing the HEV energy distribution and their consumption. Hence the battery lifetime can be improved. Mainly, real-time SOH calculation enables for precise SOC and SOP estimation of the battery. It can also be beneficial for planning maintenance and replacement schedules [21].

II. BATTERY MANAGEMENT SYSTEM (BMS)

A BMS is a device or a technology which maintains and controls batteries. The BMS consists of various actuators, sensors, controllers along with algorithm and lines of signal. Its primary responsibility is to assure safety as well as reliability of the battery. It also gives the required information of state for vehicle control, energy management and to intervene appropriately on battery system in deviating conditions. Furthermore, it is expected to collect real-time data on the temperature, terminal voltage, current, and other parameters of individual cell in a battery pack. The strategies and embedded algorithms are used to estimate battery SOC, SOP, SOH and RUL. The estimation results are given to the vehicle-control unit (VCU), which serves as the foundation or the management of energy and control of power distribution of EV [21].

A. Fundamental Functions of BMS

The key functions of BMS are collection of data, monitoring of state, safety protection, charging control along with management of energy, equalization, thermal and information [9].

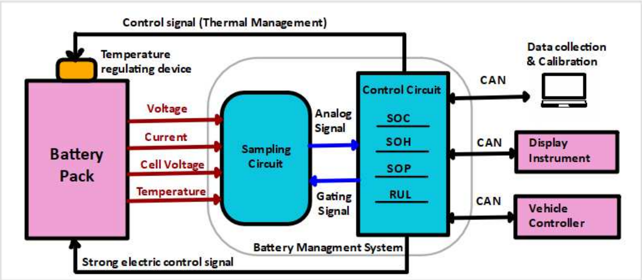

Fig. 1. Block diagram of BMS

i. Data collection

The temperature, terminal voltage, current and other information of individual cell in battery pack is collected with BMS for obtaining the accurate battery working condition and the energy management.

ii. State monitoring

In a real time, several states of battery are changing due to the time-varying, complex and nonlinear characteristics of battery. The battery state monitoring is one of the vital parts of BMS technology for control and energy management of EV battery. As a result, using embedded algorithms, the BMS must estimate the current states of the battery pack from collected real time battery data. The BMS also makes strategies for obtaining the battery states at each instant, including the SOC, SOP, SOH and state-of-energy (SOE), thereby supporting real-time battery state analysis.

iii. Safety protection

The online fault diagnosis and safety control of BMS refers to battery safety protection. The algorithm for fault diagnosis, based on the collected sensor signals are used for the online fault diagnosis. After identifying the fault types, the BMS must issue alerts and take appropriate action for safety of EV.

iv. Charging control

As the charging process has such a direct impact on the battery's lifetime and safety, the BMS normally includes a charging management module that regulates the battery's charging based on real-time characteristics, battery temperature, and charger power level.

v. Energy management

The driving conditions for electric vehicles are complicated. Random driving operations includes fast acceleration, abrupt stopping which are complicated varying dynamic loads. The BMS must control the battery energy output and the recovery energy for regenerative braking.

vi. Equalization management

Inconsistencies between the systems are unavoidable due to the accumulation of errors in the manufacturing process, transit, storage, and electronic components. In order to access the most of the energy contained in the cells and to ensure their safety, the BMS must use a passive or active equalization mechanism depending on the size of the pack, minimizing the irregularity of cells.

vii. Thermal management

The battery is impacted by the ambient temperature as well as the heat produced during charging and discharging in the normal operation. As a result, the battery thermal management module must be equipped with the BMS according to the temperature distribution.

viii. Information management

Multiple functional modules are integrated into the BMS and there must be coordination for connection among modules. As the huge volume of data being processed, the BMS must govern and filtrate battery data, as well as accumulate crucial information. BMS interacts with cloud platform for the real-time application. The energy management issues can be managed in a better way with the implementation of big-data technology.

B. Topology of BMS

The BMS topology is an essential part for extensive battery management. The EVs are designed according to the different dynamic performances like climbing ability, acceleration capability and maximum speed. The technical requirements of EV design need to connect the cells in series or parallel. The battery control unit (BCU) and battery monitoring circuit (BMC) are hardware circuits in BMS topology. BMS topology is classified into centralized and distributed according to structure design among BCU, BMC and the cells. In the centralized BMS, the BMC and BCU are incorporated on a single PCB. In distributed topology BCU and BMC are arranged separatetely [21]. The temperature, cell voltage, current, security and consistency are managed by the BMC.

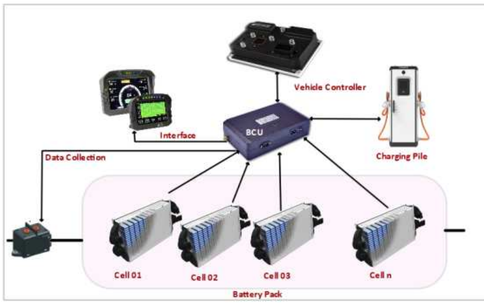

Fig. 2. Schematic diagram of centralized BMS topology

Fig. 3. Structural diagram of distributed BMS topology

III. MODELLING OF LI-ION BATTERY

Because of the complexity of electrochemical reactions inside the battery, the Li-ion batteries are influenced by various factors and uncertainties. There is a multidisciplinary problem to establish mathematical model of the battery which is an unsolved challenge in industry as well as in academia. In the BMS, current is input quantity where as terminal voltage and temperature is output quantity [21]. The battery terminal voltage is characterised by hysteresis, non-linearity, and substantial time variation due to polarizations generated by multistage properties of the positive and negative electrode materials, electrochemical reactions. The battery terminal voltage is separated into two parts namely, dynamic and static [7]. The dynamic part incorporates fast changing voltage component which is the ohmic polarization, where as the concentration and electrochemical polarization are the slow changing voltage component. The open circuit voltage (OCV) and hysteresis voltage are two primary components of the static part [17]. The existing state and past inducement approach of the battery is strongly linked by the hysteresis voltage component. For designing accurate and reliable battery-state-estimation algorithms and to develop more accurate BMS in recent energy vehicles, advanced battery modeling is required [22]. The different battery models are electro-chemical model, equivalent circuit model (ECM) and black box model. In this paper different ECMs are over viewed.ECM is generally is more used for estimating SOC due to simple structure.

A. Rint ECM

This model is simple for practical application and output equation gives the uncertainties in the state estimation [22]. The output voltage v_o is given in equation (1), Where, v_{oc} and r_o are open circuit voltage and internal resistance respectively. v_{oc} and r_o are function of temperature, SOH and SOC. The load current I_o is negative during charging and positive during discharging. The voltage output is found from equation (1).

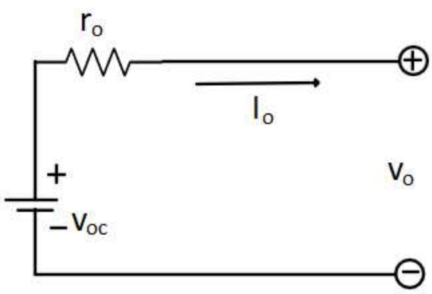

Fig. 4. Equivalent circuit of Rint ECM

$$v_0 = v_{oc} - I_O\ r_0 \tag{1}$$

B. Thevinin ECM

In this model the internal resistance includes r_o and r_p where the r_o is ohmic resistance and r_p is the polarisation resistance [22]. It is a developed form of rint model having RC parallel circuit which series with internal resistance. The transient response of ECM is given by $c_{th.}$

The voltage output is found from equation (2) and (3)

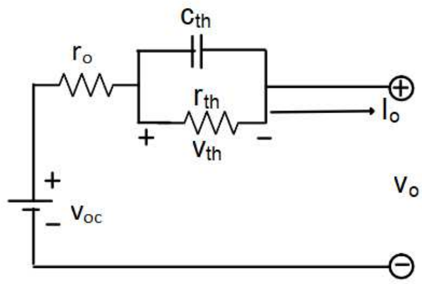

Fig. 5. Equivalent circuit of Thevenin ECM

$$v_{th} = -\frac{v_{th}}{r_{th}c_{th}} + \frac{I_O}{c_{th}} \tag{2}$$

$$v_o = v_{oc} - v_{th} - I_o\ r_o \tag{3}$$

C. Dual polarization ECM

This is the developed model of Thevenin model. The accuracy is more at charging and discharging period [20]. The voltage output is found from equation (4) – (6).

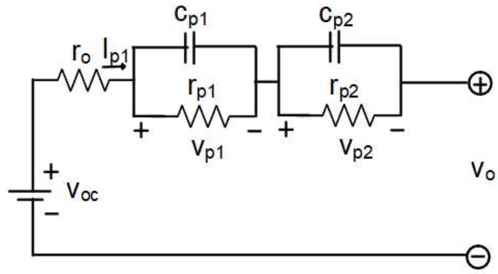

Fig. 6. Equivalent circuit of Dual polarization ECM

$$\dot{v}p_1 = -\frac{v_{p_1}}{rp_1c_{p_1}} + \frac{I_o}{c_{p_1}} \tag{4}$$

$$\dot{v}p_2 = -\frac{vp_2}{r_{p_2}c_{p_2}} + \frac{I_o}{c_{p_2}} \tag{5}$$

$$v_o = v_{oc} - v_{p_1} - v_{p_2} - I_o r_o \tag{6}$$

D. PNGV (partnership of new gen2eration of vehicle) ECM

This model is a developed form of thevenin model and the capacitor is added in series with voltage source. Data saturation and overtime problem of load current are mitigated by using this PNGV. The output voltage is given by the described equations (7)-(9).

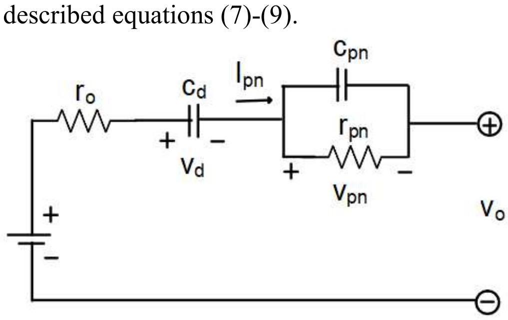

Fig. 7. Equivalent circuit of PNGV ECM

$$\dot{v_d} = \dot{v}_{oc}\ I_o \tag{7}$$

$$\ddot{v}_{p_n} = \frac{v_{pn}}{r_{p_n}c_{p_n}} + \frac{I_o}{c_{p_n}} \tag{8}$$

$$v_o = v_{oc} - v_d - v_{p_n} - I_O r_o \tag{9}$$

E. GNL (General non linear) ECM

This model is the combined form of both PNGV and Dual polarization with additional source resistance r_s. It is used for nonlinear battery modeling due to its smaller amount of self discharging characteristics [25]. The voltage output is found from equation (10) – (13).

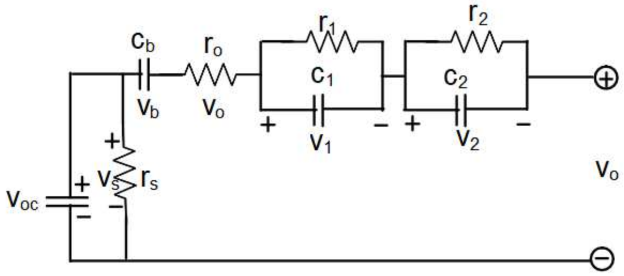

Fig. 8. Equivalent circuit of GNL ECM

$$\dot{v_b} = \dot{v}_{oc} \tag{10}$$

$$\dot{v_1} = \frac{1}{c_1} - \frac{v_b}{c_1 r_s}\left(\frac{v_1}{c_1 r_s} + \frac{v_1}{c_1 r_1}\right) - \frac{v_2}{c_1 r_s} + \frac{v_{oc}}{c_1 r_s} \tag{11}$$

$$\dot{v}_2 = \frac{1}{c_2} - \frac{v_b}{c_2 r_s}\left(\frac{v_2}{c_1 r_s} + \frac{v_2}{c_2 r_2}\right) - \frac{v_1}{c_2 r_s} + \frac{v_{oc}}{c_2 r_s} \tag{12}$$

$$v_L = v_{oc} - v_b - v_1 - v_2 - i_l r_o \tag{13}$$

F. RC Equivalent model

This model is used for obtaining dynamic performance of voltage in battery. The voltage output is given in equation

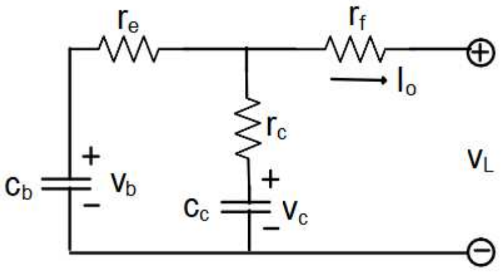

Fig. 9. Equivalent circuit of RC equivalent model

$$\begin{bmatrix} \dot{v_b} \\ \dot{v_c} \end{bmatrix} = \begin{bmatrix} \frac{-1}{c_b(r_e+r]_c)} & \frac{1}{c_b(r_e+r_c)} \end{bmatrix} \begin{bmatrix} v_b \\ v_c \end{bmatrix} + \begin{bmatrix} \frac{-r_c}{c_b(r_e+r_c)} \\ \frac{-r_e}{c_c(r_e+r_c)} \end{bmatrix} [I_o] \tag{14}$$

$$[v_L] = \left[\frac{r_c}{r_e+r_c)} \; \frac{r_e}{r_e+r_c}\right] \begin{bmatrix} v_b \\ v_c \end{bmatrix} \left[-r_t - \frac{r_e r_c}{r_e+r_c}\right][I_o] \tag{15}$$

G. Fractional order ECM

This model is used to minimize the complexity in computation and to enhance the efficiency of ECM faults in order to ensure that ECMs have the best possible trend off.

The Dual polarization model is mostly used for the better dynamic performance and less losses among other model of ECM. The voltage output is evaluated from equation (16)-(18).

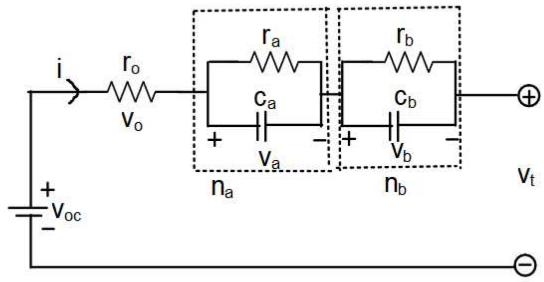

Fig. 10. Equivalent circuit of Fractional order ECM

$$d^{n_a}\, \dot{v}_1 = \frac{-1}{c_a} - \frac{v_a}{c_a r_a} \tag{16}$$

$$d^{n_b}\, \dot{v}_2 = \frac{1}{c_b} - \frac{v_b}{c_b r_b} \tag{17}$$

$$v_t = v_{oc} - v_a - v_b - i r_o \tag{18}$$

IV. ESTIMATION OF BATTERY STATUS

The estimation of battery SOC, SOP, SOH and the prediction of RUL are the part of BMS function. For safe and reliable battery operation, estimation of SOC and SOH must be accurate which provides basis for safety and energy management of EVs. Estimation of battery SOC and SOH with high accuracy is exceedingly difficult and it is being one of the technological issues of industry and challenging topic in international academic study [21].

A. Estimation of SOC

SOC acts a vital role for optimization of EV energy management, enhancing the battery capacity and utilization energy, stalling batteries from excess charging and discharging, also ensuring batteries safety and better service lifetime [24]. The SOC estimation method can be classified into four categories: characteristic parameters estimation method, data driven estimation method, ampere hour integral estimation method and the model based estimation method [8].

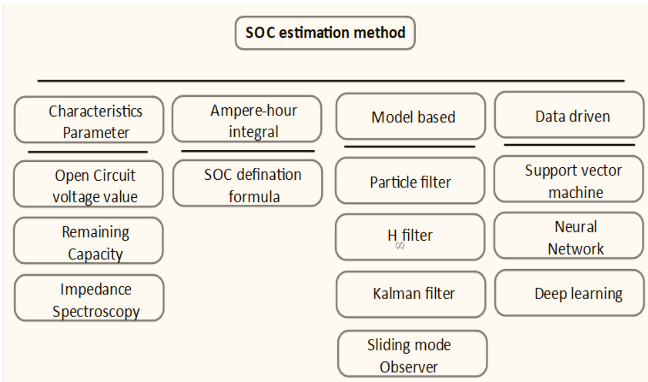

Fig. 11. Types of SOC estimation methods

The model based estimation method is mostly used for high estimation accuracy, better real time performance and excellent robustness [21].

Model based estimation method

The filter and observer techniques are used to develop a framework for model based SOC estimation on the existing ECM and its state space equation.

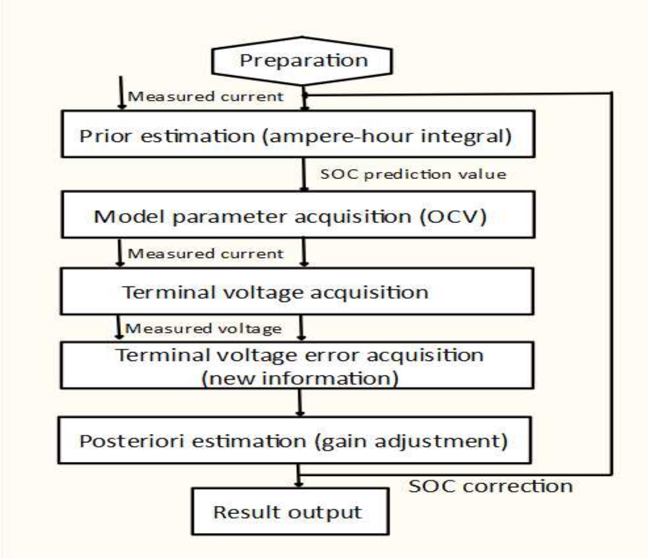

Fig. 12. Flowchart of the model based estimation method

The procedures for model based estimation method are briefly described as following:

- The present SOC estimation is determined from initial SOC or SOC at previous instant and current measurement by ampere-hour integral method.
- Determine the model parameters based on Open circuit voltage and state of charge relationship.
- The terminal voltage from state-space equation is determined.
- The Voltage error is evaluated which is the transformation with measured voltage.
- The estimated SOC is modified with a definite gain of transformation to find the final SOC correction value and this SOC value is used as input for next instant.

The gain in the last step relies on the state estimation algorithm. The performance of the model based estimation method depends on the model and estimation algorithm. For SOC estimation, Kalman-filter (KF) algorithm is mostly used [16].

B. Estimation of SOH

As battery's lifetime, their energy storage and quick charging–discharging capabilities deteriorate, SOH is a quantitative metric for determining the life period of battery. The precise SOH value is required for correct SOC estimation. It is not practicable to estimate SOC using the known SOH that can only be used as a guide for estimating the SOC [14].

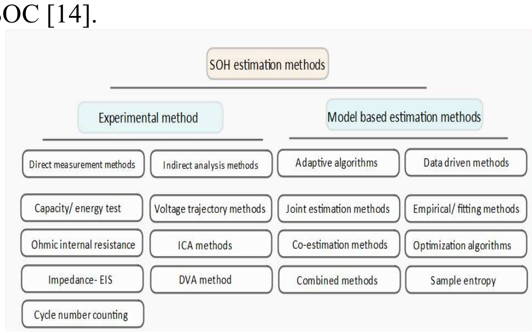

Fig. 13. Various types of SOH estimation methods

C. Estimation of SOP

SOP is defined as maximum power which can be absorbed or released by the the battery during predefined time interval. The main function of SOP is to calculate maximum power under various SOH and SOC, optimize relationship between the vehicle power performance and battery system. The vehicle performance includes the acceleration and climbing performance. The real-time SOP is subject to temperature, voltage, current, SOC and available battery capacity due to affect by the thermodynamics and the internal electro chemical dynamics. The SOP estimation method is mainly classified as four types such as, the hybrid pulse power characterization method, the voltage based method, the SOC based method, and the multi constrained dynamic method [23-24].

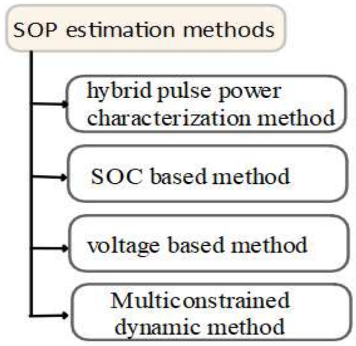

Fig. 14. Classification of SOP estimation method

D. Prediction of RUL

There is battery performance degradation by using and maintaining it throughout the whole process. The increase of cycles for charging and discharging, unidirectional chemical reactions inside the battery reduce the driving mileage of EVs. RUL prediction is the one of the unique functions of BMS. RUL is defined as the requisite cycles for maximum present capacity to degrade to specific threshold under provided rules for charging and discharging. RUL prediction is the mathematical calculations which are based on historical data [23]. Recently, data-driven method is mainly used for RUL prediction. This method is based on reduction and generalization of the battery capacity degradation approach and historical data. This is classified into three categories such as fitting based method; sequence prediction based method and fitter observation based method. Filter observation based method is generally used for prediction of battery RUL. The algorithms used for prediction of RUL are KF, Extended KF, particle filter (PF), unscented KF, unscented PF and spherical cubature PF, etc [19].

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V. CONCLUSION

In this paper the review of various functions of BMS, modeling of Li-ion battery with different ECM methods are discussed. The estimation of SOC SOH, SOP and RUL prediction are overviewed which are very challenging and key concepts for battery management as well as energy management. In future, the BMS algorithms can be tested and implemented in real EV applicalication.

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