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A Review on Battery Management System for Electric Vehicles

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Abstract: Worldwide, development on the batteries used in electric vehicles is making significant strides in solving the problems of carbon emissions and climate change issues. The efficiency of electric vehicles depends on accurate testing of key parameters and proper operation and functionality of battery management system. On the other hand, inadequate battery energy storage system monitoring and safety measures can lead to serious problems such as battery overheating, overcharging, cell unbalancing, thermal management, and fire threats. An efficient battery management system, which includes charging-discharging control, precise monitoring, temperature management, battery safety, and protection, is essential for enhancing battery performance in order to alleviate these worries. This study aims to give a comprehensive analysis of different intelligent techniques and control strategies for the battery management system in electric vehicle applications. The evaluation evaluates battery state estimate intelligent algorithms in terms of their features, structure, configuration, accuracy, advantages, and disadvantages. The paper also examines the numerous controllers employed in battery warming, cooling, balancing, and protection emphasizing sections, traits, objectives, results, benefits, and limitations.
Keywords: Electric Vehicle (EV), Battery Management System (BMS), Lithium-ion Battery, Battery Equalization or Cell Balancing, Thermal Management, Fault Diagnosis, Data Acquisition (DAQ), State-of-Charge (SoC).

I. INTRODUCTION

Nowadays, the automotive industry has made significant strides toward improving the safety of both passengers and pedestrians as a result of various technological advancements. However, the increased number of vehicles on the road is responsible for significantly increasing pollution levels in urban areas.

According to the European Union, the transportation sector accounts for approximately 27 percent of total carbon dioxide (CO2) emissions, with vehicle transportation accounting for more than 70 percent of emissions. To address these issues, electric vehicles (EVs) have gained widespread attention and popularity due to their ability to reduce environmental pollution, conserve fossil fuels, and reduce carbon emissions and global warming concerns.

EVs are a promising alternative to IC engine-powered vehicles, not only in terms of emissions, but also in terms of simplicity, dependability, comfort, and efficiency. For proper battery management system (BMS) functionality and diagnosis in terms of charge-discharge control, battery cell monitoring, cell balancing, power management, and thermal management control, EVs must, however, be widely adopted.

Lithium-ion batteries now rule the EV battery industry due to their high energy and power density, prolonged life cycles, high voltage and poor self-discharge rates. Nonetheless, lithium batteries are susceptible to ageing and temperature, requiring special attention to their working environments in order to avoid physical damage, ageing, and thermal runaways. The battery management system (BMS) is essential for electric vehicle (EV) functioning because it regulates temperature, helps to control voltage across cells, and checks battery charge, health and energy. The following are the main responsibilities of an effective BMS:

1) Data acquisition.
2) Should communicate with all the battery components.
3) Battery status and authentication should be delivered to a user interface.
4) Estimates and evaluates battery states accurately such as state of charge (SoC), state of Health (SoH) and remaining useful life (RUL).
5) Keeps the battery temperatures within a safe range.
6) Performs fault diagnosis, prognosis, and fault handling.
7) Balances the voltage, charge, and capacity of the battery cells.
8) Should ensure the prolonged battery life.

II. FUNCTIONS OF BMS

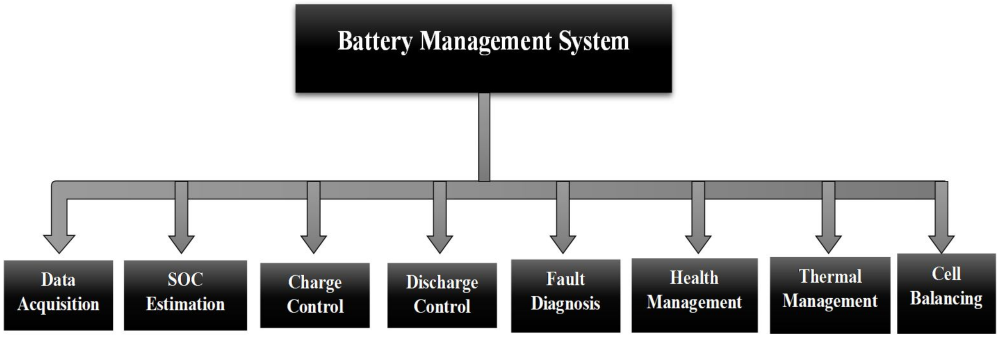

Fig. 1 Functions of Battery Management System

A. Data Acquisition (DAQ)

The software in the BMS that analyses and builds a database for system modelling relies heavily on data acquisition (DAQ) and data storage. Oversight tasks include continuous monitoring of all battery cells and collects different parameters using the sensors deployed, where data tracking can be used for diagnostics on its own but is often used in conjunction with the task of calculation to estimate the SOC of all cells in the assembly. This information is utilized in balancing algorithms, but it can also be sent to external devices and displays to reflect the driver the available energy, estimate expected range or range/lifetime depending on current usage and provide information about the battery pack's condition.

B. SoC Estimation

State of charge (SoC) is the ratio of the battery's remaining charge to its rated capacity or maximum capacity. Soc is computed to make sure that the battery is not ever undercharged or overcharged. SOC also serves as an electric vehicle's fuel gauge because it shows how much battery power is still available. With the help of new algorithms, it is possible to calculate how far an electric vehicle can travel before its battery needs to be recharged.

$$\mathrm{SoC}(t) = \frac{Q(t)}{Q_n} \quad (1)$$

Where $Q(t)$ is current capacity of the batter,Q_n is nominal capacity of that same battery.

By regulating charging and discharging, the state of charge helps the battery management system evaluate the battery's condition and keep it within the safe working range. Since SoC is a crucial parameter that represents battery performance, precise estimation may not only safeguard the battery, prevent overcharging, and lengthen battery life but also enable the application to implement logical control strategies to save energy. Due to the limited battery models and parametric uncertainties, accurate SoC estimation is still extremely complex and tough to perform.

III. SOC ESTIMATION METHODS

A. Direct Measurement

This technique makes use of some physically measurable battery characteristics, such as impedance and terminal voltage. Numerous other direct techniques have been used, including impedance measurement, open circuit voltage, terminal voltage, and impedance spectroscopy.

1) ***Open Circuit Voltage(OCV) Method:*** There is approximately a linear relationship between the SOC of the lead-acid battery and its open circuit voltage (OCV) given by

$$V_{oc}(t) = a_1 \times SoC(t) + a_0$$

Where SoC(t) is the State of Charge of battery at time t, a_0 is the battery terminal voltage when SoC = 0%, a_1 is obtained by knowing the value of a_0 and $V_{oc}(t)$ at SoC = 100%. By [2], The estimation of the SOC corresponds to the estimation of the OCV [3]. When batteries are disconnected from loads for more than two hours, the OCV method based on the OCV of the batteries is proportional to the SOC. However, such a long disconnection time may be too long for battery implementation [4].

Unlike lead-acid batteries, the OCV and SOC of a Li-ion battery do not have a linear relationship [5]. Figure 2 depicts a typical Li-ion battery relationship between SOC and OCV [6]. The OCV-SOC relationship was discovered by applying a pulse load to the Li-ion battery and then allowing the battery to reach equilibrium [7].

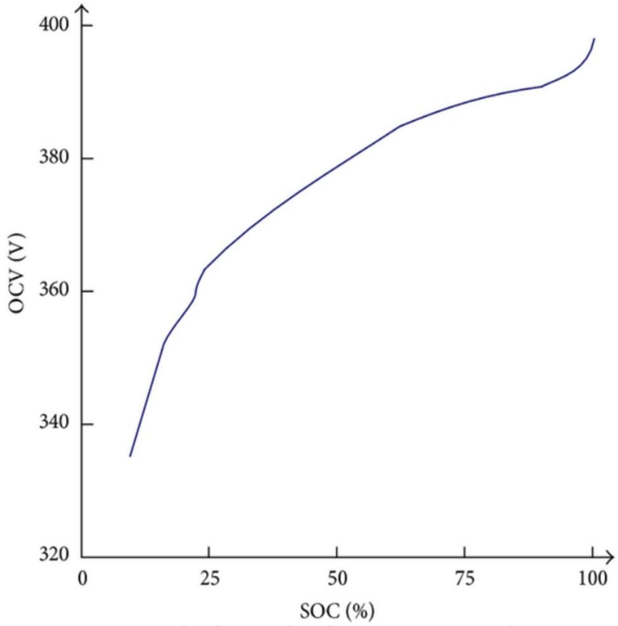

Fig. 2 Typical relationship between SoC and OCV

For any battery, OCV and SOC cannot have the same relationship. Because the typical OCV-SOC varies amongst batteries, there is a difficulty in that the OCV-SOC relationship must be determined to accurately predict the SOC. Lee et al. [8] proposed a modified OCV-SOC relationship based on the traditional OCV-SOC relationship. The proposed method uses the dual extended Kalman filter to estimate the state of charge and capacity of a lithium-ion battery.

2) *Terminal Voltage Method:* Since internal impedances cause the terminal voltage to drop as the battery drains, the electromotive force (EMF) of the battery is proportional to that voltage. The terminal voltage strategy is based on this. Because a battery's EMF is roughly linearly related to its state of charge, the terminal voltage of a battery is linearly proportional to its state of charge. The terminal voltage approach has been applied at various discharge currents and temperatures [9]. However, because the battery's terminal voltage abruptly declines at the conclusion of discharge, the predicted error of the terminal voltage approach is significant [10].
3) *Impedance Method:* Impedance measurements are one of the techniques used, and they provide information on a number of characteristics, the magnitudes of which might vary depending on the battery's state of charge. Although impedance characteristics and their fluctuations with SOC are not the same for all battery systems, it appears to be necessary to conduct a wide range of impedance tests in order to identify and use impedance parameters for calculating a battery's SOC [11,12].
4) *Impedance Spectroscopy Method:* Battery impedances are examined using impedance spectroscopy over a wide range of ac frequencies at different charge and discharge currents. The model impedance values are determined via least-squares fitting. By comparing current battery impedances to known impedances at various SOC levels, SOC can be determined indirectly [13,14].

B. *Book-Keeping Estimation*

The book-keeping estimating method uses the battery discharge current information as input. Internal battery impacts such as self-discharge, capacity loss, and discharging efficiency can be included using this method. Book-keeping estimation techniques come in two forms: Coulomb Counting and Modified Coulomb Counting Method.

1) *Coulomb Counting Method:* The Coulomb counting method calculates SOC by determining a battery's discharge current and integrating it over time.

   The SOC(t) is calculated using the Coulomb counting method, which is based on the discharging current, I(t) and previously calculated SoC values, SoC (t - 1). SoC is estimated by the following equation [1]:

$$SoC(t) = SoC(t-1) + \frac{I(t)}{Q_n}\Delta t \qquad 2$$

More errors can occur in this method because of several factors that affect the accuracy of Coulomb counting method including temperature, battery history, discharge current, and cycle life.

2) *Modified Coulomb Counting Method:* A new technique called modified Coulomb counting method is proposed to improve the Coulomb counting method. The corrected current is used in the modified Coulomb counting method to improve estimation accuracy. The corrected current is proportional to the discharging current. The corrected current and battery discharging current of battery have a quadratic relationship. Corrected current is calculated using experimental data in the following way [1]:

$$I_c(t) = k_2 I(t)^2 + k_1 I(t) + k_0 \qquad 3$$

Where k_2, k_1 and k_0 are the constant values obtained from the practice experimental data.
In this method, SoC is estimated using this following equation [1]:

$$SoC(t) = SoC(t-1) + \frac{I_c(t)}{Q_n}\Delta t \qquad 4$$

The experimental results reveal that the modified Coulomb counting approach outperforms the traditional Coulomb counting method in terms of accuracy.

3) *Adaptive Systems:* Recent developments in innovative adapting methods for SOC estimate have been made possible by the evolution of artificial intelligence. Among the recently created techniques are the radial basis function (RBF), back propagation (BP), support vector machine, fuzzy logic, fuzzy neural network, and Kalman filter. Systems that can self-design themselves and automatically adapt to changing contexts are called adaptive systems. Adaptive systems offer a promising approach for SOC estimate since batteries have nonlinear SOC and are impacted by a range of chemical variables [15].

C. Adaptive Systems

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1) *BP Neural Netwrok:* In artificial neural networks, the BP neural network is the most prevalent network. Because of its ability to do nonlinear mapping, self-organization, and self-learning, the BP neural network is used in SOC estimation [17]. In SOC estimation, the relationship between the input and target, as defined by the problem, is nonlinear and extremely intricate [16]. The artificial neural network-based SOC indicator forecasts current SOC based on a battery's recent voltage, current, and ambient temperature [18].
2) *RBF Neural Network:* For systems with incomplete information, the RBF neural network is a useful estimation tool. It can be used to investigate the connections between a major (reference) sequence and the other comparative sequences in a set. In order to estimate SOC, the RBF neural network was used. Data from battery experiments was used to test the method. The results suggest that the estimating model's operating speed and estimation accuracy can match the needs in practice, and the model has some application value [19, 20].
3) *Fuzzy Logic Method:* The fuzzy logic method is an effective way to model nonlinear and complicated systems. In [21], a viable approach for determining SOC of battery systems has been designed and tested in this work for a variety of systems. The method involves analyzing data provided by impedance spectroscopy and/or Coulomb counting methods using fuzzy logic models. In [22], a fuzzy logic-based SOC estimate approach for lithium-ion batteries has been proposed for application in portable defibrillators. The ac impedance and voltage recovery measurements were taken, and these data were used to create the fuzzy logic model's input parameters.

4) *Karman Filter:* Normally, it would be challenging or expensive to determine the SOC of a battery measuring real-time path data. In [23], it is demonstrated that using the real-time state estimation approach, the Kalman filter method may produce reliable estimates of the battery's SOC.

A Kalman filter-based SOC estimate approach for lithium-ion batteries was presented by Yatsui and Bai [24]. When used online, experimental data have demonstrated the Kalman filter's usefulness. By employing terminal current and voltage measurements, In order to predict the proportions of the important chemical compounds that are averaged on the thicknesses of the active materials in order to compute the SOC of the battery, Barbarisi et al.[25] devised an extended Kalman filter (EKF).

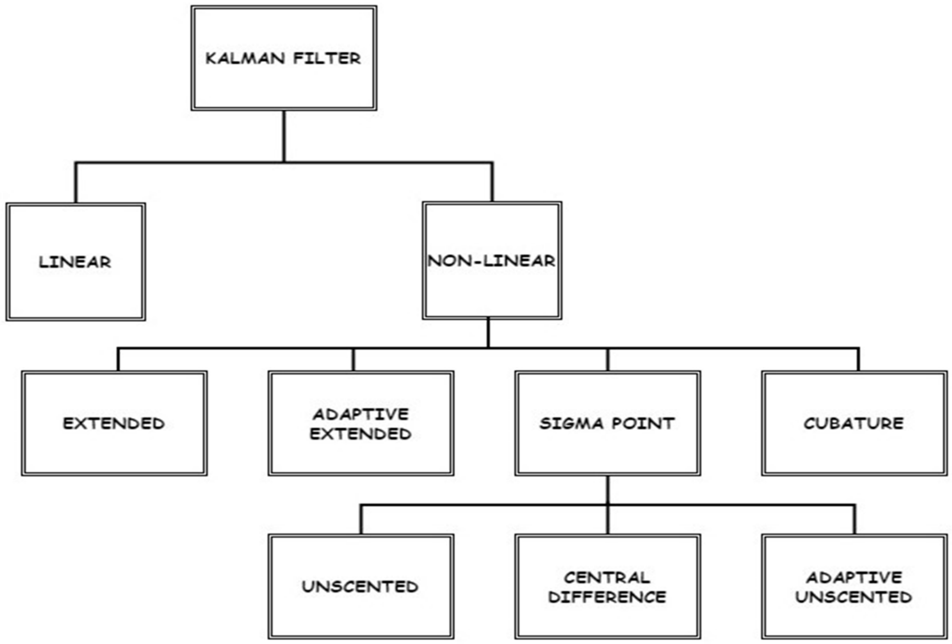

Fig. 3 The family of Kalman filter algorithms

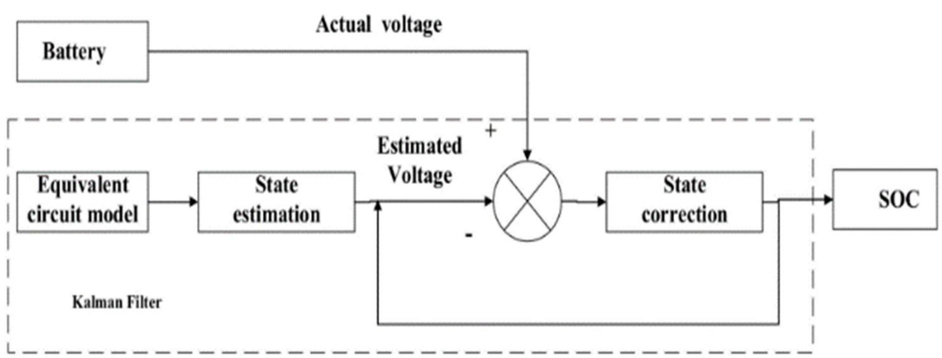

Fig. 4 The Principle of Kalman Filter [36]

The extended Kalman filter's theory states that it linearizes the nonlinear system at each time step [26]. It uses the nonlinear function linearization method to extend the nonlinear OCV function with partial derivatives in OCV-based models. A SoC estimation technique relying on a reduced-order LIB framework and an extended Kalman filter has been reported with inaccuracies of less than 2% due to the simplicity with which model parameters can be adjusted due to nonlinear behaviour [27]. Alternatively, a dual-time scale extended Kalman filter was used to estimate the SoC of a LIB, with the average SoC measured for all cells and the individual cell SoC derived from the difference between the mean and each individual cell [28]. A SoC inaccuracy of less than 2% was obtained as a result of this. Overall, the accuracy of the extended Kalman filter is determined not only by OCV function linearization, but also by model parameters; as a result, improved techniques can be characterized as either model or algorithm improvements.

The unscented Kalman filter is a nonlinear estimator derived from the traceless transformation. Unscented transformation can be used to convert nonlinear machine formulations to normal Kalman filters [29]. Higher-order terms are not ignored by the unscented Kalman filters transformation, which has high precision estimates [30]. A novel SOC estimation approach is proposed in [31] based on unscented Kalman filter (UKF) theory and a thorough battery model. The results reveal that when it comes to battery SOC estimation, the UKF method outperforms the extended Kalman filter method. Sun et al. [32] proposed an adaptive UKF approach for estimating the SoC of a lithium-ion battery for battery electric cars. In the UKF context, an idea of covariance matching is used to achieve adaptive noise covariance adjustment in the SOC estimation process.

D. Hybrid Methods

The purpose of hybrid models is to make use of the benefits of each method while achieving the best overall estimate performance. Due to the restricted amount of information that each estimating method may use, the hybrid approach can maximize the data that is already available, integrate specific model knowledge, and make the most use of the advantages of many estimating methods, improving estimation accuracy. In comparison to individual techniques, hybrid methods produce good SOC estimation results, according to the literature [33–35]. Different approaches, such as direct measurement and book-keeping estimation, are combined in hybrid methods.

1) *Coulomb Counting and EMF Combination:* A new SOC estimation approach was proposed and applied in a real-time estimation system [33] that combines direct measurements with battery EMF measurements during the steady state and accounting estimation using the Coulomb counting method during the discharge phase. During cycling, any battery will lose capacity. A simple Qmax adaptation technique is used to accurately compute SOC and remaining run-time (RRT) and to increase the SOC estimate system's capacity to cope with the ageing impact. The steady circumstances of the charge state are used in this approach to adapt Qmax to the aging impact.Even with a new battery, the Qmax adaption approach has been shown to enhance SOC and RRT estimation accuracy. The Qmax adaption technique is anticipated to considerably increase the SOC and RRT estimation accuracy when the battery capacity decreases while cycling.
2) *Coulomb Counting and Karman Filter Combination:* The "KalmanAh technique," a fresh SOC estimate method that uses the Kalman filter method to compensate for the starting value used in the Coulomb counting method, was introduced by Wang et al. [34]. The approximation beginning value converges to the true value using the Kalman filter method in the KalmanAh method. Then, for the extended working duration, the Coulomb counting approach is used to estimate the SOC. When compared to the true SOC acquired from a discharge test, the SOC estimation error is 2.5 percent. This compares favourably to a 11.4 percent estimation inaccuracy when utilising the Coulomb counting approach.
3) *Per-Unit System and EKF Combination:* Kim and Cho [35] showed how they used an EKF and a per-unit (PU) approach to find acceptable battery model parameters for high-accuracy SOC estimate of a lithium-ion deteriorated battery. The absolute values of the design factors in the equivalent model, as well as the current and terminal voltage, are translated into non - dimensional values relative to a set of base values in order to apply the battery model parameters that are affected by the ageing impact, depending on the PU system. The EKF algorithm incorporates the translated values into dynamic and measurement models.

IV. STATE OF HEALTH ESTIMATION

Estimating the battery's state of health in comparison to a newly constructed battery is known as state of health estimation. It provides information on the quantity of available discharging capacity over the course of its lifetime. In electric vehicles, the SOH is used to describe the ability to drive a given distance. In EV applications, the SOH is used to describe the ability to drive a certain distance or range. SOH is a characteristic of the specified power in HEV applications, such as the cranking power from regenerative braking. The percentage of nominal capacity is used by scholars and manufacturers as the battery's health threshold [37]. Battery failure occurs when the capacity of the battery drops to 80% of its initial capacity after charge-discharge cycling. In terms of battery properties, test equipment, and diverse applications, research have specified several rules or indications to quantify the SOH.

Capacity and power fade were combined as health characteristics by Pattipati et al. [38]. With a fully charged battery pack, capacity fade shows a reduction in driving range, whereas power fade indicates a reduction in acceleration capabilities. To calculate SOH, both of these characteristics were fed into an auto-regressive Support Vector Regression (SVR) model. The power loss was caused by an increase in cell impedance as people aged.

The total resistance ($R = R_{HF} + R_{tc}$) was obtained from EIS data using nonlinear least squares. Figure 5 shows a Randles circuit model of a battery. Where R_{HF} and R_{tc} are high frequency resistance and transfer resistance.

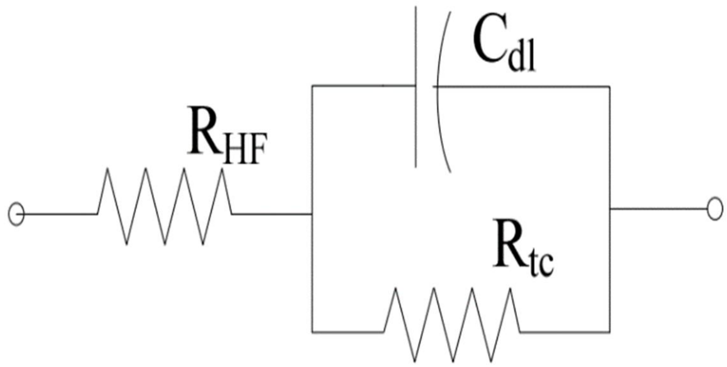

Fig. 5 Randles circuit model for a lithium-ion battery

$$Power\ Fade = 1 - \left(\frac{Power(k)}{Power(0)}\right) = 1 - \frac{R(0)}{R(k)} \quad (6)$$

$$Capacity\ Fade(\%) = 1 - \left(1 - \frac{Capacity(k)}{Capacity(0)}\right) \times 100\% \quad (7)$$

The study also suggested that SampEn might be used as a SOH indicator. SampEn is expressed as:

$$SampEn(m, r, N) = -ln\left[\frac{A^m(r)}{B^m(r)}\right] \quad (8)$$

where N is the total number of data points, m is the length of sequences to be compared, r is the tolerance parameters, $B^m(r)$ is the mean value of two similar signal segments that are composed from input vectors with m points, and $A^m(r)$ is similar to $B^m(r)$ and will match for m+1 points.

V. THERMAL MANAGEMENT

The high temperature of the battery cell is a critical issue that must be addressed effectively if EV performance is to be improved. When high temperatures trigger exothermic processes, which accelerate the temperature and lead to additional harmful reactions, a thermal runaway of the battery occurs. When the temperature rises over 90 degrees Celsius, the electrolyte, cathode, and solid electrolyte interface (SEI) layer begin to decompose. However, $LiFePO_4$ has a restricted exothermic heat discharge, giving better thermal stability than other lithium-ion batteries [39]. Wang et al. (2016) [40] discovered that if the battery temperature rises 1 degree Celsius in the temperature range of 30 to 40 degrees Celsius, the battery's lifespan is reduced by two months. As a result, heat management in the battery system for electric vehicle applications is critical, and more research is needed to create a suitable cooling and heating system for BMS.

The battery efficiency will decrease in a sub-zero environment, resulting in a low discharge capacity [41]. This has a direct impact on vehicle mobility and range, as well as the vehicle's life cycle. The 2012 Nissan Leaf is a notable illustration of this, with a range of only 63 miles at 10°C versus 138 miles under optimal conditions. Because there is no combustion engine to provide heating for pure EVs, a considerable percentage of battery energy will be required to heat the battery and the cabin, reducing the driving range by another 30–40 percent.

To achieve optimal BMS functioning, an appropriate thermal management system (TMS) is required to keep the battery temperature within the specified range [42]. The TMS regulates the battery's working temperature, requiring that each battery cell function within a certain temperature range. TMS responds immediately when the temperature of the battery exceeds the safe limit(threshold), ensuring safe operation and safeguarding the battery from dangerous events through the heating and cooling management and control system [43].

The cooling/heating insulating layer in a battery TMS uses either air or liquid as the heating/cooling ventilation. Passive cooling, passive cooling/heating, and active cooling/heating are covered by the air TMS, whereas passive cooling, active cooling, and active cooling and heating are covered by the liquid TMS. In terms of heat capacity and thermal conductivity, the liquid TMS provides superior results. TMS's operation is controlled by an electronic control unit [44].

VI. FAULT DIAGNOSIS

Battery safety is vital to guarantee the secure, dependable, and safe operation of EVs. As a result, the design of a proper diagnostics and fault handling mechanism is critical, as even slight faults can lead to serious difficulties with battery health [47]. According to a literature review [48-50], BMS fault mechanisms are typically complex and may be divided into three categories: sensor fault, actuator fault, and battery fault as depicted in figure 6.

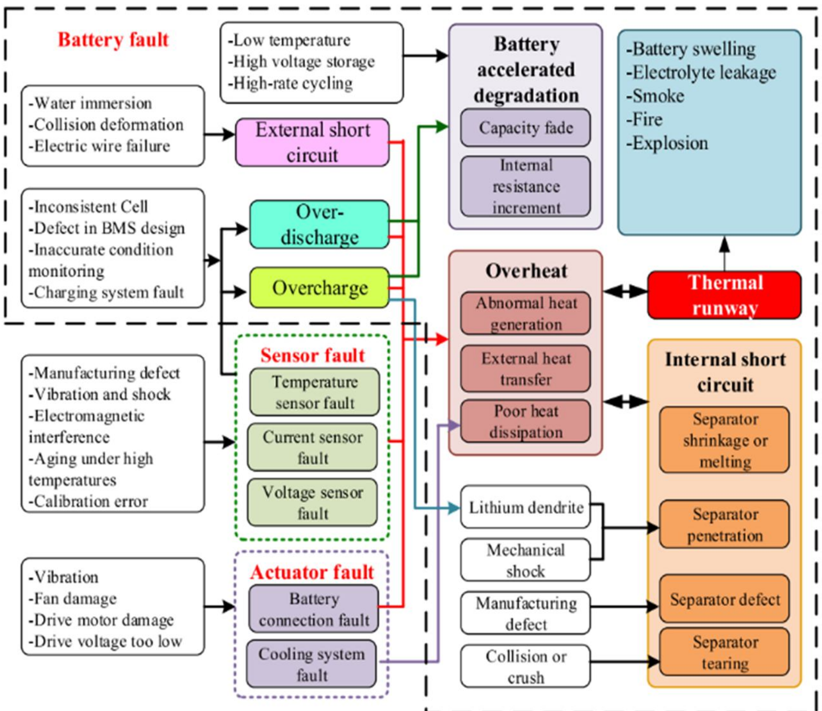

Fig. 6 The Outline of Various Faults in the Li-ion battery systems [45]

Voltage, current and temperature sensing flaws are examples of BMS sensor issues. Current sensor failures can cause SOC, SOE, SOH, and RUL estimation accuracy to be off. Furthermore, the battery must be operated within the manufacturer's suggested voltage and temperature limits. If the measured values surpass the boundary, the battery's performance may decline, possibly resulting in an accident. Furthermore, sensor defects in voltage and temperature may cause TMS or battery equalization errors in the BMS.

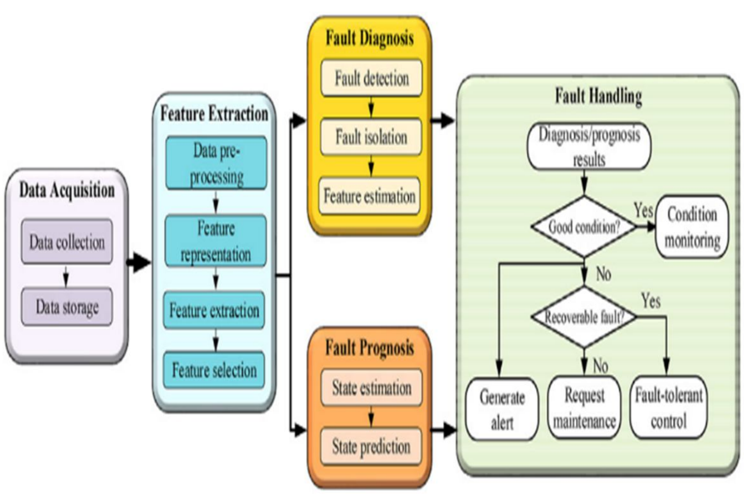

Fig. 7 General fault diagnosis framework for BMS [46]

Fuse failures, high voltage contactor faults, controller area network (CAN), bus faults, terminal connector faults, and cooling system faults are all instances of BMS actuator faults [51]. A battery connection issue can cause a rise in resistance, as well as extreme irregular heat, which promotes the temperature rise. Furthermore, a faulty battery connection may result in insufficient power supply, resulting in the melting of the battery terminals and the possibility of an accident [52]. If the cooling system fails, the battery will be unable to operate within the temperature range, resulting in thermal runaway.

Overheating, overcharging, overdischarging, internal short circuit (ISC), external short circuit (ESC), battery swelling, electrolyte leakage, and thermal runaway are all examples of battery failures that occur in BMS. Overcharging and discharging batteries can result in adverse responses and health problems, as well as battery swelling and electrolyte leakage. Overcharging and discharging batteries can cause a variety of unfavorable battery side reactions, resulting in rapid degradation. Battery swelling and electrolyte leakage may occur as a result of these side reactions and gases produced by chain reactions during the thermal runway [53].

Data gathering, feature extraction, fault diagnosis, fault prognosis, and fault treatment are all part of the methodological framework for fault diagnosis in BMS, as shown in Figure 7. First, data acquisition is used to acquire and store battery data from experimental setups or test bench models, such as current, voltage, and temperature. Following that, data preprocessing, extraction, and selection are carried out using feature extraction. The chosen data is then processed for the fault diagnosis and prognosis phases. The fault diagnosis procedure includes defect identification, isolation, and estimation. The fault prognosis stage includes the execution and evaluation of battery condition algorithms in order to provide early identification or forecast of battery issues.

Finally, the fault handling phase analyzes and evaluates the results of problem diagnosis and prognosis, and performs appropriate actions such as alarm production, battery isolation, and power supply shutdown.

VII. CELL BALANCING

The cell chemicals, initial charge capacities, and exterior impacts of each cell in the battery pack are frequently different. In addition, the battery pack's series-connected cells are regularly charged and discharged in a variety of energy storage devices. As a result of the disparities in charge-discharge speed and longevity, the state-of-charge in the battery cells may be unequal. Variations in the battery voltage and capacity of series-connected cells in the battery pack occur from variances in charging and discharging speeds in these imbalanced cells. These variations in the battery pack are the primary cause of cell capacity reduction and battery life reduction. An auxiliary cell balancing circuit should be used in the battery management system to resolve this imbalance of cell energy.

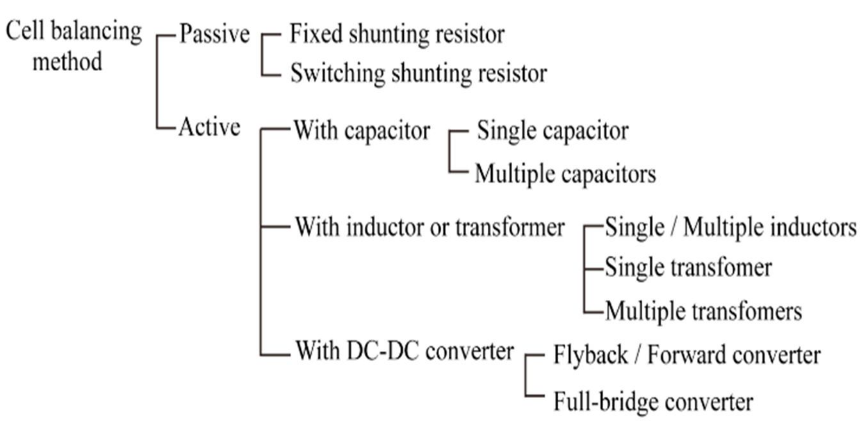

Fig. 8 Cell Balancing Methods

A. Passive Cell Balancing

Resistors are commonly used in passive cell equalizing circuits to balance cell energy by using more cell energy in a battery string. Compared to other cell equalizing circuits, this balancing method is more dependable and employs less components.

Bypassing the cells through a channel that is predominantly dissipative, the passive cell balancing approach seeks to discharge the cells. The bypass is easier and simpler to implement than active balancing methods and keeps the system more cost-effective in both cases because it can be external or integrated. The battery's duration declines, and it is less likely to be used during discharge because all of the additional energy is squandered as heat.

B. Active Cell Balancing

An active cell-balancing circuit frequently uses energy-transfer devices like capacitors, inductors, or transformers to balance the energy of the battery pack's cells. Compared to the passive cell-balancing circuit, this active one is more effective and takes less time to balance each cell. This cell equalizing circuit, on the other hand, is expensive and requires advanced system control algorithms to balance cells.

The charge is transferred between the cells using inductive or capacitive charge shuttling in the active cell balancing approach. This method has been shown to be effective since it sends energy to where it is needed rather than waste it. However, this necessitates the installation of extra components to the system, which results in an increase in cost.

VIII. CONCLUSION

Due to the availability of huge data, strong calculation processors, and high-capacity data storage devices, numerous analyses and evolutions on intelligent algorithms and control techniques of BMS in EVs have been carried out in recent decades. This paper examines the present state of intelligent algorithms for SOC, focusing on structure, input features, pros and disadvantages, and estimation error as a first contribution.

In conclusion, the critical analysis and crucial information gleaned from this review will aid automotive engineers and the EV industry in creating and implementing sophisticated BMS for EV applications. As a result, more research into BMS using intelligent algorithms and controller schemes will not only improve battery performance and lifespan, but also assure the safe and dependable operation of electric vehicles, resulting in significant development of the battery and electric vehicle markets. Achieving sustainable development objectives including clean energy, pollution reduction, job creation, and economic growth can be facilitated by the expansion of the electric vehicle (EV) and related battery markets

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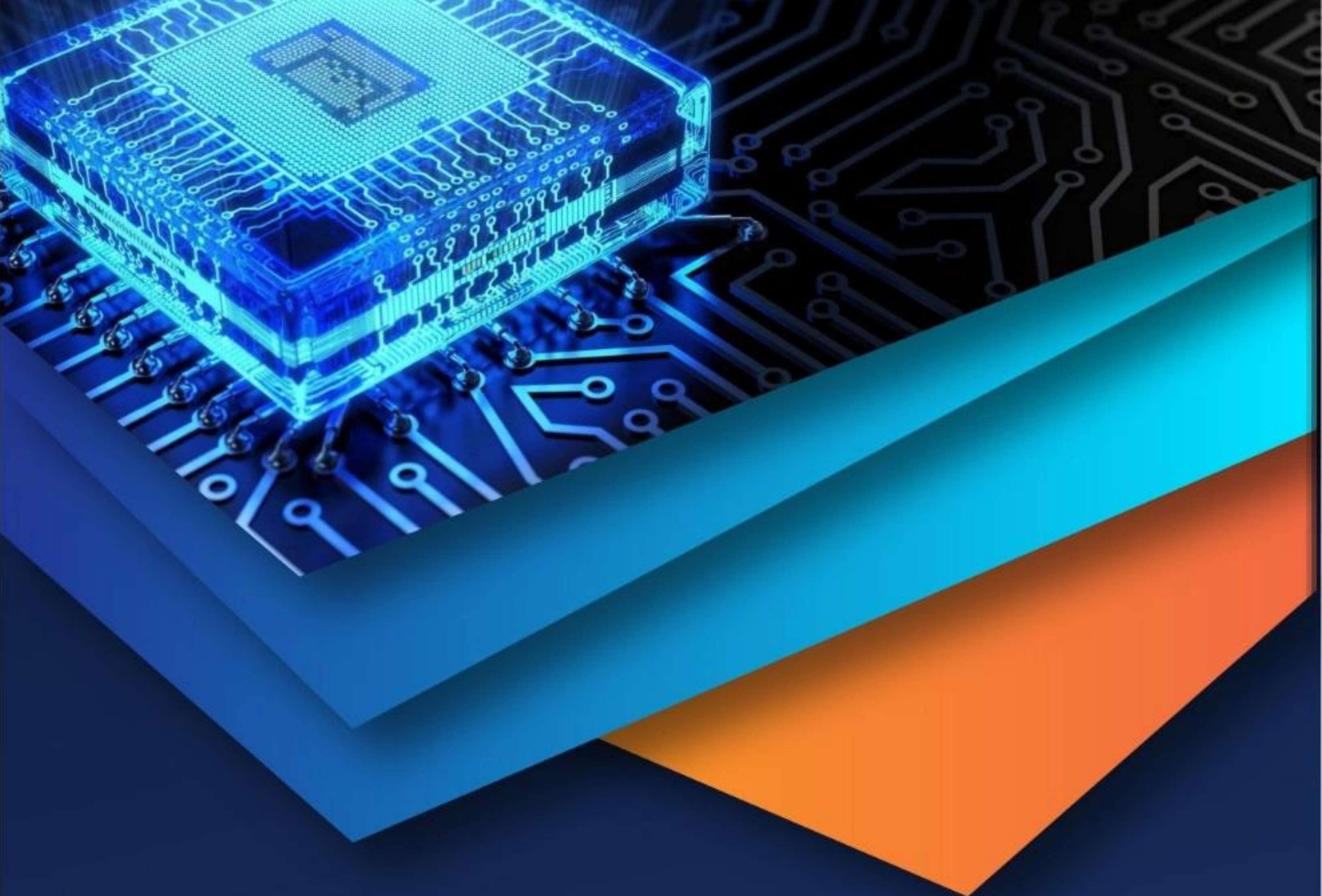

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