Energy Storage and Battery Management for Electrified Vehicles

Subjects: Engineering, Mechanical
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The transport sector is tackling the challenge of reducing vehicle pollutant emissions and carbon footprints by means of a shift to electrified powertrains, i.e., battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs). However, electrified vehicles pose new issues associated with the design and energy management for the efficient use of onboard energy storage systems (ESSs). Thus, strong attention should be devoted to ensuring the safety and efficient operation of the ESSs. In this framework, a dedicated battery management system (BMS) is required to contemporaneously optimize the battery's state of charge (SoC) and to increase the battery's lifespan through tight control of its state of health (SoH).

battery management system | energy storage system | connected vehicles | in-cloud BMS | state of charge | state of health

1. Introduction

In 2021, according to the International Energy Agency (IEA), global carbon dioxide (CO_2) emissions from the transport sector had rebounded, growing by 8% to nearly 7.7 Gt CO_2 because of the pandemic restrictions lifting [1]. Furthermore, the worldwide carbon neutrality goals dictated by national and international regulations have been leading the transport sector to face new challenges because of carbon footprint reduction [2]. Within this framework, the European Commission (EC) proposed the "Fit for 55", a series of regulatory proposals intended to achieve climate neutrality in the European Union by 2050, including the intermediate target of at least 55% net reduction in greenhouse gas emissions by 2030 [3]. In particular, the EC proposal strengthens the 2030 CO_2 targets, from −37.5% to −55% for new passenger cars and from −31% to −50% for new vans, both relative to a 2021 baseline. In addition, the proposal introduces the target to meet zero tailpipe CO_2 emissions from 2035 onwards [4]. Thereby, the incoming stricter regulations and the mid-term European Commission policies have compelled academia, research institutions, and OEMs to study and extensively invest in advanced technologies and solutions toward the full electrification of the light-duty road transport sector. BEVs and PHEVs retain a high potential for penetrating the market and contributing to reducing pollutants and greenhouse gas emissions in the following years. To sustain a wide diffusion of electrified vehicles (EVs), battery performance and durability are key factors. For this purpose, an optimized battery management system (BMS) can prevent degradation phenomena and extend the battery lifetime [5], avoiding battery replacement which can negatively affect the EVs' life cycle analysis. A proper BMS ensures the monitoring and control of the batteries. It is comprised of different types of sensors, actuators, and controllers managed with logic or algorithms [6], aimed at making the batteries operate within the proper voltage and temperature interval, guaranteeing the safety requirements and prolonging their service life. In particular, the BMS includes functions such as cell balancing, thermal management and state management [7]. A key role of the BMS is to provide an accurate battery state estimation. Commonly, the battery state mainly includes the state of charge (SoC), state of health (SoH), and state of power (SoP) [8][9]. In the case of electrochemical energy storage systems, internal battery states cannot be directly measured [10]. They can be estimated and predicted indirectly through voltage, current and temperature measurements [11]. Owing to the intricate electrochemical processes within the battery, the internal states display a markedly nonlinear correlation with measurable parameters. This concern increases in severe working conditions [10]. In addition, the rate of aging and wear phenomena increase according to the severity of the battery operating conditions, and in terms of discharge depth, number of charges and discharge cycles and temperature [12][13]. Moreover, battery degradation during the cycle affects the state estimation reliability [14]. Hence, precise estimation of the battery state remains a technical challenge, particularly given the potential variations in battery performance over time due to aging. Achieving a stable and accurate estimation is crucial for the entire lifespan of the battery.

SoC represents a main concern related to BMS design in EVs due to its importance in providing some important information, such as the remaining energy and/or remaining useable time [15] to prevent the battery from over-charging/ discharging [16]. As a result, the estimation of battery SoC has been extensively studied. Many techniques have been developed and can be grouped into direct, model-based, and data-based methods. Direct methods are only suitable for laboratory purposes, whereas model- and data-based methods have gained interest for online implementation. Model-based estimation methods have more potential to be employed in real applications due to their rational tradeoff between complexity and prediction accuracy [17]; nevertheless, a battery model definition is necessary introducing potential errors. On the contrary, the data-based approach does not need a sophisticated battery model, but a huge amount of data is necessary to train the model becoming challenging for online applications [18]. Similarly, the SoH-estimation method includes direct, model-based, and data-driven methods, the strengths and shortcomings of which are like the SoC-estimation methods [19]. It is worth dwelling on the fact that in the SoH model-based approach, the functional relationship between battery parameters and battery aging state is usually established under certain battery-operating conditions; thus, its feasibility and estimation accuracy still need to be further verified with various current rates, ambient temperatures and even types of lithium-ion batteries [11]. SoH data-driven methods have the potential to overcome these limitations at the cost of expensive training datasets [18]. Therefore, with the increasingly functional demand for BMS [20], despite the advancements in the modern onboard BMS, more detailed data-driven algorithms for SoC, SoH and fault diagnosis cannot be implemented due to limited computing capabilities. To overcome these limitations, the conceptualization and/or implementation of BMS in-cloud applications are under investigation [21][22]. The development is in an early stage of progress. The advantages expected by adopting cloud-based solutions are related to a simplification of local computing and more accurate and reliable prognostics and diagnostics of the battery system [23].

2. Energy Storage Systems for Electrified Vehicles

The ESSs, commonly referred to as batteries, serve as the predominant means for storing electrical energy. Typically, a battery comprises two electrodes, namely the anode (negative electrode) and cathode (positive electrode), along with an electrolyte. Electrical energy is stored as electrochemical energy through redox reactions between the two electrodes, facilitated by charges of opposite signs moving within the electrolyte toward the opposing electrode. The specific battery technologies are differentiated via the materials used for the electrodes and the type of electrolyte. A brief overview is proposed as follows.

Lead acid battery uses lead oxide (PbO_2) as the positive electrode, lead (Pb) as the negative electrode and about 37% sulfuric acid (H_2SO_4) as electrolyte. The electrolyte can be liquid, or it can be absorbed in a glass-fiber mat. The overall chemical reaction for the lead acid battery is [24]:

$$\mathrm{Pb} + \mathrm{PbO_2} + 2\mathrm{H_2\,SO_4} \rightleftharpoons 2\mathrm{PbSO_4} + 2\mathrm{H_2O} \quad (1)$$

Lead acid batteries stand out as the most economical energy storage technology owing to the utilization of low-cost materials. Because of their lower energy density, lead acid batteries become the preferred choice in scenarios where the stored energy is less critical, and cost-effectiveness is crucial. This is particularly evident for auxiliary vehicle systems (starters, pumps, etc.), micro-hybrid vehicles or electric scooters. The success of lead acid batteries in these contexts is attributed to their inherent safety features and notable recycling rates (up to 95%) [25].

Nickel-based batteries employ nickel hydroxide as the positive electrode alongside various negative electrode materials. The categorization of nickel-based batteries depends on the negative materials, leading to distinctions such as Ni-Fe, Ni-Cd, Ni-Zn, Ni-MH, and Ni-H_2. Typically, the electrolyte utilized is a potassium hydroxide solution. Nickel-iron and zinc are less attractive in electric hybrid and electric vehicles due to their low specific energy, high cost, reduced life cycle and heightened maintenance requirements. Conversely, Ni-Cd and Ni-MH have been widely used in battery-powered vehicles due to their extended life cycles (2000 cycles or more) and higher energy density. The overall electrochemical reactions are shown as follows [24]:

$$\mathrm{Cd} + 2\,\mathrm{NiO(OH)} + 2\mathrm{H_2O} \rightleftharpoons 2\,\mathrm{Ni(OH)_2} + \mathrm{Cd(OH)_2} \quad (2)$$

$$\mathrm{NiO(OH)} + \mathrm{MH} \rightleftharpoons \mathrm{M} + \mathrm{Ni(OH)_2} \quad (3)$$

Nevertheless, Ni-Cd suffers a high memory effect, and the use of cadmium poses critical concerns regarding its environmental compatibility. On the other hand, Ni-MH batteries exhibit a low memory effect, negligible environmental effect, and a wide operating temperature range [26]. In addition, their high power density and adequate lifetime have qualified them as the world market leader for use in hybrid electric vehicles [25]. Nonetheless, Ni-MH battery technology can be considered a mature technology that has reached its best potential in terms of cost reduction and characteristics. Therefore, this type of battery does not seem to be competitive with lithium technology batteries [27].

Nowadays, Li-ion-based batteries are most suitable and applicable in powered-battery vehicles due to their characteristics and performance compared with other cell chemistry technologies [28]. Lithium batteries exhibit high specific energy and power values, are lightweight, boast extended lifespans and do not suffer from memory effects or the harmful impacts seen in lead or cadmium batteries. Nevertheless, lithium batteries are comparatively more expensive than other battery technologies, requiring protective measures for safe operation and a cell balancing system to ensure uniform battery performance at consistent voltage and charge levels [27]. However, notwithstanding the price reduction in the Li-ion-based batteries, the increasing demand for raw materials poses significant environmental and health concerns [29]. Depending on the positive cathode materials, lithium batteries can be classified into lithium cobalt oxide ($LiCoO_2$), lithium manganese oxide ($LiMn_2O_4$), lithium iron phosphate ($LiFePO_4$), lithium nickel–manganese–cobalt oxide ($LiNiMnCoO_2$), lithium nickel cobalt aluminum oxide ($LiNiCoAlO_2$), and lithium titanate ($Li_4Ti_5O_{12}$) batteries. The overall electrochemical reaction in a Li-ion-based battery is described as follows [24]:

$$\mathrm{LiMeO_2 + C \rightleftharpoons Li_{1-x}MeO_2 + Li_x C} \qquad (4)$$

The $LiCoO_2$ lithium-ion batteries were the first to be developed. Due to the higher costs associated with cobalt oxide, subsequent advances introduced nickel and manganese oxide batteries, with the latter proving to be more economical and cost-effective [26]. Among lithium-ion batteries, the $LiFePO_4$ battery is recognized for its superior power density, substantial discharge current, and comparatively lower cost. Furthermore, the $LiFePO_4$ battery exhibits stability in both thermal and chemical operations and has 30% more lifecycles than the lithium manganese oxide battery [30]. The $LiNiMnCoO_2$ chemistry retains a small amount of the world market-share despite its energy and power densities, safety and cost [31]. $Li_4Ti_5O_{12}$ batteries are presently used in battery-powered applications because of their faster charging behavior compared with other lithium batteries due to elevated stability in charging/discharging operations. Despite these batteries being able to be operated safely at cold temperatures, a proper thermal management strategy is mandatory [29]. The main characteristics of the batteries mentioned are outlined in **Table 1**. However, this list is far from being exhaustive, and other batteries with different cell chemistries can be evaluated.

Table 1. Characteristics of different batteries [26][30][31].

Battery Type	Specific Energy (Wh/kg)	Specific Power (W/kg)	Nominal Voltage (V)	Cycle Life (# of Cycles)	Cost (USD/kWh)	Application
Lead-acid	180	35–40	2	1500–5000	120–200	Automotive ignition, starting

Battery Type	Specific Energy (Wh/kg)	Specific Power (W/kg)	Nominal Voltage (V)	Cycle Life (# of Cycles)	Cost (USD/kWh)	Application
Ni-Cd	40–60	150	1.25	2000–3000	250–350	Portable devices
Ni-MH	60–120	250–1000	1.25	500–3000	150–250	Electronic Equipment, xEV
Li-ion	120–140	200–2000	3.6	1500–4500	150–1300	Electronic Equipment, xEV

…d electric …-sulfur (Li-S) can be considered a promising candidate for next generation power supplies due to its potentially high specific energy value (about 500 Wh/kg), which is two to three times higher than that of current commercial lithium batteries [32].

With the rise in use of lithium batteries, a BMS is essential to ensure safe and optimized operations of the ESSs. To achieve this goal, correct battery state estimation is mandatory.

3. Battery Management System Overview

As stated previously, battery-powered vehicles could represent a promising solution for a more sustainable form of transportation. A reliable and cost-effective management of on-board ESSs is a key point for the development of vehicles, ensuring proper performance as well as the safe operation of the on-board ESSs. **Figure 1** shows a schematic overview of the key features of a modern BMS.

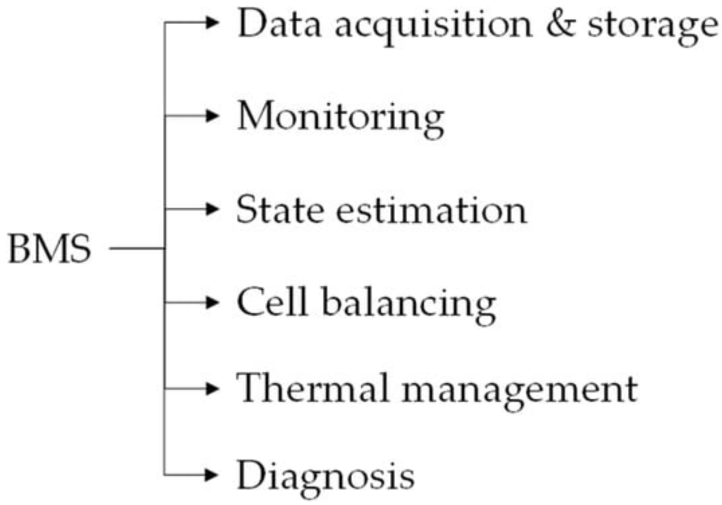

Figure 1. BMS main functions.

As can be seen, the main functions can be grouped mainly into the following categories: data acquisition and storage, monitoring, state estimation, cell balancing, thermal management and diagnosis. Each category will be briefly discussed in the following sections.

a. Data acquisition and storage

The BMS data acquisition system is composed of sensors, measurement hardware, the processor and software [6]. Temperature, terminal voltage, current and other information of each cell in the battery pack are collected in real-time to obtain an accurate overview of ESS working conditions. The requirement for voltage and current measurements vary according to the type of battery technology employed [33]. The acquired data are processed and then stored by BMS for equalization of the battery cells, thermal management, fault diagnosis and control of the other functional parts via the BMS controller [31].

b. Monitoring

In real working conditions, battery behavior changes dynamically. Thus, continuous monitoring is required to obtain information about the battery operating conditions. This function, involving the acquired data, indicates the necessity of the charge and discharge control, avoiding overcharging or undercharging conditions, etc. During operation, an abnormal variation in the battery current and voltage values may cause system failure or system burnout [31]. Accordingly, it is crucial to monitor the current and voltage of the battery to prevent over-current/voltage and undercurrent/voltage operations [34]. The performance and durability of the battery are primarily contingent on its charging and discharging processes. An efficient control of these processes can mitigate the memory effect, thus extending the battery lifespan.

c. State estimation

In real-time operating conditions, the battery state changes due to complex, time-varying and nonlinear battery characteristics [35]. Battery state estimation enhances the battery operability and increases the durability of the designed system [36]. State estimation is mainly referred to SoC and SoH estimation. An accurate estimation of the battery SoC is necessary to prevent battery failure, provide efficient cell balancing, and accurate SoH estimation. SoH estimation is crucial in selected energy management strategies to prolong battery life and appropriately arrange for the replacement of the battery [22]. Despite the importance of state estimation, the SoC and SoH values cannot be measured directly from the battery. As a result, using embedded algorithms, the BMS must estimate the current state of the battery from collected real-time battery data [35]. As thoroughly reviewed in this work, several methods are suitable for SoC estimation. According to [37], KF family algorithms represent the right trade-off between complexity and accuracy due to their self-correcting nature and acceptable computational burden for online implementation. Conversely, SoH estimation is more challenging due to the complex nonlinear aging mechanism of the battery. As reviewed in Section 2, more complex intelligent algorithms have been proposed to enhance SoH estimation accuracy. Nevertheless, their online implementation is currently challenging owing to BMS limited computer capability and data storage [38]. Estimation of the battery state not only helps to determine whether the operational environment is safe and reliable but also provides information about the charge–discharge operation, which is especially important for cell balancing [39].

d. Cell balancing

The concept of cell balancing is related to the consecutive charge–discharge cycle that may cause unequal voltage ranges in individual cells due to changes in their physical characteristics [40]. Imbalanced voltage and charge may reduce the overall performance and durability of ESSs [41]. Thus, cell balancing is necessary and can be provided by active and passive balancing techniques. In passive cell balancing, the charge in excess is dissipated as heat through a resistor. In active cell balancing, the charge is effectively transferred from a highly charged cell to a low one via a capacitor or an inductor [42].

e. Thermal management

A thermal management system (TMS) is responsible for controlling the heating/cooling apparatus to maintain the battery temperature within a specific temperature range and reduce the temperature gradients and temperature inhomogeneity across the pack. Conventionally, the TMS is implemented onboard. Nonetheless, due to the computational limits of a local BMS, the thermal model is the most common model used for battery TMS [23]. Currently, thermal management represents a challenge for future BMS.

f. Diagnosis

The BMS is essential for evaluating and diagnosing faults. The fault diagnosis technology is composed of a system database and records, an intelligent control program, communication networks and other technical measures [31].

References

1. IEA. Transport—Topics. Available online: https://www.iea.org/topics/transport (accessed on 25 April 2023).
2. Hjelkrem, O.A.; Arnesen, P.; Bø, T.A.; Sondell, R.S. Estimation of tank-to-wheel efficiency functions based on type approval data. Appl. Energy 2020, 276, 115463.
3. European Green Deal. Available online: https://climate.ec.europa.eu/eu-action/european-green-deal_en (accessed on 3 May 2023).
4. International Council on Clean Transportation. Fit for 55: A Review and Evaluation of the European Commission Proposal for Amending the CO2 Targets for New Cars and Vans. Available online: https://theicct.org/publication/fit-for-55-a-review-and-evaluation-of-the-european-commission-proposal-for-amending-the-co2-targets-for-new-cars-and-vans/ (accessed on 3 May 2023).
5. Vetter, J.; Novák, P.; Wagner, M.R.; Veit, C.; Möller, K.-C.; Besenhard, J.O.; Winter, M.; Wohlfahrt-Mehrens, M.; Vogler, C.; Hammouche, A. Ageing mechanisms in lithium-ion batteries. J. Power Sources 2005, 147, 269–281.

6. Nnikhil, K.N. A Review on Battery Management System for Electric Vehicles. Int. J. Res. Appl. Sci. Eng. Technol. 2022, 10, 3699–3710.
7. Lu, L.; Han, X.; Li, J.; Hua, J.; Ouyang, M. A review on the key issues for lithium-ion battery management in electric vehicles. J. Power Sources 2013, 226, 272–288.
8. Noura, N.; Boulon, L.; Jemeï, S. A Review of Battery State of Health Estimation Methods: Hybrid Electric Vehicle Challenges. World Electr. Veh. J. 2020, 11, 66.
9. Lai, X.; He, L.; Wang, S.; Zhou, L.; Zhang, Y.; Sun, T.; Zheng, Y. Co-estimation of state of charge and state of power for lithium-ion batteries based on fractional variable-order model. J. Clean. Prod. 2020, 255, 120203.
10. Zhou, L.; Lai, X.; Li, B.; Yao, Y.; Yuan, M.; Weng, J.; Zheng, Y. State Estimation Models of Lithium-Ion Batteries for Battery Management System: Status, Challenges, and Future Trends. Batteries 2023, 9, 131.
11. Zhang, S.; Zhang, X. Joint estimation method for maximum available energy and state-of-energy of lithium-ion battery under various temperatures. J. Power Sources 2021, 506, 230132.
12. Anselma, P.G.; Kollmeyer, P.; Lempert, J.; Zhao, Z.; Belingardi, G.; Emadi, A. Battery state-of-health sensitive energy management of hybrid electric vehicles: Lifetime prediction and ageing experimental validation. Appl. Energy 2021, 285, 116440.
13. da Silva, S.F.; Eckert, J.J.; Silva, F.L.; Silva, L.C.A.; Dedini, F.G. Multi-objective optimization design and control of plug-in hybrid electric vehicle powertrain for minimization of energy consumption, exhaust emissions and battery degradation. Energy Convers. Manag. 2021, 234, 113909.
14. Han, X.; Lu, L.; Zheng, Y.; Feng, X.; Li, Z.; Li, J.; Ouyang, M. A review on the key issues of the lithium ion battery degradation among the whole life cycle. eTransportation 2019, 1, 100005.
15. Zhang, J.; Lee, J. A review on prognostics and health monitoring of Li-ion battery. J. Power Sources 2011, 196, 6007–6014.
16. Agarwal, V.; Uthaichana, K.; DeCarlo, R.A.; Tsoukalas, L.H. Development and Validation of a Battery Model Useful for Discharging and Charging Power Control and Lifetime Estimation. IEEE Trans. Energy Convers. 2010, 25, 821–835.
17. Yang, H.; Sun, X.; An, Y.; Zhang, X.; Wei, T.; Ma, Y. Online parameters identification and state of charge estimation for lithium-ion capacitor based on improved Cubature Kalman filter. J. Energy Storage 2019, 24, 100810.
18. Ren, Z.; Du, C. A review of machine learning state-of-charge and state-of-health estimation algorithms for lithium-ion batteries. Energy Rep. 2023, 9, 2993–3021.

19. Hou, J.; Li, T.; Zhou, F.; Zhao, D.; Zhong, Y.; Yao, L.; Zeng, L. A Review of Critical State Joint Estimation Methods of Lithium-Ion Batteries in Electric Vehicles. World Electr. Veh. J. 2022, 13, 159.
20. Xu, J.; Mi, C.C.; Cao, B.; Cao, J. A new method to estimate the state of charge of lithium-ion batteries based on the battery impedance model. J. Power Sources 2013, 233, 277–284.
21. Li, W.; Rentemeister, M.; Badeda, J.; Jöst, D.; Schulte, D.; Sauer, D.U. Digital twin for battery systems: Cloud battery management system with online state-of-charge and state-of-health estimation. J. Energy Storage 2020, 30, 101557.
22. Tran, M.-K.; Panchal, S.; Khang, T.D.; Panchal, K.; Fraser, R.; Fowler, M. Concept Review of a Cloud-Based Smart Battery Management System for Lithium-Ion Batteries: Feasibility, Logistics, and Functionality. Batteries 2022, 8, 19.
23. Yang, S.; Zhang, Z.; Cao, R.; Wang, M.; Cheng, H.; Zhang, L.; Jiang, Y.; Li, Y.; Chen, B.; Ling, H.; et al. Implementation for a cloud battery management system based on the CHAIN framework. Energy AI 2021, 5, 100088.
24. Kumar, P.; Bansal, S.; Sonthalia, A. Chapter 4—Introduction to battery systems. In Handbook of Thermal Management Systems; Aloui, F., Varuvel, E.G., Sonthalia, A., Eds.; Elsevier: Amsterdam, The Netherlands, 2023; pp. 95–118.
25. Budde-Meiwes, H.; Drillkens, J.; Lunz, B.; Muennix, J.; Rothgang, S.; Kowal, J.; Sauer, D.U. A review of current automotive battery technology and future prospects. Proc. Inst. Mech. Eng. Part J. Automob. Eng. 2013, 227, 761–776.
26. Hannan, M.A.; Hoque, M.M.; Mohamed, A.; Ayob, A. Review of energy storage systems for electric vehicle applications: Issues and challenges. Renew. Sustain. Energy Rev. 2017, 69, 771–789.
27. Andwari, A.M.; Pesiridis, A.; Rajoo, S.; Martinez-Botas, R.; Esfahanian, V. A review of Battery Electric Vehicle technology and readiness levels. Renew. Sustain. Energy Rev. 2017, 78, 414–430.
28. Hasan, M.K.; Mahmud, M.; Habib, A.K.M.A.; Motakabber, S.M.A.; Islam, S. Review of electric vehicle energy storage and management system: Standards, issues, and challenges. J. Energy Storage 2021, 41, 102940.
29. Noudeng, V.; Quan, N.V.; Xuan, T.D. A Future Perspective on Waste Management of Lithium-Ion Batteries for Electric Vehicles in Lao PDR: Current Status and Challenges. Int. J. Environ. Res. Public Health 2022, 19, 16169.
30. Verma, S.; Mishra, S.; Gaur, A.; Chowdhury, S.; Mohapatra, S.; Dwivedi, G.; Verma, P. A comprehensive review on energy storage in hybrid electric vehicle. J. Traffic Transp. Eng. Engl. Ed. 2021, 8, 621–637.

31. Hannan, M.A.; Hoque, M.M.; Hussain, A.; Yusof, Y.; Ker, P.J. State-of-the-Art and Energy Management System of Lithium-Ion Batteries in Electric Vehicle Applications: Issues and Recommendations. IEEE Access 2018, 6, 19362–19378.
32. Zhu, J.; Zhu, P.; Yan, C.; Dong, X.; Zhang, X. Recent progress in polymer materials for advanced lithium-sulfur batteries. Prog. Polym. Sci. 2019, 90, 118–163.
33. Rahimi-Eichi, H.; Ojha, U.; Baronti, F.; Chow, M.-Y. Battery Management System: An Overview of Its Application in the Smart Grid and Electric Vehicles. IEEE Ind. Electron. Mag. 2013, 7, 4–16.
34. Hoque, M.M.; Hannan, M.A.; Mohamed, A. Voltage equalization control algorithm for monitoring and balancing of series connected lithium-ion battery. J. Renew. Sustain. Energy 2016, 8, 025703.
35. Mishra, S.; Swain, S.C.; Samantaray, R.K. A Review on Battery Management system and its Application in Electric vehicle. In Proceedings of the 2021 International Conference on Advances in Computing and Communications (ICACC), Kochi, Kakkanad, India, 21–23 October 2021; pp. 1–6.
36. Bashir, H.; Yaqoob, A.; Jawaid, I.; Khalid, W.; Javed, M.Y.; Sultan, W. A Review of Battery Management System and Modern State Estimation Approaches in Lithiumion Batteries for Electric Vehicle. In Proceedings of the 2022 5th International Conference on Energy Conservation and Efficiency (ICECE), Lahore, Pakistan, 16–17 March 2022; pp. 1–8.
37. Shrivastava, P.; Soon, T.K.; Idris, M.Y.I.B.; Mekhilef, S. Overview of model-based online state-of-charge estimation using Kalman filter family for lithium-ion batteries. Renew. Sustain. Energy Rev. 2019, 113, 109233.
38. Gabbar, H.A.; Othman, A.M.; Abdussami, M.R. Review of Battery Management Systems (BMS) Development and Industrial Standards. Technologies 2021, 9, 28.
39. Xing, Y.; Ma, E.W.M.; Tsui, K.L.; Pecht, M. Battery Management Systems in Electric and Hybrid Vehicles. Energies 2011, 4, 1840.
40. Spoorthi, B.; Pradeepa, P. Review on Battery Management System in EV. In Proceedings of the 2022 International Conference on Intelligent Controller and Computing for Smart Power (ICICCSP), Hyderabad, India, 21–23 July 2022; pp. 1–4.
41. Xiong, R.; He, H.; Sun, F.; Zhao, K. Evaluation on State of Charge Estimation of Batteries with Adaptive Extended Kalman Filter by Experiment Approach. IEEE Trans. Veh. Technol. 2013, 62, 108–117.
42. Sanitha Michail, C.; Chithra, M.; Nithara, P.V.; Eldho, R.P. Overview on Battery Management System and Energy Storage System of Electric Vehicle. In Proceedings of the 2022 International Conference on Automation, Computing and Renewable Systems (ICACRS), Pudukkottai, India, 13–15 December 2022; pp. 143–147.