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Review

Smart Battery Management Technology in Electric Vehicle Applications: Analytical and Technical Assessment toward Emerging Future Directions

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Abstract: Electric vehicles (EVs) have received widespread attention in the automotive industry as the most promising solution for lowering CO_2 emissions and mitigating worldwide environmental concerns. However, the effectiveness of EVs can be affected due to battery health degradation and performance deterioration with lifespan. Therefore, an advanced and smart battery management technology is essential for accurate state estimation, charge balancing, thermal management, and fault diagnosis in enhancing safety and reliability as well as optimizing an EV's performance effectively. This paper presents an analytical and technical evaluation of the smart battery management system (BMS) in EVs. The analytical study is based on 110 highly influential articles using the Scopus database from the year 2010 to 2020. The analytical analysis evaluates vital indicators, including current research trends, keyword assessment, publishers, research categorization, country analysis, authorship, and collaboration. The technical assessment examines the key components and functions of BMS technology as well as state-of-the-art methods, algorithms, optimization, and control surgeries used in EVs. Furthermore, various key issues and challenges along with several essential guidelines and suggestions are delivered for future improvement. The analytical analysis can guide future researchers in enhancing the technologies of battery energy storage and management for EV applications toward achieving sustainable development goals.

Keywords: battery storage; electric vehicle; battery thermal management; state of charge; state of health; battery equalization

1. Introduction

The automobile industry has achieved several milestones toward developing reliable and efficient technology for the safety of passengers and pedestrians [1]. On the contrary, the rise in the number of vehicles has increased air pollution in the urban sector [2]. As per reports from the European Union, the transportation segment is responsible for approximately 27% of greenhouse gas (GHG) emissions, while emissions from vehicular transportation contribute to approximately 70% [3]. Hence, to tackle emission issues, electric vehicles (EVs) have achieved wide acceptance and recognizability worldwide due to several benefits, such as their ability to reduce GHG emissions and address global warming issues [4–7]. EVs have emerged as a prosperous and promising alternative to fuel-based vehicles, resulting in more simplicity, accuracy, and reliability [8]. Nevertheless, the global trend toward their wider adoption necessitates the enhanced functionality of battery management systems (BMS) with regard to thermal management, charging/discharging techniques, power management, cell balancing, and monitoring [9].

Currently, BMS-based technology is useful in EV applications due to several advantages, such as high power and energy density, longer life cycles, high voltage, and low self-discharge rates [10,11]. However, the efficiency and accuracy of battery energy storage are compromised due to their temperature and tendency toward aging [12,13]. Therefore, it is crucial to focus on their working environment to avoid physical damage, aging, and thermal runaways. Further, it is necessary to monitor various battery parameters such as temperature, current, voltage, energy, temperature control, and fault identification [14]. To introduce an effective and smart BMS for EV applications, state estimation for batteries with regards to the state of charge (SOC), state of health (SOH), state of energy (SOE), and remaining useful life (RUL) must be carefully performed [15]. Dai et al. [16] discussed advanced battery management strategies for a sustainable energy future, multilayer design concepts, and research trends; the authors elucidated multilayer design concepts for battery management systems. Hu et al. [17] reviewed second-life lithium–ion batteries for stationary energy storage applications. BMS technology should be capable of controlling temperatures for safe battery operation within safe limits and of performing fault identification and charge balancing among battery cells [18,19].

Analytical analysis refers to a research methodology that intends to deliver necessary information, such as statistics and quantitative approaches, using library and information science [20,21]. Analytical analysis is an essential tool for delivering insight into particular and historical findings that can be utilized to construct future research paths for researchers [22–24]. It has been proven an important tool for various universities, research institutes, organizations, and industries to evaluate the quality of research by considering various indicators such as current standing, citation, impact factors, and h-indexes [25]. A few analytical papers have been published on BMS technology in EV applications. Table 1 represents a discussion of analytical manuscripts produced by various scholars as well as research gaps. The focused areas of the existing analytical study include electrolytes for sodium-ion batteries [26], recycled products and clean recovery of discarded/spent lead-acid batteries [27], recycling methods of spent lithium–ion batteries [28], thermal management of electric batteries [29], and thermal hazards-related research trends about lithium–ion batteries [30]. To the best of the authors' knowledge, no studies have conducted an analytical analysis of BMS technology in EVs. Thus, this study presents a comprehensive analytical analysis of BMS technology that has been conducted over the past 10 years (from January 2011 to December 2021) to examine its evaluation, current trends, existing issues, and problems. A comprehensive explanation of BMS operations, state-of-the-art methods, algorithms, controllers, and optimization schemes has not been reported in detail in previous studies.

Table 1. Analytical analysis manuscripts and their limitations.

Focused Topics	Research Gaps	Year	Ref.
Analytical analysis of energy management strategies for hybrid EVs.	Although the authors provided a detailed keyword analysis, the top most-cited list of manuscripts was absent.	2015	[31]
Review analysis of electrolytes for sodium-ion batteries.	This survey was missing the most prominent keyword analysis, study types, and recent article analysis.	2016	[26]
Survey on recycled products and clean recovery of discarded/spent lead-acid batteries.	The recent progress on clean recovery processes was discussed, but the research methodology was not mentioned.	2019	[27]
Analytical analysis of the recycling methods of spent lithium–ion batteries.	The average citation per year was not considered. Hence, recent manuscripts were missing in this analysis. The authors did not include the main issues and challenges.	2020	[28]
Analytical survey on thermal management of EVs.	An in-depth analyzing methodology was highlighted, but the topmost cited article analysis was missing.	2020	[29]
Analytical study of thermal hazards related to research trends about lithium–ion batteries.	Although the authors provided a detailed analysis of keywords, the surveying methodology and recent research trends were missing.	2021	[30]

To bridge the aforesaid research limitations, this study unveils new contributions with a detailed investigation and critical discussion of analytical and technical assessment for BMS technology in EV applications. The innovative contributions of this review are highlighted below.

- This analytical study examines the highly influential manuscripts in BMS technology for EV applications covering various vital aspects, including study type, subject area, co-occurrence keywords, publishers, influential authors, and dominant countries.
- A critical analysis of the BMS components, functions, state-of-the-art methods, algorithms, optimizations, and controllers for BMS technology are presented, highlighting objectives, strengths, and weaknesses.
- The current issues, challenges, and limitations of BMS technology in EV applications are explored.
- Future emerging directions and guidelines are delivered for the advancement of smart battery storage technology in EV applications.

The rest of the paper is organized into six sections. Section 2 presents the different surveying methods, inclusion and exclusion criteria for the articles, data selection processes, publication trends, data extraction methods, and research characteristics. Section 3 outlines the analytical discussion which considers citation analysis, the distribution of highly cited papers, analytical analyses of keywords, the research area, publications, and authorship. Section 4 depicts the technical evaluation of smart BMS technology, focusing on state-of-the-art methods, algorithms, optimizations, and controller schemes. Section 5 covers issues and challenges for BMSs in EV applications. Finally, conclusions and future recommendations are covered in Section 6.

2. Surveying Methods for Analytical Evaluation

The search to obtain the appropriate number of research articles based on BMS technology in EV applications was performed in the fourth week of March 2022. The Scopus database utilized to conduct the necessary search and select articles indexed in various journals from 2011 to 2020 was chosen to perform the analytical analysis. The main aim of the current study is to present state-of-the-art development in battery management schemes over the last 10 years and understand the features of highly cited articles. The necessary keywords such as state of charge (SOC), state of health (SOH), remaining useful life (RUL), thermal management (TM), battery charge equalization (BCE), and fault diagnosis and protection (FDP) were applied to find relevant articles for the proposed analytical analysis. Due to resource limitations, the "English Language" filter was used to limit the number of manuscripts found. The manuscripts obtained were organized according to "times cited-highest to lowest" criteria. Further, the "exclude self-citations" filter was employed in the Scopus database to avoid "self-citations" from highly cited articles. Several resourceful manuscripts were obtained by considering various criteria such as the title, abstract, keywords, novelty, citations, and subject area. The comprehensive screening and data selection procedures are depicted in Figure 1.

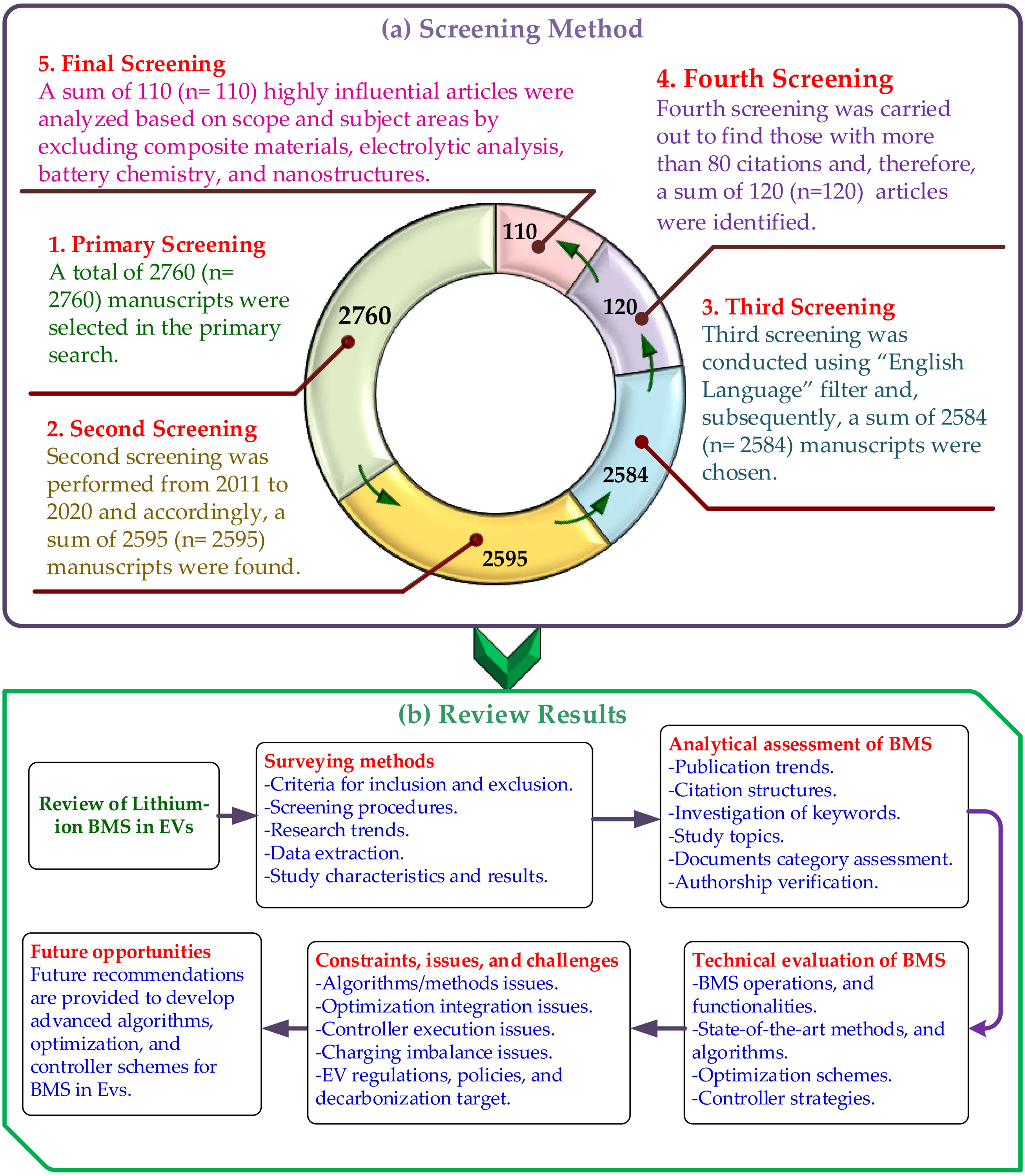

Figure 1. Methodology of extracting data and article selection from the Scopus database.

2.1. Process of Data Selection

- Based on the utilization of appropriate keywords, the primary screening from the Scopus database delivered 2760 articles (n = 2760).
- The second screening was performed by employing year limitations from 2011 to 2021 and, accordingly, a sum of 2595 (n = 2595) manuscripts were found.
- In the third phase of screening, the articles' necessary selection was completed by applying the "English language" filter, which delivered 2584 (n = 2584) articles.
- In the fourth assessment phase, only 120 (n = 120) highly cited manuscripts comprising 80+ citations were extracted.
- In the final evaluation stage, 10 articles were manually excluded from the search database based on subject areas such as battery chemistry, electrolysis analysis, material composition, electrochemical reaction, and nanowires and, subsequently, highly relevant 110 (n = 110) articles consisting of journal articles, review papers, and conferences were considered for carrying out the analytical analysis.

2.2. Research Trends

Globally, a significant amount of research has been carried out to develop a management scheme and technology for battery energy storage in EV applications. As per the Scopus database, the first article on lithium–ion BMS for EV application was published in 2011 [32]. There have since been numerous techniques and models developed by researchers and industrialists to integrate BMS in EVs. The initial phase of article selection for lithium–ion BMS for EV applications from 2011 to 2021 is presented in Figure 2. As observed from Figure 2, there was an upward trend in research around the globe from 2011 to 2021, which depicts the enthusiasm and research curiosity among research communities regarding the progress of BMS for EV applications. As observed, a total of 1120 manuscripts were published from 2019 to 2021, whereas 1080 articles were published from 2015 to 2019. The current trend suggests an increase in the number of publications in recent years (2019–2021) due to wide applications of BMS in EVs toward achieving the decarbonization target by 2050.

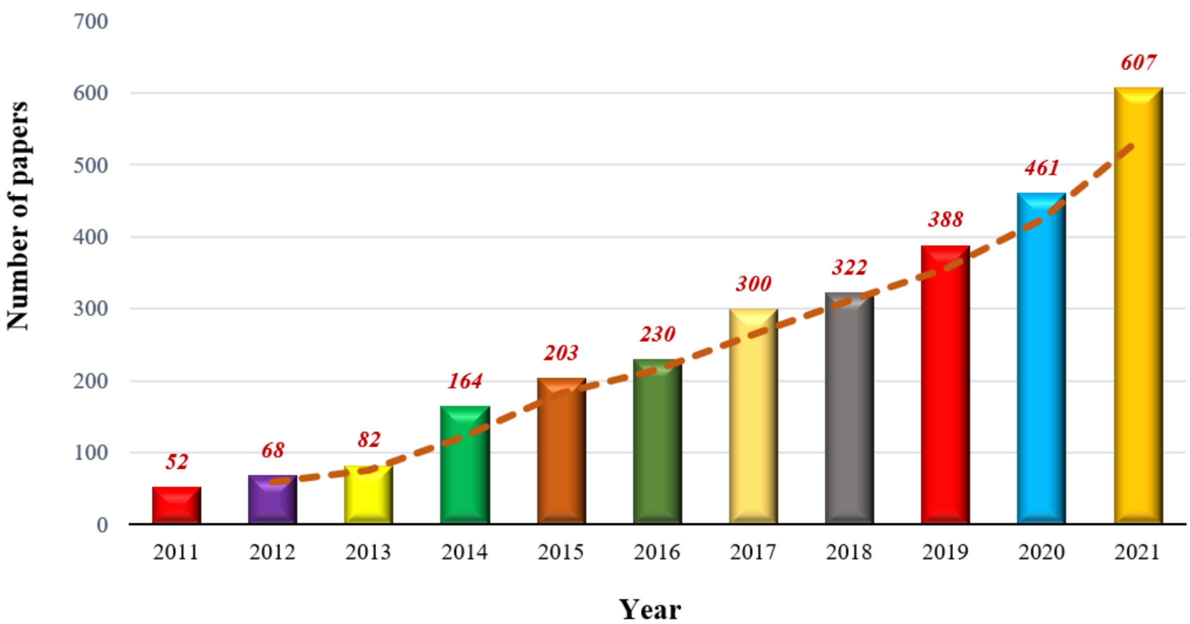

Figure 2. Research trends between the years 2011 and 2021.

2.3. Data Extraction

Data collection was carried out by utilizing the Scopus database and articles were selected individually to perform the analytical analysis. The extracted data from the

110 highly cited manuscripts consisted of the following features: (1) 110 highly cited manuscripts published between 2011 and 2020. (2) Type of research activity (review/problem formulation. (3) Research field. (4) Name of the publisher. (5) Name of the journal. (6) Journal impact factor (JIF). (7) Most prolific authors. (8) Affiliated country. (9) Title of the article. After performing the necessary data extraction with the 110 selected articles, an observation was presented to provide insight into lithium–ion BMSs in EV applications.

2.4. Research Characteristics

During the initial screening phase, 2760 articles were extracted from the Scopus database. Further, 110 highly cited manuscripts were obtained after undergoing several stages of filtering. The included manuscripts in the proposed analysis are tabulated in Table A1 with the digital object identifier (DOI), author's name, journal and publisher name, year of publication, affiliated country, total citations, and citation in the last 5 years for respective articles. The total number of citations for the chosen manuscripts was calculated as 22,364 (mean: 201.47; median: 130; range: 86–2516). Overall, 91 articles from different journals were cited more than 100 times and a further 78 articles were cited over 100 times in the last 5 years. Some of the highly influential research articles with more than 500 citations in the previous 5 years were published by Lu et al. [33], Bandhauer et al. [34], and Hannan et al. [35].

3. Analytical Evaluation and Critical Discussion

This section delivers an analysis and constructive discussion of various key indicators of BMS technology in EVs, which are discussed comprehensively in the following subsections.

3.1. Citation Analysis of the 110 Highly Influential Articles

The citation parameter for a specific research field is important for categorizing and evaluating state-of-the-art trends. Further, citation information depicts a journal's impact as well as the impact of a single publication. In this analysis, the objective is to describe the most significant manuscripts in the research field of BMS technology in EV applications. Table A1 presents the 110 highly cited manuscripts from 2011 to 2020 in the research area of BMSs in EV applications from the Scopus database and provides information for conducting future research activities. It is observed from Table A1 that the number of citations for each of the 110 manuscripts varies, with the maximum citation being 2516 and the minimum being 86. Further, the first six highly cited manuscripts contain more than 500 citations. Due to the high applicability of the research field, 91 out of the 110 manuscripts have been cited more than 100 times since the date of their publication. The review work published by Lu et al. [33] in 2013 was the most cited, with 2516 citations, while the research article from Bracco et al. [36] was the least cited, with 86 citations.

The most cited article in the research field of BMSs in EV applications, titled "A Review on the key issues for lithium–ion battery management in electric vehicles," was published by Lu et al. [33] in *The Journal of Power Sources*, with 2516 citations and an impact factor of 9.127. The article presented a literature review of lithium–ion battery-based BMS issues regarding state estimation, fault diagnosis, battery cell voltage measurement, etc. Further, key issues were outlined for future research activities to develop an efficient and robust BMS. Additionally, Bandhauer et al. [34] presented the second-most-cited review manuscript, titled "A Critical Review of Thermal Issues in Lithium–ion Batteries." The review article presented an insight into thermal issues occurring in lithium–ion batteries and their effect on capacity and power fade. The article took the second spot with 978 citations and was published in 2011 by *Journal of the Electrochemical Society*, with an impact factor of 4.316. Lastly, the third most influential review, with 618 citations, was published by Hannan et al. [33], titled "A review of lithium–ion battery state of charge estimation and management system in electric vehicle applications: Challenges and recommendations." The article was published in *Renewable and Sustainable Energy Reviews* in the year 2017. The review article focused on SOC estimation techniques and their management systems for developing future sustainable EV applications.

3.2. Distribution of 110 Highly Cited Articles between 2011 and 2020

The distribution of the 110 most-cited manuscripts in the research field of BMS technology in EV applications from 2011 to 2020 is depicted in Figure 3. The analytical graph shows that the number of manuscripts published in 2011 and 2012 is 7 and 6, respectively, while the years 2014 and 2015 showed an upward trend, with the number of published manuscripts being 17 and 19, respectively, which further decreased in the years 2016 and 2017. Later, in 2018, the number of published articles again increased to 12, which decreased to 5 in 2019. Overall, the number of published manuscripts from 2012 to 2015 indicated an upward trend, while, in general, manuscripts published from 2015 to 2019 displayed a downward trend.

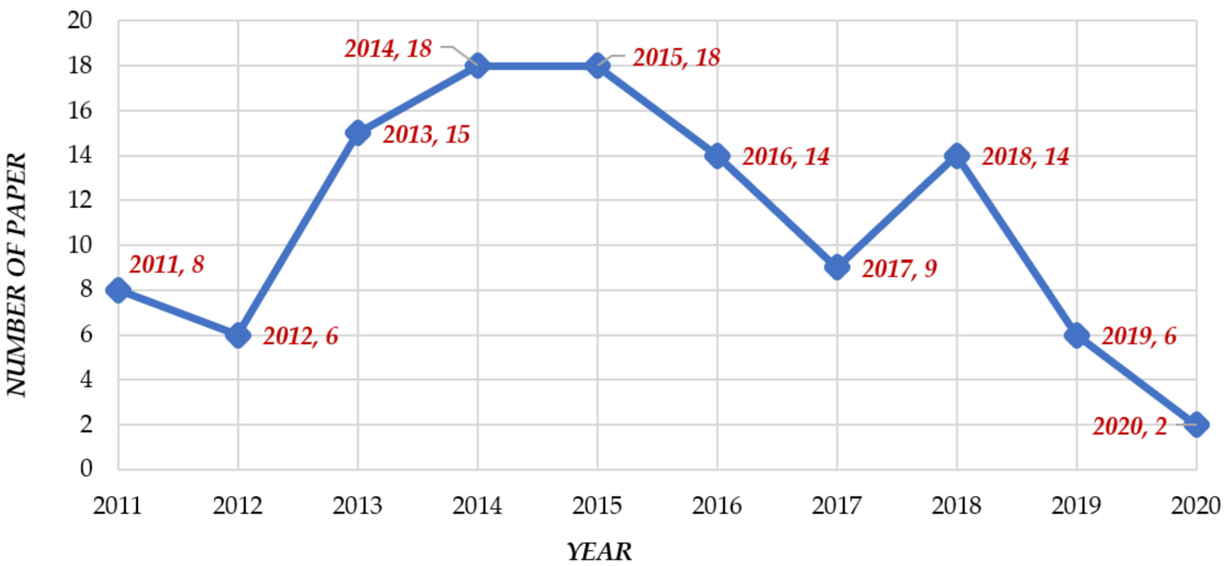

Figure 3. Distribution of 110 most cited papers from 2011 to 2020.

3.3. Analytical Analysis of Co-Occurrence Keywords

The top 15 keywords utilized in various articles from selected databases published from 2011 to 2020 are presented in Figure 4. Significant research gaps can be evaluated from the conducted analysis and an understanding of the research field can be acquired. As observed in Table A1 and Figure 4, the most influential keywords were "lithium–ion battery," "battery management system," and "electric vehicle." The statistical analysis revealed that the keyword "lithium–ion battery" was utilized 52 times, whereas both "battery management system" and "electric vehicle" were applied 32 times. Furthermore, some other crucial keywords utilized in recent years were "battery charging/discharging," "temperature," "controller," and "methods/algorithms," suggesting more research activities toward developing accurate and robust BMSs for EV applications. A pictorial representation of the important keywords is displayed in Figure 4.

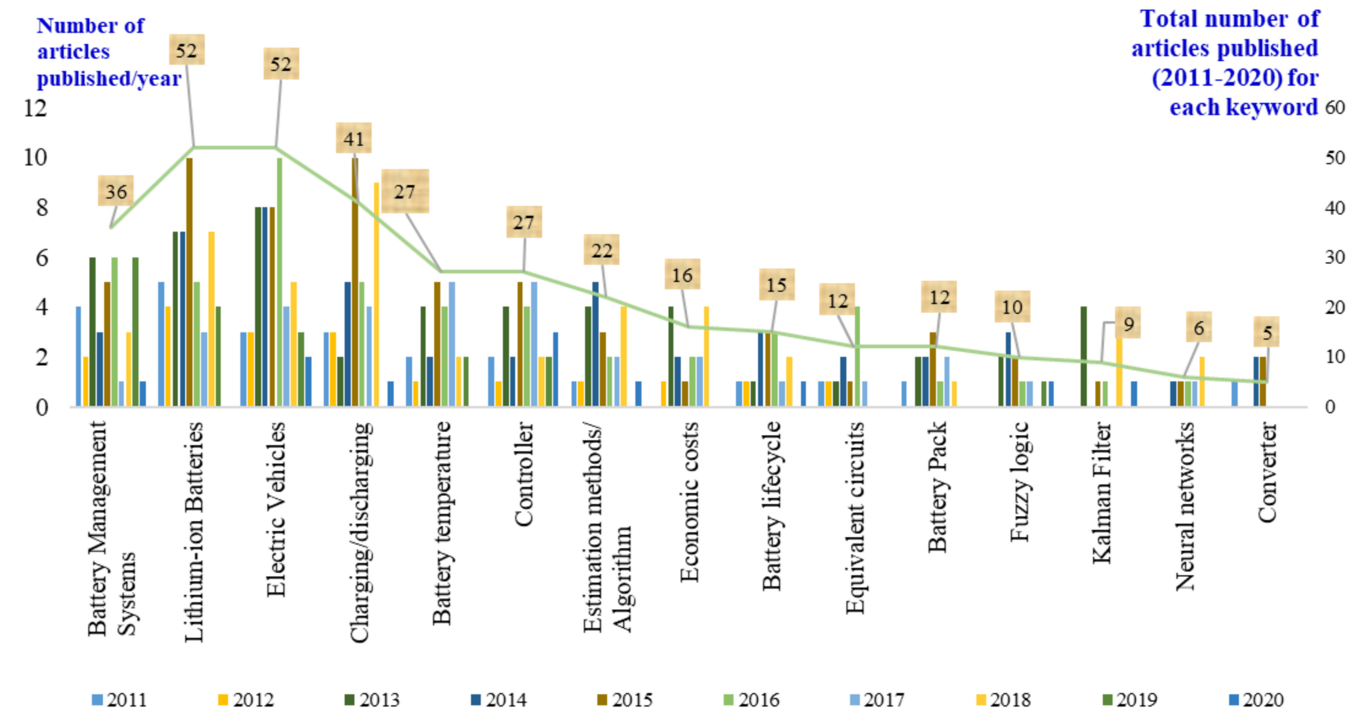

Figure 4. Top 15 widely utilized keywords distributed over the 110 most cited articles in BMS technology for EV applications.

Table A1 (Appendix A) and Figure 4 reveal that current research activities focus more on integrating BMSs with EV applications to deliver a long-term platform to achieve sustainable development goals (SDGs), specifically SDG7, by 2030 by introducing state-of-the-art algorithms, optimizations, and controller techniques. Further, an understanding can be obtained of the articles that achieved a lot of citations in the past 5 years and those with a high average citation per year (ACY).

The co-occurrence keyword analysis of the most cited articles in lithium ion-based BMS technology for EV applications is presented in Figure 5 using VOS viewer software. The impact of keywords determines the diameter of the circle and label, whereas the linking line between keywords is shown as a continuative connection. The keywords are categorized into four clusters: red, blue, yellow, and green. Distinct colors are used to designate different clusters based on the topic of expertise. The most prominent cluster is the red cluster, followed by the green cluster. Strong relationships were found between topics in the red clusters, which consisted of thermal management systems, phase change materials, heat generation, cooling, thermal management (electronics), thermal performance, cooling systems, thermal analysis, battery packs, and automotive batteries. The green cluster showed a strong link between battery health estimation components, including lithium–ion cells, battery, state of health, state of charge, algorithms, extended Kalman filters, estimation, and state-of-charge estimation. The blue cluster represents battery management systems, temperature, digital storage, plug-in hybrid electric vehicles, learning systems, batteries, and neural networks. The smallest cluster is the yellow cluster, containing only seven components, including electric vehicles, electric discharge, lithium compounds, circuit theory, equivalent circuits, energy management, and vehicle applications.

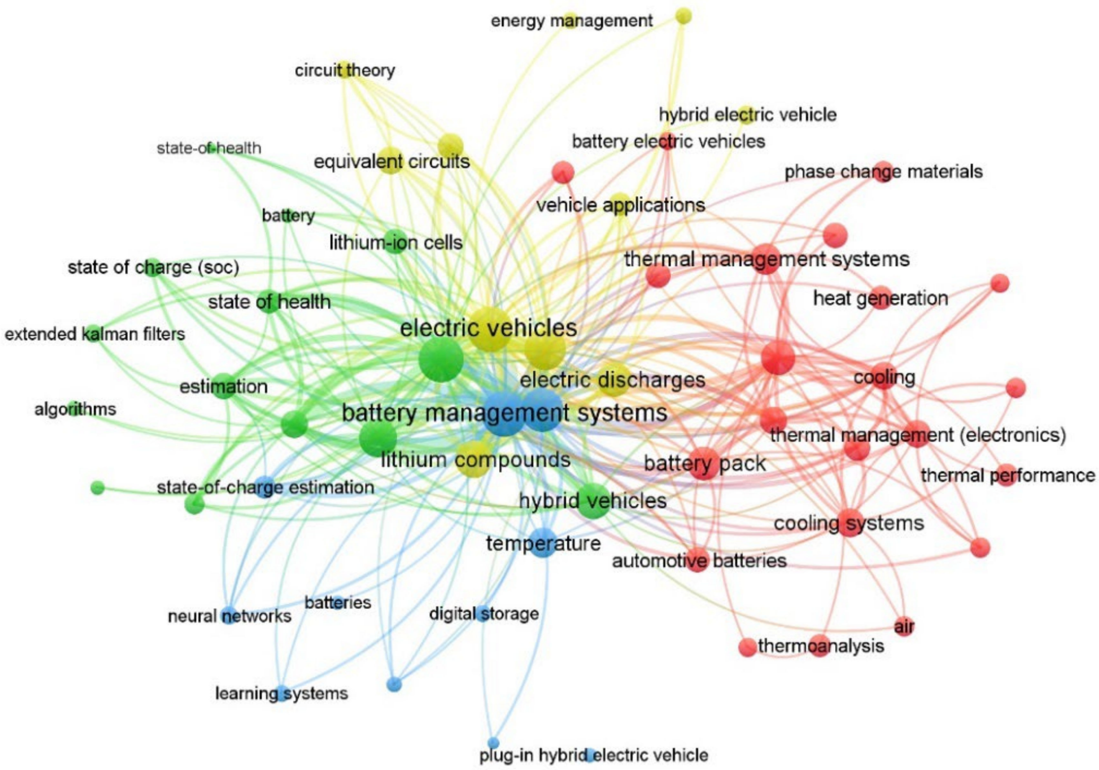

Figure 5. Representation of co-occurrence keywords for analytical analysis of BMS technology for EV applications.

3.4. Research Categories in 110 Highly Cited Manuscripts

The study types of the 110 topmost highly cited manuscripts obtained from the Scopus database are presented in Table 2. Primarily, a vast, resourceful article was published under the category of problem formulation and simulation analysis (59.45%) in the citation range of 98–350. A review article achieved the second position (24.32%), with a citation range of 120–2516. In comparison, the experimentation and performance assessment activities contributed to 8.1% of the total number of articles, with a citation range of 177–311, whereas state-of-the-art technical work represented only 4.5% of articles. The observational manuscripts were the least published and made up only 3.6% of articles from 2014 to 2019, with a citation range of 86–354.

Table 2. Study types of the 110 highly cited manuscripts in the Scopus Database.

Types of Manuscripts	Frequency of Publications	Year Range	Citation Range
Problem formulation and simulation analysis	66	2011–2019	98–350
Review (systematic/nonsystematic)	27	2011–2019	120–2516
Experimental work, development, and performance assessment	9	2013–2018	177–311
State-of-the-art technical overview	5	2012–2018	117–286
Observational	4	2014–2019	86–354

In the present scenario, many research activities are being undertaken to shift the global trend from fossil fuel-based vehicles to EV applications due to the significant advancement of BMSs for EV applications. Of the 110 most cited manuscripts, the selected 27 review articles summarized in Table 2 were published in different research fields in BMS technology. For instance, review articles on BMSs for EV applications were published by Kim et al. [37] and Xia et al. [38]. The works focused on battery thermal issues, reviewing various battery thermal management systems along with their benefits and limitations and thermal management strategies. Rezvanizaniani et al. [39] and Li et al. [40] carried out work on battery state estimation and health prognostics. Several key topics were outlined and discussed, such as SOC and SOH estimation techniques, strengths, and limitations to utilizing online BMS applications with future recommendations. A comprehensive description of current lithium–ion technology for EVs was reviewed by Miao et al. [41] who provided a comparative analysis of important components of lithium–ion batteries with other battery technologies and further described the approach for enhancing battery lifespan, accuracy, and capacity. Chemali et al. [42] framed a review article to present an overview of various battery/ultracapacitor technologies, energy management systems, and hybrid energy storage systems.

3.5. Publisher and Highly Impactful Journals Assessment

The publication of the 110 most-cited manuscripts from 2011 to 2021 under various publishers is presented in Figure 6. From the manuscripts chosen from the Scopus database, most were published by Elsevier journals (61%). IEEE journals published the second-highest number of manuscripts (30%). The third spot was acquired by MDPI journals (4%). The rest of the most cited articles were published by IOP publishing, John Wiley and Sons, SAGE Publishing, and Inderscience Publishers.

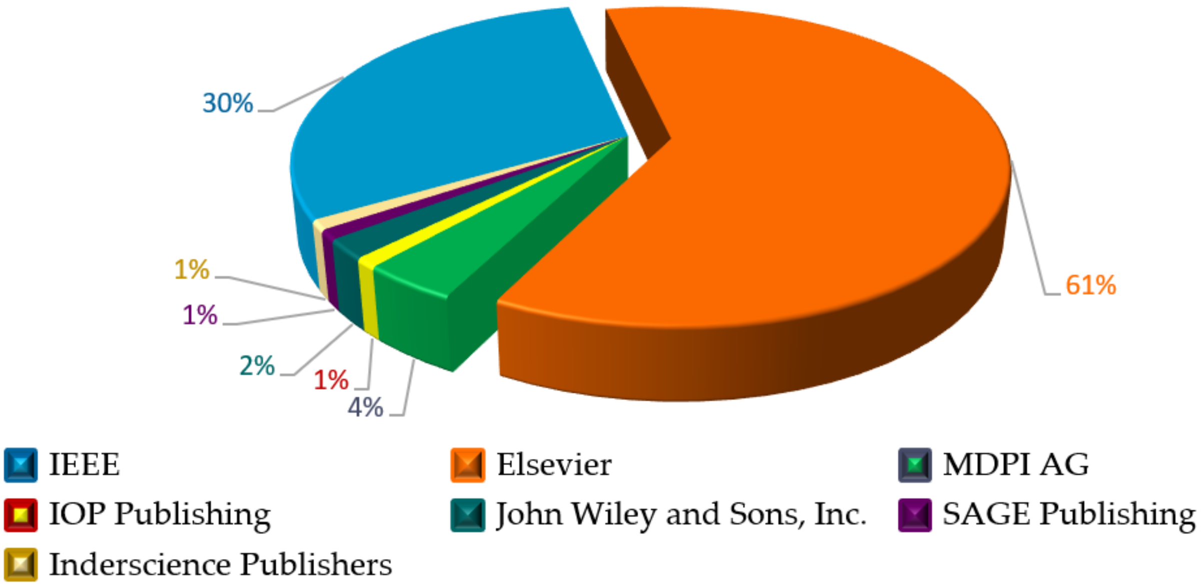

Figure 6. Distribution of published manuscripts according to publishers.

The publication frequency of the articles in various journals as well as their impact factor is illustrated in Figure 7. The 110 most cited articles selected from the Scopus database were published in 21 peer-reviewed journals. The journal impact factor varied from 3.004 (*Energies*) to 14.982 (*Renewable and Sustainable Energy Reviews*), as per Journal Citation Reports. It can be observed from Figure 7 that *The Journal of Power Sources* published the highest number of manuscripts (44), followed by *Applied Thermal Technology* and *IEEE Transactions of Vehicular Technology*, with nine publications. *Energy Conversion and Management* published six articles; *IEEE Transactions on Industrial Electronics* and *Renewable and Sustainable Energy Reviews* also published some articles. The remaining 15 journals published five or less than five manuscripts between 2011 and 2021.

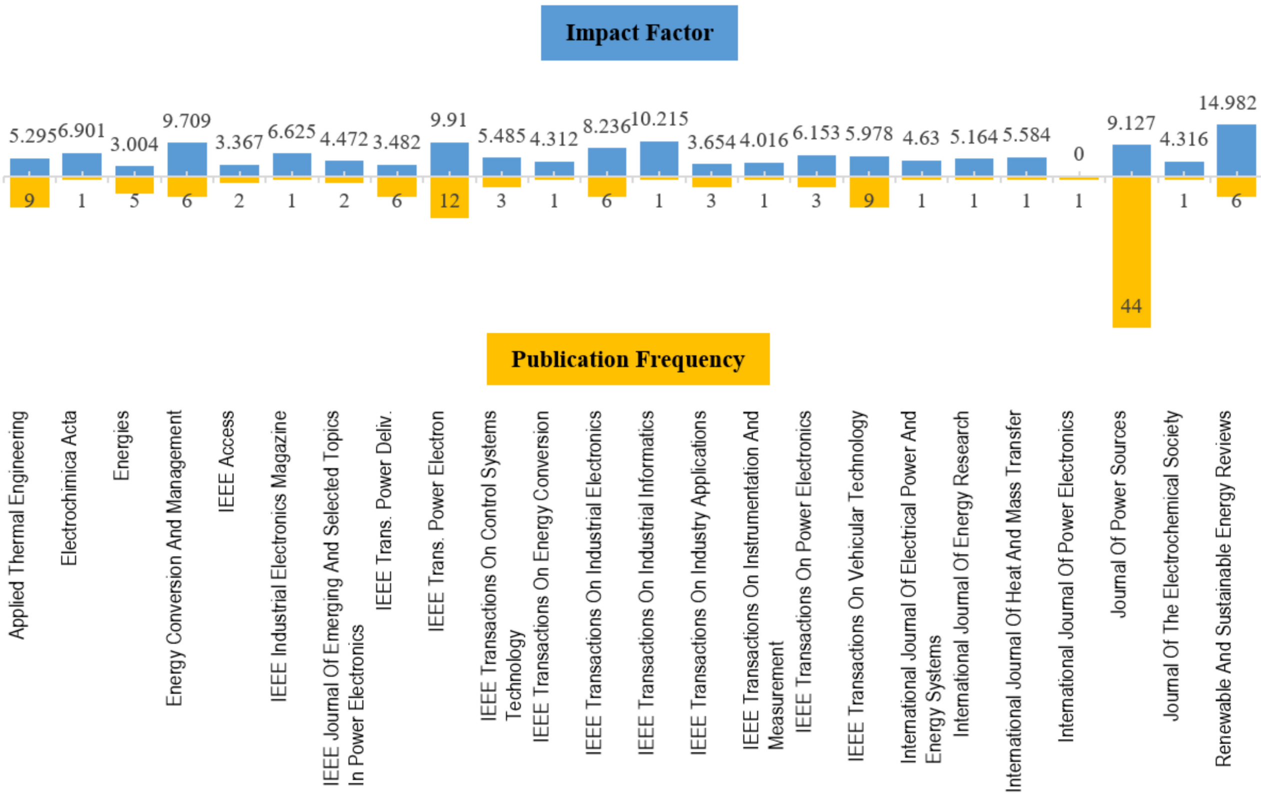

Figure 7. Distribution of 110 most cited research articles, indicating journal of impact factor and publisher.

As depicted in Figure 7, *Renewable and Sustainable Energy Reviews* achieved the highest impact factor of 14.982. The publication frequency remained at 5.40%, while *IEEE Transactions on Industrial Informatics* achieved the second-highest impact factor of 10.215, with a publication frequency of a mere 0.909%. The top three journals with the highest number of published manuscripts (55.85%) were within the impact factor range of 5.295 to 9.127.

3.6. Country Analysis and Networking in 110 Most Cited Articles

The distribution of the selected articles for analytical analysis was among several countries. Figure 8 depicts the top 10 countries with the highest number of publications. China secured first place in publishing the highest number of articles (38%), while the United States achieved the second position (35%). The other countries published a cumulative percentage of 27% of the articles. Figure 9 presents the connection diagram to depict the impact of 14 countries on the publication trend. It presents a networking diagram to depict the impact of 14 countries on the publication trend. The size of each label denotes the impact of each country, whereas the width of the connecting line denotes the collaborative approach from the researchers from different countries in the field of smart battery energy management technology in EV applications. From the statistical analysis, Figure 9 can provide a clearer idea about the countries that are the most prominent and enthusiastic in this field of research. The dominant cluster is denoted with a green color and comprises China, the United States, Denmark, Canada, and Mexico. In contrast, the second impactful cluster is displayed in red, with South Africa, Sweden, the United Kingdom, and Belgium as its key connections. The blue cluster comprises two countries, Italy and Germany, and the yellow cluster includes South Korea and Singapore. Lastly, Australia represents the only country in the purple cluster.

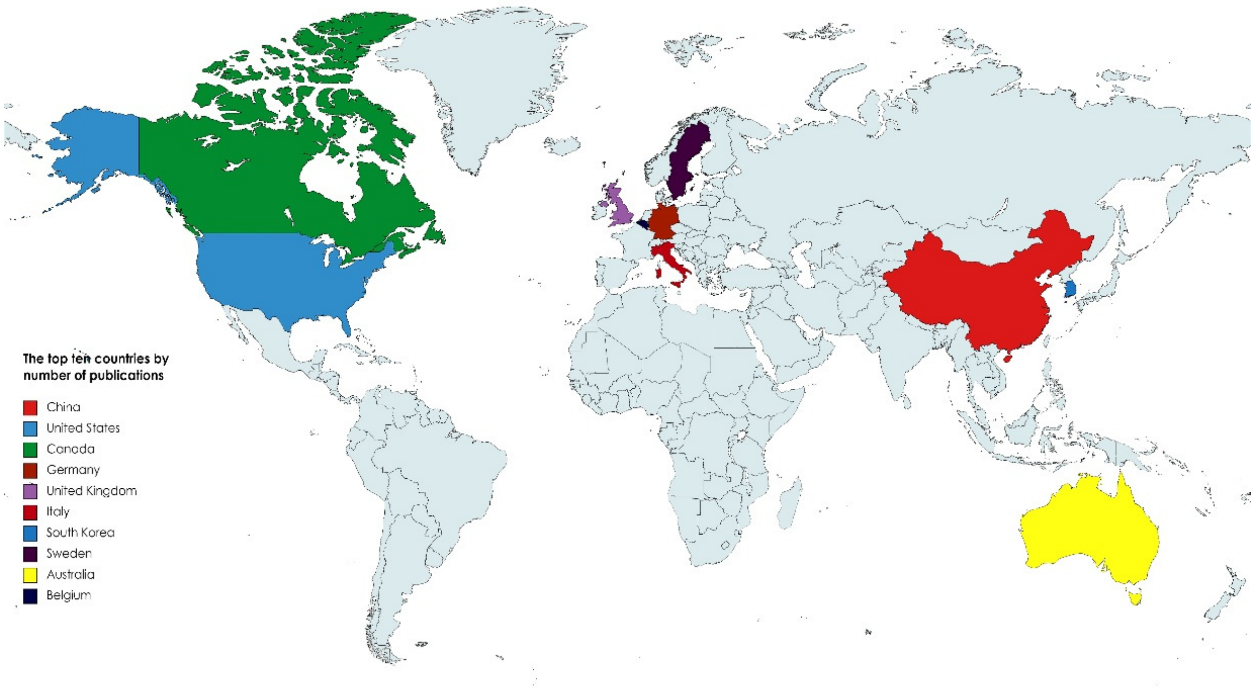

Figure 8. Distribution of the 110 most cited research articles in 10 countries with the most publications.

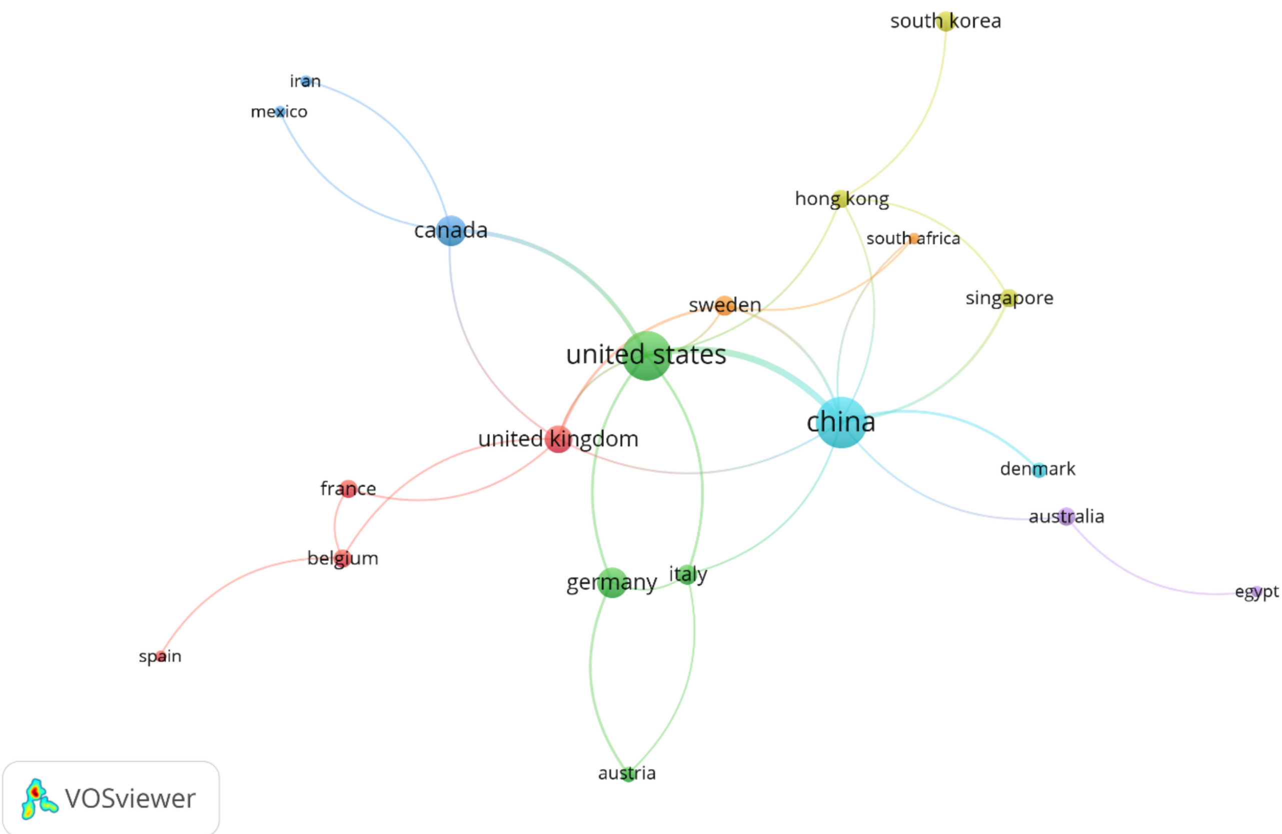

Figure 9. The networking diagram to represent the impact of 14 countries on the publication trend in BMS technology for EV applications.

3.7. Most Prominent Authors and Collaborations

Information concerning the 10 most influential authors published twice or more in the 110 selected manuscripts is presented in Table 3. The author's position, h-index, number of citations, total number of articles, country, and current affiliation are tabulated. Rui Xiong published 11 articles with an h-index and total citations of 55 and 10,111, respectively. Currently, he is affiliated with the Beijing Institute of Technology, China. Out of 11 published articles by Rui Xiong, there are 10 research articles and 1 review manuscript. Hongwen He also belongs to the Beijing Institute of Technology and contributed to seven research articles. Additionally, Jianqiu Li, Languang Lu, Minggao Ouyang, and Xuebing Han published seven articles affiliated with Tsinghua University, China. Their contribution toward review articles was limited to one, while the research group published four research articles. Michael G. Pecht from the United States had the highest number of citations (23202) among all 10 authors. Dirk Uwe Sauer from Rheinisch-Westfälische Technische Hochschule Aachen, Germany, had the most citations (11,182) after Michael G. Pecht. The last two spots were acquired by Fengchun Sun from the Beijing Institute of Technology, China, and Ephrem Chemali from McMaster University, Canada, respectively. Fengchun Sun published four research articles, while Ephrem Chemali published one review article and two research articles.

Table 3. Ten most prolific authors' profiles with 3 or more manuscripts.

Author	Current Affiliation	Country	Articles	Citations	h-Index	Author's Position
Rui Xiong	Beijing Institute of Technology	China	11	10,111	55	6- 1st author 4- Co-author 1- Senior author
Hongwen He	Beijing Institute of Technology	China	7	8199	40	2- 1st author 4- Co-author 1- Senior author
Jianxiang Qiu Li	Tsinghua University	China	7	10,468	52	6- Co-author 1- Senior author
Languang Lu	Tsinghua University	China	7	9379	46	1- 1st author 6- Co-author
Minggao Ouyang	Tsinghua University	China	7	18,305	68	1- 1st author 5- Co-author 1- Senior author
Xuebing Han	Tsinghua University	China	5	6391	32	3- 1st author 2- Co-author
Michael G. Pecht	University of Maryland	United States	4	23,202	71	4- Senior author
Dirk Uwe Sauer	Rheinisch-Westfälische Technische Hochschule Aachen	Germany	4	11,182	50	4- Senior author
Fengchun Sun	Beijing Institute of Technology	China	4	8175	47	1- 1st author 3- Co-author
Ephrem Chemali	McMaster University	Canada	3	489	8	3- 1st author

The focused areas and research interests in the problem formulation of different authors varied. For instance, Rui Xiong and Hongwen He primarily focused on battery state of charge and capacity estimation [43–46], battery model-based energy management schemes for EV applications [47,48], and the development of a hardware-in-loop approach for state estimation [49]. Further, Rui Xiong focused on performing a critical review based on SOH methods for BMS [50]. However, Jianqiu Li, Languang Lu, Xuebing Han, and Minggao Ouyang from Tsinghua University developed review articles based on battery management issues [33] and SOC estimation techniques [51] for EV applications. Additionally, their research articles concentrated on SOH estimation [52,53].

As per the discussion and evaluation from other perspectives on the 110 most cited manuscripts from the Scopus database, it can be concluded that the majority of influential manuscripts published in recent years have been based on research work rather than review activity. The recent trend suggests an inclination from the research fraternity toward introducing an accurate, robust, and efficient BMS for the EV platform. Furthermore, battery state estimation plays a crucial role, which can be estimated using several methods [13,48,54–61]. Different researchers carried out a variety of literature reviews that emphasized topics related to BMSs, including battery SOC estimation, SOH prediction, and thermal management.

A co-authorship analysis of the most prominent authors published twice or more from the selected database is presented in Figure 10. A total of 304 authors were identified from the selected 110 articles on lithium ion-based BMS technology for EV applications. Among the 304 authors, only 60 authors contributed to publishing two or more articles. Only 27 authors were found with interconnection and were categorized into five different clusters according to the number of published documents, as presented in Figure 10. Rui Xiong from China had the highest number of published articles, with 11 papers, including 4 articles with Hongwen He, 2 with Fengchun Sun, 1 with Michael G. Pecht, and 1 with Chunting Chris Mi and J. Xu. Van Mierlo Joeri from Vrije Universiteit Brussel contributed three articles with Y. Li, K. Liu, M. Berecibar, P. Hossche and N. Omar.

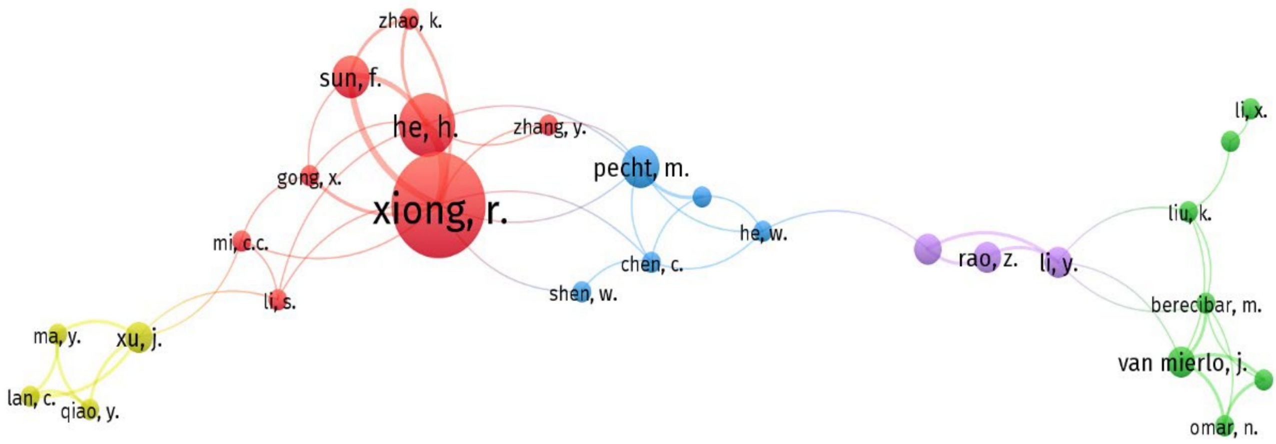

Figure 10. Co-authorship analysis of the selected most cited articles in the field of BMS technology for EV applications.

4. Technical Evaluation of BEMS in EVs

This section critically discusses the various technical aspects of BMS, focusing on key components, functions, algorithms, methods, optimizations, and control schemes in BMS in EV applications.

4.1. Key Components and Functionalities of BMS

This section reveals the key components and functionalities of BMS. A detailed evaluation of various key research domains of BMS technology is provided in the following subsections.

4.1.1. Battery Thermal Management

Battery thermal management is a vital issue concerning battery energy management systems. Tang et al. [62] modeled and analyzed the coupling system of a liquid-cooled battery thermal management system (BTMS) and heat pump air conditioning system (HPACS) for battery electric vehicles (BEVs) to predict cooling capacity and system coefficient of performance (COP) of the BTMS using support vector regression (SVR). The correlation coefficient (R) of cooling capacity and system COP for the proposed PSO-SVR model were improved by 2.1% and 2.8, respectively [63–65]. The development of battery thermal management solutions and thermal models was discussed by Wang et al. [63]. Thermal runaway and the response of Li-ion batteries in cold temperatures were also investigated.

Moreover, a specific design for an air-cooled battery system was theoretically explored and numerically designed by Park et al. [64] to determine the required thermal parameters. As a typical battery system in HEV comprises several battery cells stacked on top of each other, cooling performance is influenced mainly by airflow in the coolant channel. The authors revealed that the advection thermal resistance was approximately 2.4 °C W^{-1}. Zhao et al. [65] developed a model where thermal-lumped treatment was applied to the individual battery in the module. The authors analyzed the impacts of the interface area of the battery and the channel outside the wall, heat exchange area between batteries, liquid flow rate, and charge/discharge C-rate on the thermal behavior of the battery module using the introduced strategy. The maximum temperature in the battery module was lowered by approximately 12.5 K.

4.1.2. State of Charge

State of charge (SoC) is considered one of the core research areas in battery energy management systems. Most of the selected papers introduced new methods and approaches to estimate the SoC. Tian et al. [66] introduced a deep learning approach to estimate the SOC of $LiFePO_4$ batteries. A closed-loop framework was developed for improving robustness. The proposed method could quickly adapt to new scenarios via transfer learning. The root mean square error was less than 3.146% and 2.315% for aged batteries and different battery types, respectively [35]. The energy-sharing SOC balancing control strategy presented by Huang et al. [67] was based on a distributed BESS architecture in which the cell balancing and DC bus voltage regulation systems were merged into a single system. Small power converters were used to provide SOC balance between the battery cells and DC bus voltage management. The authors revealed that the overall efficiency of the complete system was 95–97%. Based on the measured current and voltage, an ANN-based battery model was designed by He et al. [68] to estimate SOC. The neural network-based SOC estimation was improved by using an unscented Kalman filter. The proposed model was validated using EV drive cycles under various temperature settings. A SOC technique based on a thorough electrochemical model of a lithium–ion battery was presented by Klein et al. [69]. The authors presented an output error injection observer based on a reduced set of partial differential-algebraic equations. The authors revealed that the SOC error was less than 10%.

4.1.3. Energy Management Strategies

Zhou et al. [70] introduced a heuristic rule-based local controller (LC) embedded within the deep reinforcement learning (DRL) loop to eliminate irrational torque allocation, considering the characteristics of powertrain components. The authors reported that the robustness was approximately 92.95 ± 1.24. Hannan et al. [71] delivered a thorough examination of state-of-the-art lithium–ion batteries, including primary structures and overall performance evaluation along with battery fault diagnosis, temperature control, heat management, protection and equalization, state estimation, charge and discharge control, cell condition monitoring, and assessment aimed at improving overall system performance. The price of a Li-ion battery pack is 25–30% of the price of an electric car. A comparison of several EMSs for an electric aircraft's fuel cell-based emergency power supply was presented by Njoya et al. [72]. Supercapacitors, lithium–ion batteries, and fuel cells with the integration of DC-AC and DC-DC converters were thoroughly discussed. According to the analysis, the equivalent consumption minimization model, frequency decoupling/fuzzy logic control, classical proportional-integral control, rule-based fuzzy logic model, and state machine control strategy were among the most commonly used EMSs in fuel-cell vehicle applications.

4.1.4. Battery Materials and Technology

Battery materials and technology are a crucial part of battery energy management systems. Various authors have evaluated battery materials and relevant technologies. For example, Li et al. [73] built a sandwiched cooling structure out of copper metal foam saturated with phase change material (PCM). The system's thermal efficiency was tested and compared to two control stages including cooling with pure PCM and cooling with air. The findings revealed that thermal management using natural convection air could not meet the lithium–ion battery's safety requirements. The paraffin remained in a solid state for the lower discharge rate of 0.5 C. For EV battery strings, a modularized charge equalization based on the monitoring integrated circuit (IC) was introduced by Kim et al. [74]. The suggested technique achieved effective charge equalization while keeping the monitoring IC under easy control. Instead of a dedicated charge equalizer for each cell, a central equalization converter in the master module was used. This proposed control strategy reduced the SOC error gap from 21.3% to approximately 1.3%.

4.1.5. Battery Modeling

Battery modeling plays another crucial role in battery management strategies. Numerous authors have developed new and improved battery modeling methods in their research. For example, He et al. [75] compared and evaluated an improved Thevenin model, including PNGV, RC, and Rint, called dual-polarization (DP). Moreover, the authors added an extra RC to mimic electrochemical and concentration polarization separately. The authors found that the SOC terminal error was within 1.56%. To construct a battery model with sufficient precision and complexity, He et al. [76] first outlined the seven sample battery models under the simplified electrochemical or comparable circuit categories. The model equations were then formulated and model parameters were determined using an online parameter identification method. For constructing a model based on an SoC estimate strategy, a parametric modeling method was introduced by Sun et al. [77]. The proposed approach estimated the SoC of selected and unselected cells using micro and macro time scales.

4.1.6. Fault Diagnosis and Protection

Fault diagnosis and protection are vital parts of battery energy management systems. Here, different authors explored different fault diagnosis strategies, while some authors also outlined fault protection strategies. For instance, Chang et al. [78] proposed a medium-time scale diagnosis method to detect battery micro-faults. Medium-time scale fault real vehicle data were used to verify the effectiveness of the method. An optimized heat pipe thermal management system (HPTMS) for fast-charging lithium–ion battery cells/packs was introduced by Ye et al. [79]. A numerical strategy was created and thoroughly validated using experimental data. The thermal performance of the HPTMS was then investigated using this proposed model under transient situations and steady-state conditions. The authors demonstrated that the lithium–ion batteries charged at a high C rate (up to 8 C rate). Hendricks et al. [80] demonstrated how the failure modes, mechanisms, and effects analysis (FMMEA) of battery failure can be used to improve battery failure mitigation control systems. The average error was less than 1.2% at each temperature.

4.1.7. Remaining Useful Life

Wang et al. [81] adopted several statistical methods to perform the prediction and compared the results of different models on experimental data (NASA dataset). The maximum predicted end of life (EOL) was 1602, with a difference rate of 1.14%. Dong et al. [82] focused on two key ways of determining a battery's health: (1) RUL prediction and (2) battery SOH monitoring. These were calculated using the support vector regression-particle filter (SVRPF). Novel capacity degradation criteria were included in models for battery SOH monitoring based on SVR-PF. Furthermore, an RUL prediction technique was introduced, offering the RUL value and updating the RUL probability distribution to the end-of-life cycle. The RUL threshold value was changed to 85% of nominal capacity. Rezvanizaniani et al. [83] examined battery prognostics and health management (PHM) strategies, focusing on the important needs of battery producers, EV designers, and EV drivers. A range of methodologies for monitoring battery health status and performance, and the evolution of prognostics modeling tools, were also discussed. This study aims to provide practical and cost-efficient solutions for dealing with battery life difficulties in dynamic operation situations.

4.1.8. Vehicle Performance Assessment

Vehicle performance assessment is directly related to the battery energy management system. Hence, numerous authors have examined vehicle performance assessment-related issues. For example, Rezaei et al. [84] proposed a single PCM heat exchanger in a reversible heat pump for the air conditioning of EVs. PCM increased the EV range by 19% and 11% in cooling and heating modes, respectively. The proposed system increased the vehicle range by 19% and 11% compared with the conventional heat pump systems. Ecer et al. [85] introduced a novel integrated multiple criteria decision-making (MCDM) model for BEV selection. The suggested aggregation framework was capable of assisting customers, decision-makers, and authorities to make reliable decisions in evaluating BEVs. Methods for monitoring the SOH, SOC, available power, capacity, RUL, and impedance parameters of batteries were examined by Waag et al. [86]. Here, the authors focused on the strengths and shortcomings of online BMS applications. Omar et al. [52] carried out a comparative performance evaluation among several lithium–ion battery characteristics and rechargeable ESSs, including electrical-double layer capacitors, nickel-metal hydride, and lead-acid. The investigation revealed the advantages of lithium–ion batteries in achieving satisfactory current rate capabilities, power density, and energy density.

4.1.9. Energy Utilization and Efficiency

Energy utilization and the efficiency of battery storage systems are of vital concern to scholars. Hence, many studies have been conducted on enhancing energy consumption and efficiency in EV applications. For example, Zhang et al. [87] proposed an energy-saving optimization and control (ESOC) method to improve the energy utilization and efficiency of autonomous electric vehicles. The proposed ESOC effectively avoided the high-power output of the vehicle's powertrain. Einhorn et al. [88] introduced an active cell energy balancing solution for lithium–ion battery stacks based on a flyback DC/DC converter topology. Simulation and prototype validation were performed to determine the energy gain for 10 series-connected cells during discharge cycles. The efficiency of the proposed topology was improved by utilizing the capacity and SOC as the balancing criterion rather than the voltage. The usable energy of the battery stack was improved by 15%. Zheng et al. [89] focused on error analysis to determine the energy utilization and SOC of lithium–ion batteries, considering the measured data, state parameters, and algorithms. A flow diagram was developed to investigate energy consumption and error sources, ranging from signal measurement to algorithms for online SOC estimate methods in EVs.

4.1.10. Aging and Battery Degradation

Another important concern in battery energy management systems is aging and battery degradation. Many studies have been performed to solve aging- and battery degradation-related issues. For example, Xu et al. [90] proposed a Q-learning-based strategy to minimize battery degradation and energy consumption. Besides Q-learning, two rule-based energy management methods have also been proposed and optimized using a particle swarm optimization algorithm. Q-learning reduces battery degradation by 20% and extends vehicle range by 2%. The RUL and SoC estimation were tested against temperature uncertainty and incorrect primary SOC values by Xiong et al. [91]. A double-scale particle filtering model was created on two different timescales to predict SOC and other characteristics. The suggested strategy considered the battery parameter in short time-varying features and the battery state in swift time-varying characteristics. The maximum SOC estimation and prediction errors were both less than 2%. Han et al. [92] examined battery life cycles based on the actual operating conditions in EVs. The test results were compared among five different commercial lithium–ion battery cells at different temperatures. The results of the life cycle experiments were fitted to the genetic algorithm to recognize the battery aging mechanism.

4.1.11. Battery Equalization/Charge Control

To enhance battery charge efficiency, battery equalization/charge control plays an important role in battery energy management systems. Therefore, many in-depth investigations have been conducted in this area. For instance, Shang et al. [93] proposed a direct cell-to-cell battery equalization based on a boost DC-DC converter (BDDC) and quasi-resonant LC converter (QRLCC). The QRLCC was used to achieve zero-current switching, reducing power losses. The BDDC was used to increase the equalization voltage gap. Furthermore, the topology could limit the equalization current based on the voltage difference by changing the duty cycle. The authors revealed that the energy conversion efficiency was higher than 98%. Duong et al. [94] presented a unique technique that combined a simple model with multiple adaptive forgetting factors recursive least-squares (MAFF-RLS) to properly capture the battery cell balancing under varying dynamic conditions. The experimental outcomes indicated that the proposed technique could characterize the battery model parameters while estimating SOC with a battery cell balancing error of less than 2.8%.

4.1.12. Validation under Different Operating Conditions

An appropriate validation process under different case studies and operating conditions must be introduced to verify the performance of algorithms and controllers. Schuster et al. [95] proposed the electrochemical and thermal coupled model to examine the heating performance of lithium–ion batteries under mutual pulse, convective, and self-internal heating. Klass et al. [96] employed the SVM technique to predict the SOH of lithium–ion batteries under different SoCs and temperature ranges in EV applications to assess online battery degradation. A 30% difference in impedance resulted in a 60% difference in peak cell current. Hannan et al. [97] verified the machine learning-based SOC estimation technique under different temperatures and in diverse EV drive cycles. The battery capacity and error rate decreased as the aging cycle progressed. A summary of the comparative study of various BMS functions is presented in Table 4.

4.2. State-of-the-Art Algorithms, Optimizations, and Controllers Applied in BMS Technology in EVs

This section discusses recent and state-of-the-art algorithms, optimizations, and controllers applied in BMS technology for EV applications. A detailed technical comparison is carried out, emphasizing target, input features, structures, configurations, dataset, accuracy, and strengths and weaknesses.

4.2.1. Algorithms and Methods in BMS

Recently, several algorithms have been implemented in BMSs for EV applications. The execution of algorithms and methods is conducted in BMSs for various purposes such as state estimation, remaining useful life prediction, thermal management, fault diagnosis, and charge equalization.

Table 4. Comparative analysis of BMS components and functions in EV applications.

Subject Area	Ref.	Target/Focused Areas	Key Contributions	Limitations/Research Gaps	Battery Type	Validation Approach	Performance Metrics
Battery Thermal Management	[62]	To predict cooling capacity and system coefficient of performance (COP) of battery thermal management systems (BTMSs).	The coupling system of a liquid-cooled BTMS and a heat pump air conditioning system (HPACS) for battery electric vehicles (BEVs) were designed and analyzed.	The internal thermal characteristics of the battery were not considered in this study.	Lithium-ion power battery pack	Compared with SVR model.	Correlation coefficient I of cooling capacity and system COP were improved by 2.1% and 2.8%, respectively.
	[64]	To determine the required thermal parameters.	A specific design for an air-cooled battery system was theoretically explored and numerically designed.	Due to the layout limitation of the battery system in the HEVs, both the inlet and outlet should be located on the same side.	Lithium-ion batteries	A theoretical analysis was performed.	The advection thermal resistance was 2.4 °C W^{-1}.
State of Charge	[66]	A closed-loop framework was developed for improving robustness.	To estimate the SOC of $LiFePO_4$ batteries.	Only current and voltage data were used to fine-tune the DNN	$LiFePO_4$ batteries	Compared with other relevant machine learning approaches.	The root mean square error was less than 3.146% and 2.315% for aged batteries and different battery types, respectively.
	[67]	The cell balancing and dc bus voltage regulation systems were merged into a single system.	Compact size, tiny power converters were used to provide SOC balance between battery cells and DC bus voltage management.	Battery deterioration, overheating, and even catching fire in a worst-case scenario.	Lithium-ion batteries	A scaled-down distributed BESS prototype with the proposed energy sharing controller was built in the laboratory.	The overall efficiency was 95–97%.
Energy management strategies	[70]	A hybrid method was proposed using a mixed experience buffer consisting of environmental disturbances.	A novel DRL algorithm was introduced to formulate an intelligent HEV for EMS.	Some unreasonable and meaningless torque allocations may occur during exploration	Lithium-ion batteries	Compared with deep Q-networks (DQN)-based EMS	Robustness (%) = 92.95 ± 1.24.
	[71]	A comprehensive study on the state of the art of Li-ion batteries including the fundamentals, structures, and overall performance evaluations of different types of lithium batteries.	Improving the system's overall performance and efficiency.	Environmental impact and recycling, protection circuitry, and excitability of Li-ion safety.	Lithium-ion batteries	Compared with other relevant literatures	The price of a Li-ion battery pack was 25–30% of the price of an electric car.

Table 4. *Cont.*

Subject Area	Ref.	Target/Focused Areas	Key Contributions	Limitations/Research Gaps	Battery Type	Validation Approach	Performance Metrics
Battery materials and technology	[73]	A sandwiched cooling structure out of copper metal foam saturated with phase change material (PCM).	The system's thermal efficiency was tested in the lab and compared to two control stages: cooling with pure PCM and cooling with air.	Thermal management using natural convection air could not meet the Li-ion battery's safety requirements.	Lithium-ion batteries	Thermal efficiency of the system was experimentally evaluated and compared with two control cases.	The paraffin remainId in a solid state for the lower discharge rate of 0.5 C.
	[69]	The authors presented an output error injection observer based on a reduced set of partial differential-algebraic equations.	Reliable and safe operation.	Detailed stability analysis of the observation error was not possible due to the complexity of the problem.	Lithium-ion batteries	Compared with other cell chemistries.	SOC error of less than 10%.
Battery modeling	[75]	To improve the use of lithium–ion batteries in EV applications.	The proposed DP approach had the best dynamic performance and provided a more accurate SoC estimation.	In future research, another artificial intelligence-based algorithm can be utilized to improve SOC estimation.	$LiMn_2O4$ battery module	The dynamic performances of the battery models were compared with a robust extended Kalman filter.	SOC terminal error was within 1.56%.
	[74]	To achieve effective charge equalization while keeping the monitoring IC under easy control.	The battery string was modularized into a master module.	Large circuit size and high implementation cost.	Lithium-ion batteries	Compared with relevant literature.	The SOC gap decreased from 21.3% to approximately 1.3%.
Fault diagnosis and protection	[79]	To predict battery life, which consists of life cycle variables and numerous failure causes, and their impact on battery safety and health.	Temperature homogeneity was improved by using a cylinder vortex generator in front of the heat pipe condensers in the coolant stream.	Limitation of low specific heat capacity.	Lithium-ion batteries	The numerical model was comprehensively validated with experimental data.	Lithium–ion batteries charged at a high C rate (up to 8 C rate).
	[80]	To improve battery failure mitigation control systems.	Enhanced failure mitigation control.	Testing cost is higher.	Lithium–ion batteries	An SBPM-based SOH monitor was compared with a polynomial model.	The average error was less than 1.2% at each temperature.
Remaining useful life	[98]	A combined SOC and SOH estimation approach toward the lifespan of Li-ion batteries.	The presented model was effective with online SOH estimation and offline SOC estimation.	Complex computation and mathematical model. Accurate input parameters required.	Lithium–ion batteries	Compared to the second order EKF.	The voltage errors stayed below 0.7%.
	[82]	Focused on two key ways of determining a battery's health: RUL prediction and battery SOH monitoring.	Enhanced the RUL probability distribution to the End-of-Life cycle.	Problem of degeneracy.	Lithium–ion batteries	Compared the estimation and prediction capability between the SVR-PF and standard PF.	The RUL threshold value was changed to 85% of nominal capacity.

Table 4. *Cont.*

Subject Area	Ref.	Target/Focused Areas	Key Contributions	Limitations/Research Gaps	Battery Type	Validation Approach	Performance Metrics
Vehicle performance assessment	[84]	Performance assessment of EVs under real driving conditions in cold and hot starts.	To mitigate the unfavorable effects of conventional HVAC systems on the EV range.	Model parameters can only be parameterized accurately for new batteries.	Lithium–ion batteries	Compared to the RLS, LMS, and WRLS filters.	The proposed system increased the vehicle range by 19% and 11% compared with conventional heat pump systems.
	[85]	A novel, integrated MCDM model for BEV selection.	To assess BEV alternatives comprehensively from the customer's point of view.	Battery weight was not considered in this study.	Lithium–ion batteries	Compared with the existing literature.	The suggested aggregation framework was capable of assisting customers, decision makers, and authorities in order to make reliable decisions in evaluating BEVs.
Energy utilization and Efficiency	[88]	To determine the energy gain for 10 series-connected cells during discharging cycles.	An active cell balancing solution for li-ion battery stacks.	Technical and economical limitations.	Lithium–ion batteries	Compared with the rated capacities of the used cells.	The usable energy of the battery stack could be improved by 15%.
	[87]	Proposed an energy-saving optimization and control (ESOC) method.	To improve the energy utilization efficiency of autonomous electric vehicles.	The regenerative braking situation was not considered in this work.	Lithium–ion batteries	Compared the proposed ESOC with model predictive control (MPC) and energy optimal control (EOC).	The proposed ESOC effectively avoided the high-power output of the vehicle's powertrain.
State of Health	[99]	End-to-end prognostic framework applicable to SOH/RUL tasks.	To capture the hierarchical features between several variables affecting battery degeneration.	Training time and inference latency were not considered in this study.	Lithium–ion batteries	Compared with the existing NNs.	Lower average RMSE 0.0072 and global average RMSE 0.0269 for SOH and RUL tasks.
	[100]	A novel deep-learning-enabled estimation method for battery state of health.	To perform accurate state of health estimation for battery systems on real-world electric vehicles.	The existing SOH estimation methods were mostly limited to laboratory research.	Lithium–ion batteries	The vehicle's data were derived from the Serving and Management Center for EVs (SMC-EV) in Beijing.	Maximum error $\leq$ 0.1323% Mean relative error (MRE) $\leq$ 0.0546% Root mean square error (RMSE) $\leq$ 0.232% Mean squared error (MSE) $\leq$ 0.0538

Table 4. *Cont.*

Subject Area	Ref.	Target/Focused Areas	Key Contributions	Limitations/Research Gaps	Battery Type	Validation Approach	Performance Metrics
Aging and battery degradation	[91]	To predict the SOC and other characteristics.	To identify the incorrect primary SOC values	Easily caused an unstable SOE estimate.	Lithium–ion batteries	Compared the performance of the developed approach with Kalman filter methods.	The maximum SOC estimation and prediction errors were both less than 2%.
	[90]	Two heuristic strategies were proposed and optimized by particle swarm optimization.	Q-learning was proposed to actively determine the engagement of the ultracapacitor.	Different component sizes were still required for further investigation.	Lithium–ion batteries	Compared with the rule-based method.	Q-learning reduced battery degradation by 20% and extended vehicle range by 2%.
Battery equalization/charge control	[93]	To achieve zero-current switching.	Reduced, power losses, increasd the equalization voltage gap, and reduced the size and cost of implementation.	Long equalization time, high switching loss, and over equalization.	Lithium–ion batteries	A quantitative and systematic comparison with the existing active balancing methods.	The energy conversion efficiency was higher than 98%.
	[94]	To properly capture real-time fluctuations and the varied dynamics of the parameters while maintaining computational simplicity.	Precisely characterize the battery model parameters.	Divergence problem.	$LiFePO_4$	The proposed technique compared to the conventional RLS technique.	The SOC with an absolute error of less than 2.8%.
Validation under different operating conditions	[95]	To mimic the process of heating li-ion batteries from sub-zero temperatures.	An electrochemical and thermal coupled model.	Insufficient balancing or cooling methodologies.	Lithium–ion batteries	Compared to conventional topologies	The strength of variation and the number of outliers both generally increased as aging progressed.
	[96]	To design a system that can perform conventional tests virtually.	New features such as capacity estimates and temperature dependency.	Methods were only valid within the trained data range. Limitations of the load.	Lithium–ion batteries	The outcome of this study was compared with the relevant existing literature.	A 30% difference in impedance resulted in a 60% difference in peak cell current.

Kai et al. [101] developed an improved SOC estimation technique based on the adaptive square-root unscented Kalman filter method. The proposed work was implemented on 18,650 model dynamic lithium–ion batteries with a rated capacity of 2.2 Ah. The improved Kalman filter method was validated with other techniques such as enhanced Kalman filter and unscented Kalman filter.

Qu et al. [102] introduced a hybrid SOH and RUL prediction for lithium–ion batteries based on the LSTM model. The work employed NASA battery datasets, namely, B0005, B0006, and B0018. The model operation was enhanced by applying the particle swarm optimization (PSO) technique by optimizing key parameters such as the weights and biases of the model. Additionally, model training was conducted based on different training ratios such as 30:70, 50:50, and 70:30.

A hybrid Kalman filter and particle filter method-based SOC estimation was conducted by Zheng et al. [103] The proposed method was based on differential voltage analysis for SOC estimation. The model employed three $LiFePO_4$ battery cells with a rated capacity of 60 Ah. Furthermore, validation of the method was conducted with test data from three battery cells operated above 1800 cycles. It was noted that temperature dependency was not assumed in the conducted work, which may have significantly impacted the SOC estimation outcomes.

Ansari et al. [104] developed a backpropagation neural network (BPNN)-based RUL prediction method for lithium–ion batteries. The proposed work was conducted by utilizing four battery datasets from the NASA database, namely, B0005, B0006, B0007, and B0018. The BPNN model hyperparameters were selected using a trial-and-error method. The validation of the proposed model was conducted using different combinations of training datasets.

Park et al. [105] proposed an LSTM-based RUL prediction algorithm for lithium–ion batteries. The algorithm employed a systematic sampling technique for the appropriate extraction of data samples to develop a 31-dimensional data format. The developed 31-dimensional data format consisted of battery parameters such as voltage, current, temperature, and discharge capacity. The proposed LSTM model delivered satisfactory outcomes, however, more sophisticated RUL prediction techniques could be developed by integrating the LSTM model with other intelligent models.

Part et al. [106] presented an ANN-based supervised learning for thermal management in EV applications. The ANN model was employed and trained with data extracted from EV driving operations. The model delivered satisfactory outcomes and reduced power consumption by 48.5% and 6.9% in the integrated and separate operating modes, respectively.

With regards to the application of algorithms in thermal management in battery technology, Zhu et al. delivered an LSTM model-based data-driven algorithm for analyzing the thermal effect in batteries [107]. To conduct this work, an open-source battery database from MIT, Stanford was considered which consisted of three battery datasets with different cycle numbers. Model training was conducted based on three training ratios, i.e., 80:20, 50:50, and 20:80. The work accurately predicted future temperature; however, the research was confined to using a time-series approach.

Another important area in BMS technology is related to fault diagnosis. In this regard, Yao et al. developed a support vector machine (SVM)-based intelligent algorithm to perform fault diagnosis on lithium–ion batteries [108]. The proposed experimental setup consisted of a battery test bench (Digtron Battery Test System: BTS-600), vibrating test bench, information collector, voltage sensor, and host computer. The presented SVM model-based work was quick to detect faults with a modified covariance matrix (MCM) as compared to a covariance matrix (CM).

Charge equalization is also regarded as a key research area in BMS technology for EV applications. Zhang et al. [109] developed an effective active equalization control method to conduct SOC estimation of lithium–ion batteries. The work considered various battery parameters such as voltage, internal resistance, and temperature to analyze inconsistencies in battery SOC. It was estimated that under active equalization control, the error in measured voltage was limited to 3 mV.

Table 5 represents a summary of the recent methods and algorithms for BMSs in EV applications.

4.2.2. Optimization Approaches in BMS for EV Applications

Optimization techniques have been implemented to improve and enhance model operations. Model enhancement results in appropriate SOC, SOH, and RUL estimation, thermal management, and fault diagnosis of the lithium–ion battery in EV applications.

Qui et al. [110] presented SOC, SOH, and RUL estimations based on an improved particle filter technique. The PF technique was enhanced by implementing the cuckoo search optimization technique. Five $LiCoMnNiO_2$ batteries were used to conduct the proposed experiment. The proposed method was validated with conventional PF and unscented PF methods. Although the proposed work was largely based on outcomes, the utilization of battery parameters from discharge profiles may be considered in further research.

Lipu et al. [111] introduced a backtracking search algorithm (BSA) for the SOC estimation of lithium–ion batteries. The work employed a BSA-integrated BPNN approach to select suitable model hyperparameters. The analysis was conducted based on dynamic stress test (DST) and federal urban driving schedule (FUDS) drive profiles datasets for testing the model at different temperatures. The proposed model was validated with other models such as the radial basis function neural network (RBFNN), generalized regression neural network (GRNN), and extreme learning machine (ELM).

Wang et al. [112] proposed a genetic algorithm (GA)-based optimization technique to obtain the optimal electric braking torque and current distribution factor by considering battery SOC, OCV, and heat loss. Furthermore, a neural network-based PI control model was established to regulate the rotating speed of the flywheel motor. The proposed model was established for the battery-flywheel system for energy recovered during the EV braking. The work delivered theoretical and analytical support; however, further work could achieve cost improvements.

A SOH estimation of a lithium–ion battery was conducted by enhancing the support vector regression (SVR) model with improved ant lion optimization (IALO) [113]. Three NASA battery datasets, namely, B05, B07, and B34 were considered to verify the proposed work. Furthermore, charge and discharge voltage curve data were considered to map SOH estimation. The accuracy of the SVM-IALO model was compared to that of other models such as the SVR and SVR-ALO. The SVR-IALO model demonstrated satisfactory outcomes in terms of accuracy and time complexity; nonetheless, performance can be further examined using reliable battery datasets.

Wang et al. [114] presented a fruit-fly optimization technique-based RUL prediction of a lithium–ion battery. Fruit-fly optimization was used to optimize the Hurst exponent (H) that denotes the dependence of the fractional Brownian motion model for RUL prediction. Four NASA battery datasets, namely, B5, B6, B7, and B18 were employed. The proposed fruit-fly optimization technique delivered appropriate outcomes; however, the computational complexity was a crucial factor that should be rectified in future work.

To conduct the thermal management of a lithium–ion battery, Deng et al. [115] employed GA to optimize the convective heat transfer and surface friction coefficients. The constraints considered to perform the experiments were the maximum temperature of the battery pack and the maximum temperature difference between cells. It was concluded that length and thickness played an important role in the performance of the cooling system.

Zhang et al. [116] proposed a multi-objective PSO-based optimization technique to deliver optimal results based on the thermal conductivity and thickness of phase change material, length of the heat pipe, and velocity of inlet water. Table 6 represents the optimization approaches for BMS in EV applications.

Table 5. State-of-the-art methods and algorithms for BMS in EVs.

Methods and Algorithms	Objectives	Ref.	Input Features	Structure/ Configuration	Type of Dataset	Accuracy/Error Rate	Strengths	Weaknesses	Research Gaps
UKF	SOC	[101]	Ohmic internal resistance, polarization resistance, and polarization capacitance.	2RC Thevenin model.	18650 model dynamic lithium–ion battery.	Accuracy of 99.04%.	High SOC estimation accuracy, better stability, and fast convergence speed.	More sophisticated model should be considered for SOC estimation.	Parameter identification could be improved.
LSTM-PSO	SOH and RUL	[102]	Capacity.	C1-0.5 C2-0.3 w-0.9 (PSO).	NASA battery dataset.	0.006 (RMSE) for B0005.	High robustness with improved estimation capability.	Model complexity and high training time.	Integration of model-based methods for different types of batteries.
EKF and PF	SOC	[103]	Cell terminal voltage.	Number of PF particles: 1001.	Three $LiFePO_4$ battery cells.	1.75% (MAE), 1.10% (RMSE).	Capability to handle a large volume of data for SOC estimation.	The SOC estimation was conducted with just one battery parameter.	A suitable selection of data samples could be carried out with different sampling techniques.
BPNN	RUL	[104]	Voltage, temperature, current, and capacity.	Learning rate 0.005, hidden neurons 10, epochs 500.	NASA battery dataset.	0.0819 (RMSE), 0.0423 (MAPE), 0.0681 (MAE), 0.0717 (SD).	High prediction accuracy and robustness.	The model hyperparameters were not selected appropriately.	Optimization technique may be employed for selecting model hyper parameters.
LSTM	RUL	[105]	Voltage, temperature, current, and capacity.	LSTM cell 10, iterations 500, learning rate 0.001.	NASA battery dataset	0.0168 (RMSE), 0.0146 (MAE), 1.05 (MAPE).	Appropriate extraction of data samples was achieved.	Validation using other battery datasets was not conducted.	Bidirectional LSTM-based intelligent model can be framed.
ANN	Thermal manage- ment	[106]	Controllable, environmental, and feedback inputs.	Hidden neurons 16.	Not mentioned.	Power consumption was reduced by 48.5% and 6.9%.	Regulated battery temperature with acceptable range.	Validation of the proposed model was not conducted.	Further research can focus on online learning.
LSTM	Thermal manage- ment	[107]	Temperature.	Learning rate-0.001.	$LiFePO_4$/graphite lithium–ion batteries.	0.044, 0.055, and 0.622 (RMSE) at different training ratios.	Predict wider temperature Change efficiently.	More improvements in selecting hyperparameters need to be considered.	The correlation between battery parameters and varying temperature profiles must be investigated.
SVM	Fault diagnosis	[108]	Cell voltage.	Penalty factor C [−10, 20], function parameters [−5, 10].	$LiMn_2O_4$ Lithium–ion cells.	Accuracy of more than 95% was achieved.	Timely detection of fault and severity.	The validation of SVM was not conducted comprehensively with other methods.	Battery system fault hierarchical management strategy can be studied.
SVM	Battery charge equaliza- tion	[109]	Voltage, resistance, and temperature.	Not mentioned.	18650 lithium–ion batteries.	The maximum SOC estimation error was approx. 4%, voltage variance was within 2%.	High accuracy.	Prototype or hardware validation of the method was not conducted.	Other KF-based methods and improved an Thevenin battery model could be employed in future study.

Table 6. Optimization approaches for BMS in EV applications.

Optimization Technique	Objectives	Ref.	Input Features	Structure/Configuration	Type of Dataset	Accuracy/Error Rate	Strength	Weakness	Research Gaps
Cuckoo optimization	SOC, SOH, and RUL	[110]	Capacity.	Not mentioned.	$LiCoMnNiO_2$ batteries.	3.3, 2.4, 1.0 0.5 (Relative error at different cycles).	Reduced Pdf width and resampling rate, low convergence time.	Reliable battery datasets from NASA and CALCE may be used.	Battery parameters related to discharging profiles may be considered.
Differential Search Optimization	SOC	[117]	Voltage, current, and temperature.	The population size was 50 while the iteration was 500.	HPPC, DST, FUDS.	MAE of 0.193% in DST and 0.346% in FUDS at 25 °C.	High robustness and stability.	Comparative study with recent optimization schemes can be conducted.	Validation through a hardware-in-the-loop test in real-time can be performed.
BSA	SOC	[112]	Voltage, current, and temperature.	The population size was 100 while the iteration was 250.	DST and FUDS.	SOC error at 0 °C [−4.8, +9.8].	High accuracy.	The data collected experimentally can be validated with other reliable battery datasets.	Model validation can be conducted with other optimization schemes.
Ant lion optimization	SOH	[113]	Voltage curve from charge and discharge profile.	The population size was 20 and the number of iterations was 200. Penalty factor C and kernel function parameter σ were set as (0.01,100).	NASA battery dataset.	0.53 (RMSE), 0.71(MAPE) for battery B05.	Improved estimation accuracy.	Validation with other battery datasets was not performed.	Further study to improve convergence speed can be explored.
Fruit fly optimization	RUL	[114]	Capacity.	The Hurst exponent was 0.6638. The population size was 50 and the maximum number of iterations was 100.	NASA battery dataset	RMSE 2.0813%. MSE 4.3333%.	Better prediction outcomes.	Low prediction accuracy under large datasets and varying environmental conditions.	Better model-hyperparameters should be selected.
GA	Thermal management	[115]	Temperature.	Not mentioned.	Four square lithium–ion batteries.	Maximum error of 3.17% in convective heat transfer coefficient (h).	Low pressure drops compared to conventional serpentine channels.	Aspects of channel thickness and length ratio should be comprehensively studied.	Work on channel thickness and length ratio aspect can be conducted in future.
PSO	Thermal management	[116]	Thermal conductivity, PCM thickness, heat pipe length, and inlet velocity.	The population size was 100. The number of generations was 300. Learning factor C1 2. Learning factor C2 2.	Lithium–ion battery dataset.	Optimized design 3.26 mm for PCM thickness and 92.4 mm for heat pipe length.	Delivered best heat dissipation performance.	Inefficient to work in dynamic and unknown environments.	Appropriate utilization of recent optimization techniques can be applied.
Firefly algorithm	SOC	[118]	Voltage, current, and temperature.	The population size was 50 while the iteration was 500.	SDT and HPPC	RMSE below 1%. SOC error below 5%.	Improved convergence speed and enhanced exploration and exploitation capacities.	Complex execution and high computational costs.	Validation using an EV dataset was not considered.

4.2.3. Controllers Schemes in BMS for EV Applications

The controller technology in BMS is important for maintaining battery heating, cooling, charging, and discharging within a prescribed boundary to achieve optimal performance. Various work has been accomplished to implement controllers in BMS.

Afzal and Ramis [119] developed a hybrid GA and fuzzy logic controller-based thermal management system for lithium–ion batteries. The objective functions selected in the proposed study were average Nusselt number, friction coefficient, and maximum temperature. The proposed controller technique achieved the desired results by achieving the maximum temperature within the desired range.

Park and Ann [120] proposed a stochastic model predictive controller (SMPC) implemented to create a battery-cooling controller. The proposed controller technique successfully reduced the computational load by introducing an unequally spaced probability distribution mode, which is a common issue with conventional stochastic model predictive control. The computational load was reduced by 91%, with a performance declination of only 4%.

Rahman et al. [121] proposed three controller technologies, namely, the sliding mode controller (SMC), integral sliding mode controller (ISMC), and double integral sliding mode controller (DISMC) for EV applications, consisting of a battery, fuel cell, and supercapacitor. The controller was employed to achieve the control objectives in terms of current tracking, voltage regulation, and stability. It was observed that the least error was achieved by DISMC compared to the SMC, ISMC, and proportional-integral (PI) controllers.

In another work, Hussain et al. [122] introduced a real-time bi-adaptive controller-based energy management system for hybrid battery-supercapacitor technology in EV applications. The PI controller was employed to protect the supercapacitor from overcharging, whereas a fuzzy logic controller was used for optimal power sharing between the battery and the supercapacitor. Validation of the proposed method was conducted with three different cycles such as the New York City cycle (NYCC), Artemis urban (AU) cycle, and New York composite cycle (NY company).

Miranda et al. [123] developed an FL control technique to increase the efficiency and dynamic performance of electric motors in EV applications by conducting a power split. A PSO-based optimization technique was employed to deliver the optimal mass of the electric components such as the electric motor and battery. The best optimal solution was delivered at a driving range of 124.2 km with a 235.8 kg battery (387.8 V and 91.2 Ah). Although high stability and robustness were achieved, the model was not implemented using an experimental setup. This could be investigated in future studies.

Ahmad et al. [124] employed an integral backstepping sliding mode controller (IBS-SMC) and a backstepping sliding mode controller (BS-SMC) to design a robust charging system, achieving various objectives such as output voltage regulation and power factor correction in grid-to-vehicle (G2V) mode. Furthermore, to achieve the effect of chattering and super twisting, a sliding mode controller was designed. The proposed controller technique delivered satisfactory outcomes with better dynamic responses and robustness, among other external noises.

Table 7 represents a summary of the various controller schemes applied to BMS for EV applications.

Table 7. Controller schemes for BMS in EVs.

Controller Schemes	Objectives	Ref.	Input Features	Structure/ Configuration	Type of Dataset	Accuracy/Error Rate	Strengths	Weaknesses	Research Gaps
GA-PSO-FL	Maximize rate of heat transfer and minimize yearly cost.	[119]	Not mentioned.	W [0 1.2], C1, and C2 [0 2]	Lithium–ion battery.	Not mentioned.	Achieved a safe operating temperature.	Complex method and long training time.	Further investigation on the influence of weight components and inertia factors can be explored.
SMPC	Maximize the vehicle driving range and minimize energy consumption.	[120]	Heat generation of the battery.	Not mentioned.	Lithium–ion battery.	Not mentioned.	Low computational time and low energy consumption.	Required a large number of model coefficients.	Further research can be conducted with a hybrid energy storage system.
ISMC	Eliminate the steady-state error and mitigate the chattering effect.	[121]	Fuel cell voltage, battery voltage, supercapacitor Voltage, and load current.	Ideality factor 1.052.	Fuel cell, battery, and supercapacitor.	Steady-state error 1.8 V.	Achieved all desired objectives accurately.	The chattering issue was not considered.	Implementation of other control strategies can be investigated.
PI and FLC	Maximization of the effectiveness of the supercapacitor bank utilization.	[122]	Not mentioned.		Battery and supercapacitor.	High performance value for different drive cycles.	Easy implementation.	Conventional method and did not describe the novelty.	Implementation of the proposed model on hardware using FPGA.
BS-SMC	Development of an appropriate charging system.	[123]	Not mentioned.	$c1$ 2000 $c2$ 700 $p1$ 0.015 $p2$ 0.018	Battery.	Steady state error 5.4562.	High robustness with external disturbances.	Complex model with computational complexity.	Utilization of an AI-based non-linear controller may be employed.
FL-PSO	TO improve the dynamic efficiency of electric motors in EV applications.	[124]	Current (A)	Not mentioned.	Not mentioned	Best optimal solution was delivered at 124.2 km drive range with a 235.8 kg battery (387.8 V and 91.2 Ah).	High stability and robustness.	Validation of the proposed controller was not conducted.	The proposed model may be conducted with an experimental setup.

5. Open Issues and Challenges of BMS Technology in EV Applications

The presented analytical analysis comprising 110 highly cited articles on lithium–ion BMSs in EV applications utilized the Scopus database. Nevertheless, the extraction of resourceful articles and manuscripts lacked several journal databases such as Google Scholar and Web of Science, which may have affected the originality of the analysis. The extraction of articles from other databases was not performed due to the complexity of the compilation process for the 110 articles extracted from the Scopus database. Additionally, several high-impact articles may not have been considered in this work due to the usage of several filters. The filtering of the articles was based on publication years from 2011 to 2021, the English language requirement, and the inclusion of articles based on several criteria. The assessment process tended to deviate from its originality due to the occurrence of inter-crossing and a combination of many disciplines. The consideration of research areas based on state estimations such as SOC, SOH, RUL, TM, BCE, and FDP was prioritized, but work related to nanomaterial and battery chemistry was not considered. Some limitations of the proposed analytical research analysis are mentioned; nonetheless, some issues and challenges in the integration of lithium–ion BMS for EV applications must be explored, which are presented in the following subsections.

5.1. Algorithms/Method Issues

Implementing intelligent algorithms for BMS technology has demonstrated promising outcomes but constitutes some limitations. Satisfactory results can be obtained with neural network approaches but require ample space for storage and processing time. Further, regression- and probabilistic-based techniques deliver satisfactory results against noise, uncertainty, and data-overfitting issues; nevertheless, accurate solutions are not achieved for high-dimensionality and non-linear problems. Future predictions with time-series-based techniques are accurate; however, it requires the determination of past information selection and feedback steps. Deep learning techniques deliver accurate results, but their operational skill is constrained by the requirement of a large volume of data and high computational processors. Thus, further studies including data collection, suitable parameter selection, and performance verification under uncertainties are essential to developing advanced algorithms and methods in BMS.

5.2. Optimization Integration Issues

The integration of optimization techniques is a challenging and time-consuming process. Various optimization schemes can be integrated with different intelligent algorithms, but their outcomes vary with regard to execution time and convergence speed. Further, developing an optimization technique requires in-depth knowledge for initializing parameters and executing the operational loop. Although BMS techniques have been significantly improved by including optimization techniques with an intelligent algorithm regarding accuracy, prediction efficiency, and robustness, some issues persist concerning complex computation and long processing times. Unsatisfactory convergence, searching capability, and parameter settings may result in inaccurate predictions. Hence, further exploration is required to overcome optimization integration issues.

5.3. Controller Execution Issues

Controller schemes have been widely explored in BMS technology for various applications such as temperature control, minimizing capacity loss, increasing battery life, and avoiding non-uniformity in battery aging [125–127]. The fuzzy logic controller has been utilized in BMS technology for EV applications [128–130] for temperature regulation, SOC balancing, etc., but its outcomes are limited by human expertise intervention. Further, model predictive control (MPC) for BMS technology [131–133] is implemented due to its various benefits such as optimal control, smoothing power, and robustness against uncertainty but suffers from several shortcomings in terms of high maintenance costs and a lack of flexibility, resulting in improper controller operations [134,135]. The implementation of droop control technology is observed in some work [136,137] due to its simplicity and ability to operate independently with internal communications between converters; nevertheless, it suffers from poor transient performance. Therefore, further investigation is essential to address the abovementioned issues.

5.4. Appropriate Configuration and Hyperparametric Adjustment

One of the key issues for developing a BMS-based sustainable transportation system relates to the selection of suitable hyperparameters and algorithms for the integration of BMS in EVs. Various hyperparameters, such as hidden layers, the number of hidden neurons, epochs, iterations, learning rates, biases, weights, batch sizes, time steps, etc., are usually considered to frame a sophisticated algorithm. The computational complexity in terms of overfitting and underfitting can be minimized by utilizing optimal hyperparameters and grouping functions. Further, implementing hit-and-trial methods consumes more human energy and time. Therefore, it is necessary to develop an optimized and robust framework for hyperparameter adjustment and control to accomplish desired BMS outcomes.

5.5. Charging Imbalance Issues in Lithium–Ion Battery Packs

The charging technique implemented in BMS for EV applications plays a key role in obtaining an appropriate operational balance among battery temperature, efficiency, battery health, SOC, and lifecycles. A slow charging process might hinder the widespread acceptance of EVs. Additionally, the fast-charging technique causes excessive heat generation and reduces operating life. Further, the issue of charging imbalance is prevalent due to material defects, alterations in physical characteristics, battery health degradation, aging cycles, manufacturing technology, and tolerances. The charge imbalance also results in unpredictable state estimation, leading to unexpected circumstances. Hence, an efficient charging technique is necessary for uplifting performance toward sustainable development.

5.6. Data Abundance, Variety, and Integrity

The main challenges in putting intelligent algorithms into practice are data diversity and abundance. The accuracy of intelligent methods depends on having enough good-quality data. However, gathering a sufficient amount of diverse, large-scale data takes time and effort. Typically, data are gathered through trials with a 1 Hz sampling frequency. With varying forms of voltage and current values, the data length between EV driving cycles varies [138]. One EV drive cycle, for example, is calculated to last 1372 s by federal urban driving schedule (FUDS), 360 s by dynamic stress test (DST), 916 s by Beijing dynamic stress test (BJDST), and 600 s by US06 drive cycle [139]. Multiple EV drive cycle repetitions are used to prepare data since intelligent algorithms need a vast pool of data for training operations [140]. Having more data can help to find better outcomes, but it can also make the computer work harder and take longer to train, which might cause over-fitting problems [141]. As a result, concerns with data variety and quantity need specific consideration.

Another obstacle to putting intelligent approaches into practice in real-world settings is data integrity. Some well-known automotive research teams [142,143] have made a high-quality battery dataset that is freely accessible to the public. This dataset contains a fixed pattern of charge–discharge current that ensures the various protocols of EV drive cycles. Studies to gather the various EV drive cycle data are conducted in a laboratory setting with the suggested temperature and charge/discharge current rates. The current and voltage profiles of EV drive cycles obtained by simulated data do not match those of actual data collected in a real-world setting. Therefore, more research is required to verify intelligent algorithms in real-world scenarios.

5.7. Battery Energy Storage Material Issues

Despite the good properties of lithium–ion batteries, estimating SOC is significantly impacted by the performance variations between positive and negative electrodes. Lithium cobalt oxide (LCO) batteries have a low capacity and exhibit good performance; nonetheless, they are expensive and have a limited supply of cobalt. The lithium nickel manganese cobalt oxide (LNMC) and lithium nickel cobalt aluminum oxide (LNCA) batteries deliver outstanding performance with regard to high capacity and extended lifespan; however, they are expensive due to a lack of nickel and cobalt supplies. Batteries made of lithium manganese oxide (LMO) have a high voltage, a reasonable level of safety, decent performance, and a sufficient supply of manganese; nevertheless, they have a low capacity and short lifespan [144,145]. In [146], the authors employed two different chemistries of lithium–ion batteries such as lithium titanate (LTO) and lithium iron phosphate ($LiFePO_4$) to examine the accuracy of the SOC estimation method. Validation was performed through a test bench platform and an aging cycle test. Initially, the experiments were conducted using fresh lithium–ion battery cells where a $LiFePO_4$ battery demonstrated better accuracy than LTO, indicating an RMSE of 0.5305% at 25 °C. However, the LTO battery illustrated better outcomes under the aging cycle test, estimating an RMSE of 0.00334% after 1000 aging cycles.

5.8. Prototype Design and Real-Time Validation

To date, a variety of experimental studies have been conducted to confirm the viability of intelligent methods to examine diagnosis, thermal management, and condition estimation. However, there has not been a thorough investigation of the application of intelligent approaches in real-time BMS with compact memory units and low computing costs. Therefore, further investigation is required to create an embedded prototype system for state estimation and control in real-time BMS. A study in [147] validated the machine learning-based SOC estimation approach in real-time using the hardware-in-the-loop (HIL) experimental platform. A DC source, current sensor, battery monitoring device, host computer, battery management unit, and CAN analyzer were used in the creation of the HIL test bench. The results showed that the SOC and capacity errors in the HIL test were 2% and 19.7%, respectively. The authors of [148] evaluated the adaptive network-based fuzzy inference system (ANFIS)-based SOC estimation in real-time with HIL experimental setup utilizing the dSpace MicroLabBox hardware controller. The HIL results were highly similar to the simulated outcomes, demonstrating the appropriateness of the suggested model for real-time EV applications.

5.9. IoT integration and Cloud Computing Technology

Through cloud storage, cloud computing, and big data platforms, the accuracy and resilience of intelligent algorithms and controllers of BMSs in real-world settings can be significantly improved. The use of huge memory devices, computing, and analysis in conjunction with intelligent approaches is made possible by big data technology. The constant transfer of EV voltage, current, temperature, and other data to the big data platform enables the training of intelligent methods using real-time data to produce more accurate results. The estimation of the battery condition, including SOC, SOE, SOH, and RUL predictions, as well as thermal runaway and fault diagnosis over the course of the battery's lifetime, can be tracked and saved in the cloud. The battery monitoring and control center will then pre-process the data, run the analysis, and provide useful decisions for enhancing performance in the future. Haldar et al. [149] examined real-time battery monitoring and management in Evs based on the internet of things (IoT). To assess battery health and discharging behavior for Evs in real-time, the authors created a wireless battery management system. An IoT-based BMS was created by Sivarman and Sharmeela [150] to control charge imbalance, monitor SOC and SOH, and diagnose faults. Kim et al. [151] unveiled a cloud-based battery monitoring system for EV applications. Using Raspberry Pi3 IoT boards, a cyber-physical testbench was used to validate the proposed system. The findings showed that the condition monitoring algorithm accurately estimated SOC and capacity while the data mining method evaluated fault diagnosis.

5.10. EV Regulations, Policies, and Decarbonization Target

Implementing energy policies and regulations would lead to achieving several economic and social objectives ranging from energy cost reduction, economic prosperity, system reliability, and security. Three main points, such as clean development mechanisms (CDM), joint implementation (JI), and emission trading (ET), which are proposed with regard to the Kyoto Protocol, have been defied by the United Nations (UN) [152,153]. Several studies have been carried out on decarbonizing the energy sector in Europe. In this regard, an economic transformation for the energy sector in Europe has been undertaken to reduce greenhouse gas emissions by 80–95% in 2050 by employing a linear dynamic optimization model [154]. As per the energy model suggested by Lappeenranta University of Technology (LUT), the power sector in Europe will be 100% based on RES until 2050. It is expected that favorable decarbonized policy implementation would result in a demand surge for EV transportation by electric cars, buses, and motorcycles to 1.8, 1.5, and 0.6 billion-per km in 2050, respectively, while a decrease of 0.8, 0.6, and 0.2 billion-per km by 2050 by combustible fuel vehicle. Further, favorable regulations and policies would shift the market trend from combustible fuel vehicles toward Evs [155].

5.11. Environmental Concerns and Recycling Process

Torabi et al. [156] focused on environmental and decarbonization problems with Evs. The effects of Evs on lowering carbon emissions should be the subject of further exploration. As oil price rises and the need for vast amounts of energy for sustainable transportation increases, automotive electrification, such as Evs, HEVs, and PHEVs, grows in popularity. Toyota predicted that more than 7% of all transportation would be made up of EVs by 2020 [28]. Despite their positive impacts on the environment by reducing the number of oil-based cars, lithium–ion batteries emit CO_2 and GHGs during their manufacturing and disposal [157]. The US EPA previously investigated the use of nickel- and cobalt-based cathodes in lithium–ion batteries as well as the processing of electrodes using solvents. They discovered significant environmental effects, including resource depletion, global warming, ecological toxicity, and effects on human health [158]. Utilizing a lithium–ion battery recycling process might reduce this risk and conserve natural resources by using nickel and cobalt less frequently [158,159]. Therefore, it is necessary to further analyze how EVs can affect the environment and contribute to achieving the Sustainable Development Goals (SDGs).

6. Conclusions and Emerging Future Directions

The work presents an analytical analysis of smart BMSs for EV applications. A total of 110 high-impact articles from the Scopus database were considered between 2011 and 2021. Primarily, citation analysis was performed, depicting a significant impact on the desired research area of the manuscript. Further, several investigations have been carried out consisting of essential keywords such as published articles in a year, number of citations, highly cited articles in the last 5 years, affiliated country, journal name, publisher, and research areas. The primary aim of this paper is to showcase the most influential articles and offer insight into the evolution of battery energy storage technology for EV applications. In addition, 13 major research areas of BMS in EVs have been discussed thoroughly. Moreover, notable methods and algorithms in the highly impactful articles for BMS have been investigated. The articles provide various effective suggestions and directions for future improvement trends for smart BMS in EVs, which are as follows.

- The application of smart BMS in EV applications is now being widely accepted as the future of mobility for delivering sustainable development in the transportation sector. However, there are some issues with BMS in EV applications, such as short driving range, short battery lifespan, long charging times, high initial costs, poor vehicles, and ineffective EV-based policies. Thus, further analysis is essential for developing accurate BMS technology in better controlling mechanisms, favorable market policies, global collaboration, and sustainable development for enhanced EV performance.

- BMS utilization significantly controls the battery heating and cooling in EVs and hence increases the stability and reliability of battery operation. Nonetheless, due to thermal effects, deep diving range loss occurs in EVs, reducing the overall system's efficiency. Additionally, the involvement of thermal effects due to thermodynamics and the kinetics of electrochemical processes may deliver poor efficiency and performance and pose a danger to the functionality of BMS. To prevent issues as mentioned earlier, dynamic instability can be minimized by applying a supercapacitor integrated with lithium–ion battery storage and dynamic regulation and frequency management. Furthermore, issues related to system aging and power curtailment can be minimized by utilizing optimized BMS and dynamic thermal rating in real-time applications.
- To operate BMS in EVs effectively and appropriately, it is crucial to accurately predict a lithium–ion battery's SOC, SOH, and RUL. An inaccurate prediction of SOC would lead to overheating, overcharging, and over-discharging problems. Moreover, inaccurate predictions of the SOH and RUL of a battery would result in prematurely replacing the battery or waiting until an explicit failure event occurs, thereby increasing the capital cost. Therefore, more research activities in terms of deep learning algorithms should be implemented for state estimation to improve the prediction accuracy, robustness, and reliability of BMS in EV applications. Further, the estimation of battery SOC, SOH, and RUL can be enhanced by employing multi-scale and co-estimations that could improve the system's operational efficiency and minimize the computational complexity of BMS.
- The controllers applied in BMS play a vital role in battery equalization and fault diagnosis. Battery inconsistency issues relate to changes in their internal parameters, such as internal resistance and capacitance, due to various factors such as battery aging and temperature variation. Additionally, fault diagnosis in BMS is important as it can prevent various issues such as thermal runaway, short circuits, electrolyte leakage, battery swelling, over-discharging, and overheating. Therefore, appropriate controller techniques are required to obtain the safe operation of BMSs in EV applications.
- The hybridization or integration of intelligent algorithms has enhanced outcomes over non-hybrid intelligent algorithms. The hybridized algorithm is developed by integrating an intelligent algorithm with an optimization model or a combination of two intelligent algorithms that need complex mathematical computation, a higher configuration processor, and human expertise, leading to undesirable results. Therefore, future studies are necessary while considering practicability issues for developing an effective hybrid model.
- To date, the validation of intelligent algorithms of battery SOC, SOH, RUL, TM, BCE, and FDP has been validated with experimental tests. Nonetheless, the real-time execution of intelligent algorithms with a low computational burden and small memory devices has not been carried out. Therefore, further research is necessary to design an advanced battery testing system and establish an embedded prototyping product or hardware-in-the-loop system for real-time algorithm execution, control, analysis, and management in BMS.
- Although BMS-integrated EV has gained substantial ground toward grid decarbonization and sustainable development, some environmental issues, such as soil and groundwater contamination, causing landfill fire and air pollution, have been ignored. Further, the improper disposal of batteries would result in health hazards as well as water and air pollution. Hence, to prevent inappropriate disposal, lithium–ion batteries should be reused and recycled effectively to reduce the carbon impact and minimize the environmental issue. The appropriate utilization of battery materials, discharge time, power output, rated power, specific energy, and expenses would prove beneficial for achieving SDG.
- The efficiency and robustness of the algorithms implemented in BMS techniques can further be improved by integrating real-time monitoring, big data, and cloud-based technology. The accuracy and efficiency of the implemented algorithm in BMSs can be

precisely evaluated by utilizing the real-time data from EVs regarding voltage, current, temperature, etc. Further, battery state estimation data can be acquired through monitoring and stored in a cloud-based database. The future performance of the system can be improved by performing various steps consisting of data extraction, data analysis, and future prediction. Thus, the efficiency of BMS can be significantly enhanced to deliver better outcomes.

- Many intelligent functionalities are difficult to address in BMSs for EV applications due to the low computational resources, typically around 300 MHz. The cloud BMS topic has recently been discussed in several works to overcome this limitation. Yang et al. [160] introduced a general framework utilizing an end-edge-cloud architecture for cloud-based BMSs with the composition and function of each link. Madhankumar et al. [161] introduced a technique to examine the health and life of a battery. Wang et al. [162] investigated digital twin technology and cloud-side-end collaboration for future battery management systems. Nonetheless, there are some concerns with respect to the implementation of this technology. Therefore, further research can be conducted to overcome these issues.

Top-quality, highly cited research articles significantly influence the corresponding research fields. In the presented analytical analysis, 110 highly cited articles were selected after several filtering processes to present a broad view of the research activities in BMSs for EV applications. Further, the analysis discussed recent trends in publishing articles, issues, and recommendations. Therefore, understanding the features of most cited articles presents several advantages, as follows:

- Future research activities can benefit from the characteristics of highly cited articles in the field of BMSs for EV applications.
- Highly cited articles could form a foundation for young researchers to develop and promote up-gradation in a particular field.
- The analytical analysis presented provides an outline and investigation of the selected most cited articles and guides academicians, researchers, and engineers to explore possible research collaborators around the globe.
- The discussion and analysis offered in this article will lead journal editors, reviewers, and other resourceful researchers to evaluate the submitted article.
- The analytical analysis can assist decision-makers and government/private officials in drafting a long-term energy plan toward developing a prosperous and healthy society and achieving global decarbonization targets by 2050.

Overall, it can be observed that analytical analysis for the most cited articles between 2011 and 2021 is expected to contribute to the sustainable operation and management of battery storage systems for EV applications. Thus, further investigation of smart battery management technology will not only enhance battery lifetime and performance but also expand the battery and EV market, thereby achieving a pathway for SDGs concerning emission reduction, clean energy, employment opportunities, economic development, and sustainable cities.

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Appendix A

Table A1. 110 top-cited and highly influential manuscripts (2011–2020) in the area of battery management technology for EV applications.

Refs.	Keywords	Journal Name	Publisher	Article Type	Year	Country	Total Citations	Contributions	Research Gaps/Limitations
[33]	BFD; BMS; BSE; Battery uniformity and equalization; CVM; PHEV	JPS	Elsevier Ltd.	Review	2013	China	2516	Reviewed BMS and its key issues.	Other BMS technologies, such as ultracapacitor, were not reviewed.
[163]	Charge and discharge; CT; ED; HGR; HEV; LIB; LIC; LTP; OP; RC; SE; TM	JESOA	IOP Publishing	Review	2011	United States	974	Thermal issues related to lithium–ion batteries were discussed.	Other lithium–ion battery issues such as cell unbalancing and fault diagnosis may be discussed.
[35]	BMS; EV; LIB; SOCE; SOC	RSERF	Elsevier Ltd.	Review	2017	Malaysia	618	SOC estimation in EV application was discussed.	Other state estimations, such as SOH and RUL, were not covered.
[86]	BM; On-line estimation algorithm; PP; SOC; SOH	JPS	Elsevier Ltd.	Review	2014	Germany	574	Monitoring for lithium–ion battery operation was reviewed.	Issues and future prospects were not discussed comprehensively.
[75]	EV; ECM; Experiment; LIB; SOCE	Energies	MDPI AG	Article	2011	China	557	Presented various ECM models to improve lithium–ion battery performance in EV applications.	Further exploration with filter-based techniques should be conducted.
[164]	EV; ES; PCM; PB; TEM	RSERF	Elsevier Ltd.	Review	2011	China	549	A review based on thermal management-based BMS in EV applications was performed.	Issues and future suggestions related to thermal management were not covered comprehensively.
[165]	BMS; BT; Charge/discharge; EV; OC; SOH; SOC; EV; Management; SPG	IIEM	IEEE	Article	2013	United States	470	The application of BMS in EVs and smart grids was reviewed.	Issues and challenges were not covered.
[166]	BM; EV; Electrochemical; EC; Lithium Sulphur	RSERF	Elsevier Ltd.	Review	2016	United Kingdom	352	Lithium-sulfur battery technology was reviewed.	The review was not comprehensive and depicted the initial stage of Li-S implementation in various applications.

Table A1. *Cont.*

Refs.	Keywords	Journal Name	Publisher	Article Type	Year	Country	Total Citations	Contributions	Research Gaps/Limitations
[83]	LIB; Mobility; Prognostics and health management; Safety; SOH; SOC	JPS	Elsevier B.V.	Review	2014	United States	349	Battery state estimations such as SOC and SOH were reviewed.	Comprehensive descriptions of future prospects were not mentioned.
[98]	EV; KF; LIB; RLS; SOH; SOC	JPS	Elsevier B.V.	Article	2015	China	341	A hybrid SOC and SOH estimation using a filter technique was proposed.	Validation using other filter-based techniques was not covered.
[167]	BMS; Li-ion technology; Real applications; SOHE	RSERF	Elsevier Ltd.	Review	2016	Spain	333	SOH estimation techniques were reviewed.	Other important battery state estimations, such as SOC, were not covered.
[63]	HP; LIB; BTM; Low carbon vehicles; Pure electric and hybrid cars	RSERF	Elsevier Ltd.	Review	2016	United Kingdom	332	A review on two aspects, battery thermal model development and thermal management strategies, was conducted.	Issues related to the thermal management of batteries were not covered comprehensively.
[168]	Aging mechanism; DV; Incremental capacity; LIB; SOH	JPS	Elsevier B.V.	Article	2014	China	332	The aging mechanism of five different batteries was analyzed.	Further research on lithium-manganese battery to achieve on-board identification was not covered.
[169]	BM; LIB; PC; Temperature effects; TMS	ECMAD	Elsevier Ltd.	Review	2017	Hong Kong	304	Battery thermal management and its related issues were reviewed.	Future suggestions to eliminate thermal management issues were not covered.
[72]	Batteries; dc-dc converters; EM; FC; hybridization; optimization; SC	ITIED	IEEE	Article	2014	Canada	299	A comparative analysis of various EMS schemes for a fuel-based cell was proposed.	A design for a multiobjective optimization of EMS to optimize all the performance criteria was not included in the method.
[76]	BMS; BM; EV; LIB	ECMAD	Elsevier Ltd.	Conf. Paper	2012	China	279	A comparative study of various model-based methods was conducted.	Filter-based techniques could be employed for suitable model parameters selection.

Table A1. *Cont.*

Refs.	Keywords	Journal Name	Publisher	Article Type	Year	Country	Total Citations	Contributions	Research Gaps/Limitations
[170]	Air-cooled module; EV; LIB; TMS; Temperature rise; Temperature uniformity	JPS	Elsevier Ltd.	Article	2013	United States	265	3D CFD simulations were performed for an air-cooled PHEV Li-ion battery module.	Further research on filling the air gaps and analyzing heat transfer was not performed.
[171]	AEKF; BMS; EV; LIB; SOC	ITVTA	IEEE	Article	2013	China	254	SOC estimation based on a filter technique was conducted.	Meta-heuristic optimization techniques may be employed for better outcomes.
[172]	BMS; LIB; SOC; SOH; SOL	Energies	MDPI AG	Review	2011	Hong Kong	253	BMS in the EV application was reviewed.	The review was not comprehensive.
[74]	BMS; CE; EV; LIB	ITPEE	IEEE	Article	2013	South Korea	227	Development of a Modularized Charge Equalizer.	Research based on a high stack of Li-ion batteries can be conducted.
[64]	Air cooling; EV; HEV; LIB	JPS	Elsevier Ltd.	Article	2013	South Korea	226	Air flow configuration to cool batteries in EV applications was proposed.	Further study can be conducted with fuel-cell-based vehicles.
[173]	Bayesian Inference; EV; ES; HM; LIB; ML	ITIED	IEEE	Article	2016	China	224	Battery health was analyzed with sample entropy.	Appropriate selection of battery parameters may be conducted for better outcomes.
[88]	Batteries; BMS; dc-dc power converters; EV; ES	ITVTA	IEEE	Article	2011	Austria	224	A cell balancing technique was discussed for lithium–ion batteries.	Further work to implement a capacity balancing strategy can be conducted.
[174]	BTM; CM; Cooling model; LIB	ATENF	Elsevier Ltd.	Article	2016	United States	220	A 3D- electrochemical, thermal modeling of the battery cooling method was conducted.	Appropriate use of low mass flow rates to regulate temperature rise should be conducted.
[68]	BMS; EV; LIB; NN; SOCE; Unscented Kalman filter	IEPSD	Elsevier Ltd.	Article	2014	United States	216	SOC estimation with NN model was performed.	Appropriate selection of model hyperparameters should be conducted by employing optimization techniques.

Table A1. *Cont.*

Refs.	Keywords	Journal Name	Publisher	Article Type	Year	Country	Total Citations	Contributions	Research Gaps/Limitations
[175]	BMS; BM; BSE; Capacity estimation; HEV; LIB	JPS	Elsevier	Article	2015	Germany	208	State estimation methods for lithium–ion batteries in EV applications were reviewed.	Issues and challenges were not discussed.
[176]	Heating; LIB; Low temperature; Modeling; TMS	ELCAA	Elsevier Ltd.	Article	2013	United States	203	Development of heating strategies for lithium–ion batteries operating at subzero temperatures.	Effect of the heating model on battery cycle life should be quantified.
[177]	Convection cooling; Discharge; LIB; MM; TMS	IJERD	John Wiley & Sons, Inc.	Article	2013	Canada	199	Implementation of appropriate cooling strategies for lithium–ion batteries.	The effect of forced cooling and application of PCMs at the battery pack boundaries should be further investigated.
[67]	BMS; CB; Cell Equalization; DCDC Converter; EV; LIB; BP; SG; SOC	ITIED	IEEE	Article	2015	United States	198	An energy-sharing SOC balancing control scheme was developed.	Future work can be conducted based on other battery applications such as DC micro grids and aerospace battery systems.
[73]	LIB; Metal foam; PCM; TMS	JPS	Elsevier Ltd.	Article	2014	China	195	A cooling structure for lithium–ion batteries was developed.	Validation with other models was not comprehensively performed.
[71]	EV; EMS; LIB; SOC; SOH	IEEE Access	IEEE	Review	2018	Malaysia	194	A review based on various lithium–ion battery technologies was conducted.	The battery state estimation was not reviewed comprehensively.
[178]	Battery; EV; LIB; PI; Sliding-mode observer; SOC	ITVTA	IEEE	Article	2014	China	188	Developed a SOC estimation technique for lithium–ion batteries.	Complex methodology.
[179]	BTM; Liquid cooled cylinder; Local temperature difference; MT	ECMAD	Elsevier Ltd.	Article	2015	China	185	Cooling technique based on a mini-channel liquid-cooled cylinder was presented.	Further work may be concentrated on analyzing the entrance size with regard to heat dissipation.

Table A1. *Cont.*

Refs.	Keywords	Journal Name	Publisher	Article Type	Year	Country	Total Citations	Contributions	Research Gaps/Limitations
[180]	Capacity; Degradation; EV; Impedance; LIB; SOH	JPS	Elsevier B.V.	Review	2018	China	179	SOH estimation techniques were analyzed and reviewed.	Issues and challenges were not comprehensively described.
[181]	Cooling configuration; EV; LIB; Temperature distribution; TMS	JPS	Elsevier B.V.	Review	2017	China	177	Thermal issues and cooling configurations were reviewed.	Future suggestions for developing enhanced cooling strategies were not covered.
[182]	LIB; EV; SOH; RLU; Thermal runway; Aging	JCLEPRO	Elsevier B.V.	Review	2018	Malaysia	177	SOH and RUL techniques were reviewed.	The review was not comprehensive based on SOH and RUL.
[69]	BMS; electrochemical model; LIB; PDE observer design	IETTE	IEEE	Article	2013	United States	176	Presented a state estimation strategy for lithium–ion batteries.	Development of a parameter estimation technique for estimating parameter changes.
[183]	BTM; LIB; Next generation battery; VCC	ATENF	Elsevier Ltd.	Review	2019	South Korea	173	Various battery thermal management systems were reviewed.	The issues associated with various battery thermal management systems were not covered comprehensively.
[184]	Convergence behavior; EKF; LIB; Robust estimation; SOCE	JPS	Elsevier Ltd.	Article	2013	Germany	166	Conducted a comparative study for the SOC estimation of lithium–ion batteries.	Appropriate data sampling techniques can be used for better outcomes.
[185]	BMS; LIB; LSTM; ML; NN; RNN; SOC	ITIED	IEEE	Article	2018	Canada	165	SOC estimation with LSTM networks.	Requires a sufficient amount of data to deliver satisfactory SOC results.
[186]	LIB; Nail penetration; PCM; TMS; Thermal runaway	JPS	Elsevier B.V.	Article	2017	United States	163	Development of a phase change composite material for thermal runaway protection.	Features such as higher energy density cells, cell state-of-charge, and spacing between cells should be studied in the future.
[89]	BMS; EV; Estimation error; LIB; SOC	JPS	Elsevier B.V.	Review	2018	China	162	SOC estimation techniques were reviewed.	Issues and challenges related to SOC estimation were not covered.

Table A1. *Cont.*

Refs.	Keywords	Journal Name	Publisher	Article Type	Year	Country	Total Citations	Contributions	Research Gaps/Limitations
[79]	HP; LIB; Numerical model; TMS	ATENF	Elsevier Ltd.	Article	2015	Singapore	162	Optimization of a heat pipe thermal management system.	Other charging scenarios should be considered for better validation of the proposed method.
[93]	BMS; dc-dc power converters; EV; equalizers; LIB; zero-current switching	ITPEE	IEEE	Article	2015	China	161	Direct cell-to-cell battery equalizer based on quasi-resonant LC converter and boost converter is proposed.	Future work can be performed with a battery pack with more than a hundred cells in EV application.
[187]	LIB; Online estimation; SOC; SOF; SOH	ITVTA	IEEE	Article	2018	China	159	SOC, SOH, and SOF estimation is performed.	The execution of RC model in SOF estimation can be performed to estimate non-instantaneous power.
[188]	Batteries; electrochemical modeling; OC; PHEV; PM; stochastic control	IETTE	IEEE	Article	2013	United States	158	Power management techniques for optimal balance e lithium–ion battery pack health and energy consumption cost.	Battery health models can be integrated with a control algorithm to develop accurate power management techniques.
[82]	Capacity degradation parameter; LIB; RUL; SOH; SVM	JPS	Elsevier B.V.	Article	2014	China	154	SOH and RUL estimation of lithium–ion batteries is conducted.	The delivered outcomes can be improved with the inclusion of other battery parameters.
[189]	BTM; EV; Liquid; TE; VTM	ECMAD	Elsevier Ltd.	Review	2019	China	152	Discussed battery management system, and a systematic review of the liquid-based system is performed.	The issues related to the liquid-based system in EV were not discussed.
[190]	Aging; batteries; lifetime estimation; NN; SOC; SOH	ITVTA	IEEE	Article	2017	Canada	151	SOC and SOH estimation of the lithium–ion battery was conducted.	Careful selection of data samples should be performed.

Table A1. *Cont.*

Refs.	Keywords	Journal Name	Publisher	Article Type	Year	Country	Total Citations	Contributions	Research Gaps/Limitations
[191]	Battery cooling; Electrode modification; HG; LIB; TMS; TP	JPS	Elsevier	Review	2015	Canada	150	The heat generation and dissipation of Lithium–ion batteries are reviewed.	Future suggestions could be discussed more comprehensively.
[192]	BTM; HP; LIB; PCM; Thermal network model	JPS	Elsevier B.V.	Article	2014	United Kingdom	144	Battery thermal-related issues were investigated.	Further research is required to validate the model with other existing literature.
[77]	Dual-scale; Inconsistency; LIB; Model-based; SOC; Uncertainty	JPS	Elsevier B.V.	Article	2015	China	139	SOC estimation of the lithium–ion battery pack for EV applications was performed.	Validation with other models was not performed.
[193]	BMS; DNN; ESS; LIB; LM; SOCE	JPS	Elsevier B.V.	Article	2018	Canada	138	DL technique-based SOC estimation of a lithium–ion battery was performed.	Suitable model hyperparameters should be selected for accurate outcomes.
[91]	Double scale; LIB; PF; Remaining available energy; SOC	ITIED	IEEE	Article	2017	China	136	SOC estimation for lithium–ion batteries with a particle filter.	Validation with other models was not performed.
[95]	Aging; EV; Dispersion; Distribution; Production; Variation	JPS	Elsevier	Article	2015	Germany	135	Characterization of 484 cells was performed by capacity and impedance measurements.	The increased variation with new cells should be investigated.
[194]	Ageing mechanism; Battery health diagnostics and prognostics; Data-driven approach; EV; LIB; SE	RSERF	Elsevier Ltd.	Review	2019	United Kingdom	130	Data-driven based SOH and RUL estimation techniques for lithium–ion batteries were reviewed.	DL-based SOH and RUL estimation techniques were not included.
[195]	BMS; BP; EV; ECM; LIB	JPS	Elsevier	Article	2016	United Kingdom	130	Exploration of varied properties of cells connected in parallel.	Ageing testing and analysis may be performed to evaluate the impact of connecting cells in parallel on ageing.

Table A1. *Cont.*

Refs.	Keywords	Journal Name	Publisher	Article Type	Year	Country	Total Citations	Contributions	Research Gaps/Limitations
[196]	LIB; MECM; SOC; UKF	JPS	Elsevier	Article	2014	China	129	Model-based SOC estimation of lithium–ion batteries.	Validation was not conducted comprehensively.
[92]	Capacity loss model; CL; EV; LIB; SOH	JPS	Elsevier B.V.	Article	2014	China	129	An experiment based on dynamic life cycle was developed and capacity loss was simulated by employing a semi-empirical method.	Further experiments can be perfumed with battery packs for EV applications.
[197]	Capacity and power fade; Cycle-life prognosis; LIB; NMC-LMO cathode; PHEV; Semi-empirical model	JPS	Elsevier	Article	2015	United States	126	Aging model was developed for Lithium–ion batteries.	The developed aging model can be used to examine the aging propagation among cells in a battery.
[96]	Capacity; EV; LIB; Resistance; SOC; SVM	JPS	Elsevier	Article	2014	Sweden	126	SOH estimation of a lithium–ion battery was conducted.	Suitable selection of battery parameters and their data samples should be performed for accurate SOH.
[80]	BR; Failure modes, mechanisms, and effects analysis; LIB; Physics-of-failure	JPS	Elsevier B.V.	Review	2015	United States	125	Failure modes and mechanisms of lithium–ion batteries were discussed.	Further research based on design and testing should be conducted to develop a better and more reliable battery management system.
[198]	AC; Local temperature difference; MT; PB; TMS	ATENF	Elsevier Ltd.	Article	2015	China	124	Thermal model was developed for a cylindrical lithium–ion power battery pack.	The outcomes when the cell is in the flow direction should be analyzed carefully.
[199]	CS; HP; HEV; LIB; Transient input power	ATENF	Elsevier Ltd.	Article	2014	France	124	Development of a heat pipe to mitigate the temperature of a battery module.	The effectiveness of flat heat pipes under different road conditions should be studied.

Table A1. *Cont.*

Refs.	Keywords	Journal Name	Publisher	Article Type	Year	Country	Total Citations	Contributions	Research Gaps/Limitations
[200]	Battery in the loop; capacity; HIF; LIB; Multiscale; SOC	ITPEE	IEEE	Article	2018	China	122	SOC estimation framework for lithium–ion batteries with a filter technique.	Suitable meta-heuristic techniques could be employed for better model parameter selection.
[201]	BTM; EV; Electro-thermal model; Finite volume method; LIB	JPS	Elsevier Ltd.	Article	2012	United Kingdom	122	Thermal modelling for a lithium–ion battery was constructed.	A cell electrical dynamics model can be developed and effects on the voltage and temperature can be studied.
[202]	BTM; Passive system; PCM; Semi-passive system	JPS	Elsevier B.V.	Review	2018	France	121	A review based on a battery thermal management system was conducted.	Issues related to battery thermal management systems for EV applications were not covered comprehensively.
[203]	BIM; BMS; EV; LIB; Perturbation; PCC; SG; SOC; SOH	ITIED	IEEE	Article	2014	United States	121	Proposed an online impedance measurement.	Further work to estimate SOH could be conducted by utilizing the online measurement.
[204]	BA; BMS; Charge control optimization; EV; Experimental validation	ITVTA	IEEE	Article	2017	China	120	Developed a mathematical formulation to optimize the control problem.	Real-time optimization can be achieved by combining a coupled electro-thermal-aging model with an adaptive estimator.
[205]	BMS; EV; LIB; PF; Prognostics and health management	IEIMA	IEEE	Article	2016	Hong Kong	120	An RUL prediction framework was developed for lithium–ion batteries.	Further research should be based on the hybridization of the proposed model with other data-driven models.
[206]	Advanced vehicle control systems; BMS; BP; Charging time; EPSC; PHEV; AC; Computational speed; OC; LIB	PRACE	IEEE	Conf. Paper	2011	United States	120	Explored the utilization of charging strategies for charging.	Battery charging parameters with aging should be studied with the proposed model.

Table A1. *Cont.*

Refs.	Keywords	Journal Name	Publisher	Article Type	Year	Country	Total Citations	Contributions	Research Gaps/Limitations
[207]	BMS; BM; BT; EMS; ESS; HESS; LIB; UC	JESTPE	IEEE	Review	2016	Canada	119	Reviewed various energy storage and management systems for EV applications.	The fuel-cell based energy storage was not considered in the review.
[208]	BR; Battery second use; Grid stabilization; LIB	Energies	MDPI AG	Review	2019	United States	118	Discussed various battery technologies.	The work was not comprehensive and lacked the addressment of BMS and its applications.
[209]	EV; LIB; Mini-channel cooling; TMS	ATENF	Elsevier Ltd.	Article	2016	United States	117	Proposed a thermal management system.	Factors such as pressure drop and pump power should be carefully studied.
[210]	HEV; LIB; BP; Pin fin heat sink; TMS	JPS	Elsevier B.V.	Article	2015	United States	117	The assessment of an air-cooled module was conducted.	The trend based on the relationship between inlet air velocity and temperature should be further investigated.
[211]	Galerkin; HEV; LIB; Model order reduction; Model simplification; Porous electrode	JPS	Elsevier B.V.	Article	2012	Canada	117	A simplification of the lithium–ion battery model was presented.	The proposed method can also be implemented in charging applications.
[212]	Battery; BMS; CS; FEV; HEV; Lead-acid battery; LIB; SC	PMDEE	SAGE Publishing	Review	2013	Germany	116	Current battery technology for the automotive industry was discussed.	Battery management system application was not discussed comprehensively with regard to its various applications.
[213]	EV; LIB; Liquid metal cooling; TMS	ECMAD	Elsevier Ltd.	Article	2016	China	115	New technology based on coolant was proposed for thermal management.	Future work can be based on optimizing the cooling channel.
[214]	BM; ED; HPPC-test; LIB; Performance tests; PD; RC	Energies	MDPI AG	Article	2012	Belgium	114	Lithium–ion battery technologies were investigated.	Future suggestions for the implementation of lithium–ion battery technologies were not presented.

Table A1. *Cont.*

Refs.	Keywords	Journal Name	Publisher	Article Type	Year	Country	Total Citations	Contributions	Research Gaps/Limitations
[215]	HGR; Internal preheating; LIB; Low temperature	JPS	Elsevier	Article	2015	China	112	A method to preheat lithium–ion batteries at low temperatures was developed.	Further investigation based on the selection of amplitude and frequency of AC current should be studied.
[216]	EV; Flat plate loop heat pipe; LIB; TMS	ATENF	Elsevier Ltd.	Conf. Paper	2016	Indonesia	111	A thermal management model based on a flat plate loop heat pipe for EV applications was studied.	The phenomenon of temperature shoot-up during start should be reduced for better outcomes.
[217]	BC; BD; Charge optimization; EV; LIB	JESTPE	IEEE	Article	2014	United States	110	Developed a model to minimize vehicle charging costs.	Future work can be based on the implementation of pro work in onboard vehicle chargers.
[218]	Batteries; BMS; EV; EC; Parameter extraction	ITCNE	IEEE	Article	2014	Finland	109	A Thevenin-equivalent circuit-based lithium–ion battery model was developed.	Further work can focus on temperature and rate effects.
[219]	SOCE; HEV; KF; PHEV	JPS	Elsevier Ltd.	Article	2013	Canada	106	SOC estimation framework for lithium–ion batteries.	Improved KF techniques can be employed for better SOC outcomes.
[220]	BD; EV; V2G	JPS	Elsevier B.V.	Article	2016	United States	105	Employed comprehensive thermal and EV powertrain models to estimate SOC, current, internal resistance, etc.	Other capacity fading models from other battery technologies can be implemented with the proposed work.
[65]	Channeled liquid cooling; LIB; TMS; Numerical simulation; Thermal model	IJHMA	Elsevier Ltd.	Article	2018	China	104	The thermal behavior of lithium–ion batteries was studied during charging and discharging.	Work based on optimizing channeled liquid flow was not conducted.

Table A1. *Cont.*

Refs.	Keywords	Journal Name	Publisher	Article Type	Year	Country	Total Citations	Contributions	Research Gaps/Limitations
[221]	Comparison; LIB; NLF; Online implementation; SOCE	ITIAC	IEEE	Article	2018	China	104	Various models were analyzed for the SOC estimation of lithium–ion batteries.	Real-time implementation of the proposed method can be carried out.
[94]	BMS; $LiFePO_4$ battery; Model parameters estimation; Multiple adaptive forgetting factors; RLSE; SOCE	JPS	Elsevier B.V.	Article	2015	Australia	103	A SOC estimation framework was developed for lithium–ion batteries.	Appropriate selection of battery parameters such as voltage, current, and temperature was not carried out.
[222]	Entropy weight method; Grey relational analysis; Incremental capacity analysis; LIB; SOH	JPS	Elsevier B.V.	Article	2019	China	102	A SOH estimation of lithium–ion batteries framework was developed.	The proposed model can be integrated with other models and SOH estimation accuracy can be calculated.
[223]	Coolants; CP; CS; LIB	ATENF	Elsevier Ltd.	Review	2018	China	101	Studied different coolants and cooling strategies for lithium–ion batteries.	Further investigation to select a better coolant should be conducted.
[224]	BMS; CM; CE; EV; LIB; SOCE	-	IEEE	Conf. Paper	2012	Austria	100	Proposed a design of a battery management system.	Further investigation should be conducted to demonstrate the effectiveness of the battery management system.
[225]	Battery thermal efficiency; BTM; Cell thermal design; Extreme fast charging; HG; LIB	JPS	Elsevier B.V.	Article	2017	United States	99	Reviewed thermal management in the battery storage system.	The impact of cell design on temperature variation within the cell and the temperature imbalance within the pack should be studied.
[226]	BT; EV; Electro-thermal model; HG; LIB	JPS	Elsevier Ltd.	Article	2014	Singapore	99	Modeling of the electrical and thermal behavior of lithium–ion batteries was constructed.	Rapid and fast charging scenarios during driving conditions were not covered in the study.

Table A1. *Cont.*

Refs.	Keywords	Journal Name	Publisher	Article Type	Year	Country	Total Citations	Contributions	Research Gaps/Limitations
[227]	Battery; BT; PHEV	JPS	Elsevier Ltd.	Article	2011	United States	98	Study to analyze battery degradation through experiments for lithium–ion batteries was proposed.	Development of smart degradation control strategies should be performed.
[228]	Adaptive extended Kalman filter; BP; EV; Filtering; SOC; Unit model	JPS	Elsevier Ltd.	Article	2013	China	96	SOC estimation of a lithium–ion battery pack was presented.	Application of intelligent AI-based models should be undertaken for better outcomes.
[229]	BMS; EV; Health indicator; LIB; Moving window; RUL	ITVTA	IEEE	Article	2019	China	95	RUL prediction of the lithium–ion battery was proposed.	Other data sampling strategies could be employed and the outcomes can be compared.
[97]	BPNN; BSA; EV; LIB; SOC	IEEE ACCESS	IEEE	Article	2018	Malaysia	95	SOC estimation for lithium–ion batteries was proposed by the neural network model.	An accurate selection of battery parameters and data samples should be conducted.
[230]	Internal resistance; LIB; On-board diagnosis; SOH	JPS	Elsevier B.V.	Article	2011	Germany	95	A new instrument was developed in a lab to satisfy the requirements of electrochemical impedance.	Further study is required to validate the newly developed instrument.
[231]	EV; LIB; Mini-channel cooling; NP; TMS; Thermal runaway	ATENF	Elsevier Ltd.	Article	2017	United States	93	Proposed mini channel cooling for the battery system to investigate the ability to mitigate thermal runaway.	Further investigation is required to study the effect of multifunctional material-based electrodes for mitigating thermal runaway.
[232]	ECM; BMS; EV; LIB; NN; SOC	ITVTA	IEEE	Article	2016	Australia	93	Developed an SOC estimation framework for lithium–ion batteries.	Appropriate selection of neural network hyperparameters was not considered.

Table A1. *Cont.*

Refs.	Keywords	Journal Name	Publisher	Article Type	Year	Country	Total Citations	Contributions	Research Gaps/Limitations
[233]	Battery; BD; EV; LIB; Modeling; SOC; SOH	ITIAC	IEEE	Article	2015	United States	93	Investigated the features of a lithium–ion battery pack with parallel connections.	Delivered low accuracy; further research may consider the implementation of cell impedance and resistance.
[234]	Battery charging optimization; EV; Electrothermal-aging model; Fast charging; LIB	TII	IEEE	Article	2018	Sweden	91	A model-based framework was developed to enable accurate and effective fast charging of lithium–ion batteries.	Further investigation regarding the adjustment of charging patterns for a certain application must be explored.
[235]	ANN; DC; EV; LIB; SOC	ITIAC	IEEE	Article	2015	United Arab Emirates	90	An SOC estimation framework was developed.	Model hyperparameters should be selected appropriately.
[236]	TMS; EV; LIB; Thermoelectric coolers	ITVTA	IEEE	Article	2013	Saudi Arabia	90	Developed a battery thermal management system for lithium–ion batteries.	Further optimization can be conducted to achieve appropriate thermal responses and energy consumption.
[237]	EV; LIB; Model simplification; Pseudo-two-dimensional model; SOC	JPS	Elsevier B.V.	Article	2015	China	89	An SOC estimation technique was proposed with an improved single particle model.	The effectiveness of the proposed SOC estimation technique could be observed in real-time applications.
[238]	BS; Fault isolation and estimation; Learning observers; Luenberger observers; System transform	IETTE	IEEE	Article	2014	United States	89	Developed a fault isolation mechanism for lithium–ion batteries.	Only lower-order systems were considered for experimentations.
[239]	EV; Lithium-ion battery; Fault diagnosis; Equivalent circuit model; Long short-term memory recurrent neural network; Modified adaptive boosting	TPE	IEEE	Article	2020	China	88	An equivalent circuit model was developed to analyze the internal short circuit detection of lithium–ion batteries.	The influence of an online balance process on internal short circuit detection should be studied.

Table A1. *Cont.*

Refs.	Keywords	Journal Name	Publisher	Article Type	Year	Country	Total Citations	Contributions	Research Gaps/Limitations
[240]	BAM; Battery lifetime estimation; ESS; PHEV	IJPELEC	Inderscience Publishers	Article	2012	United States	88	Framed a battery life estimation technique based on DOD and temperature.	Further work should be conducted to explore real-time driving features.
[241]	EMS; SOC; HEV; LIB; PPC	Complexity	Wiley Hindawi	Article	2020	China	87	Developed a framework to estimate the maximum power capability of lithium–ion batteries.	Hybridized state estimation can be performed for better prediction accuracy.
[242]	Battery; BMS; EV; LIB; SOC	JPS	Elsevier B.V.	Review	2016	Germany	86	State of power (SOP) estimation frameworks for lithium–ion batteries were reviewed.	Future work may focus on improving the robustness of SOP techniques under various conditions, such as wide temperature ranges, including low temperatures.

AB = Automotive Batteries, AC = Air Cooling, ACS = Automobile Cooling Systems, AI = Artificial Intelligence, AM = Aging of Materials, AP = Accurate Prediction, AT = Atmospheric Temperature, ATENF = Applied Thermal Engineering, AV = Amphibious Vehicles, BD = Battery Degradation, BFD = Battery Fault Diagnosis, BM = Battery Modeling, BMS = Battery Management Systems, BP = Battery Pack, BTM = Battery Thermal Managements, CE = Capacity Estimation, CS = Cooling Systems, CT = Circuit Theory, CV = Commercial Vehicles, DDC = DC-DC Converters, DR = Discharge Rates, DS = Digital Storage, EB = Electric Batteries, EC = Equivalent Circuits, ECM = Equivalent Circuit Model, ECMAD = Energy Conversion and Management, ED = Electric Discharges, ELCAA = Electrochimica Acta, EMC = Electric Machine Control, EMS = Energy Management Systems, EPTN = Electric Power Transmission Networks, ES = Energy Storage, ESS = Energy Storage Systems, EV = Electric Vehicles, GG = Greenhouse Gases, HED = High Energy Densities, HEV = Hybrid Electric Vehicle, HG = Heat Generation, HP = Heat Pipes, HR = Heat Resistance, HT = Heat Transfer, HV = Hybrid Vehicles, IEIMA = IEEE Transactions on Instrumentation and Measurement, IEPSD = International Journal of Electrical Power and Energy Systems, IETII = IEEE Transactions on Industrial Informatics, IETTE = IEEE Transactions on Control Systems Technology, IIEM = IEEE Industrial Electronics Magazine, IJERD = International Journal of Energy Research, IJESTPE = IEEE Journal of Emerging and Selected Topics in Power Electronics, IJHMA = International Journal of Heat and Mass Transfer, IJPE = International Journal of Power Electronics, ITCNE = IEEE Transactions on Energy Conversion, ITIED = IEEE Transactions on Industrial Electronics, ITVTA = IEEE Transactions on Vehicular Technology, ITIAC = IEEE Transactions on Industry Applications, ITPEE = IEEE Transactions on Power Electronics, JESOA = Journal of the Electrochemical Society, JPS = Journal of Power Sources, LA = Lithium Alloys, LAB = Lead Acid Batteries, LB = Lithium Batteries, LC = Lithium Compounds, LE = Laboratory Environment, LIB = Lithium–ion Batteries, LIC = Lithium–ion Cells, LS = Learning Systems, ML = Machine Learning, MM = Mathematical Models, MT = Maximum Temperature, MTR = Maximum Temperature Rise, NF = Nonlinear Filtering, NN = Neural Networks, OCV = Open Circuit Voltage, OT = Operating Temperature, PC = Power Converters, PCM = Phase Change Materials, PE = Parameter Estimation, PHEV = Plug-In Hybrid Electric Vehicle, PHV = Plug-in Hybrid Vehicles, PMDEE = Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering, PRACE = Proceedings of the American Control Conference, RH = Reconfigurable Hardware, RO = Reliable Operation, RSERF = Renewable and Sustainable Energy Reviews, RUL = Remaining Useful Lives, SB = Secondary Batteries, SC = Solar Cells, SG = Smart Grid, SOC = State Of Charge, SOCE = State-of-charge Estimation, SOH = State of Health, SPG = Smart Power Grids, TB = Thermal Behaviors, TC = Temperature Control, TD = Temperature Differences, TE = Thermoelectric Equipment, TM = Thermal Management, TMS = Thermal Management Strategy, TR = Thermal Runaways, TU = Temperature Uniformity, TVC = Thermal Variables Controls.

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