vehicles

Review

Artificial Intelligence Approaches for Advanced Battery Management System in Electric Vehicle Applications: A Statistical Analysis towards Future Research Opportunities

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Abstract: In order to reduce carbon emissions and address global environmental concerns, the automobile industry has focused a great deal of attention on electric vehicles, or EVs. However, the performance and health of batteries can deteriorate over time, which can have a negative impact on the effectiveness of EVs. In order to improve the safety and reliability and efficiently optimize the performance of EVs, artificial intelligence (AI) approaches have received massive consideration in precise battery health diagnostics, fault analysis and thermal management. Therefore, this study analyzes and evaluates the role of AI approaches in enhancing the battery management system (BMS) in EVs. In line with that, an in-depth statistical analysis is carried out based on 78 highly relevant publications from 2014 to 2023 found in the Scopus database. The statistical analysis evaluates essential parameters such as current research trends, keyword evaluation, publishers, research classification, nation analysis, authorship, and collaboration. Moreover, state-of-the-art AI approaches are critically discussed with regard to targets, contributions, advantages, and disadvantages. Additionally, several significant problems and issues, as well as a number of crucial directives and recommendations, are provided for potential future development. The statistical analysis can guide future researchers in developing emerging BMS technology for sustainable operation and management in EVs.

Keywords: battery management; lithium-ion battery; electric vehicles; optimizations; algorithms

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1. Introduction

The vehicle industry has made great efforts in creating dependable and effective technologies to guarantee the security of passengers [1]. However, as the number of cars grows, so does the amount of air pollution in urban areas [2]. Approximately 27% of greenhouse gas (GHG) emissions are produced by the transportation industry, with vehicle transportation accounting for more than 70% of those emissions, according to data from the European Union [3]. Electric vehicles (EVs) have gained widespread popularity and recognition as a solution to these emissions problems due to their ability to reduce GHG emissions and address global warming issues [4]. EVs have replaced fossil-powered automobiles and delivered enhanced performance in terms of simplicity, accuracy, and dependability [5]. Nevertheless, EVs have some limitations, including a short travel distance, a long charging interval, and battery performance degradation under various uncertainties [6]. Thus, in order to address crucial problems, including thermal runaway, cell unbalancing, overcharging, over-discharging, overheating, and fire dangers, an enhanced and intelligent battery management system (BMS) is required [7].

The BMS plays a key role in managing and optimizing the performance of EVs. The BMS is a critical component of EVs, ensuring the safety, longevity, and performance of the battery pack while enhancing the overall driving experience for users [8]. The development of an effective and intelligent BMS is essential to estimate remaining useful life (RUL), state of energy (SOE), state of charge (SOC) and state of health (SOH), as well as to perform charge balancing, temperature management, and fault diagnostics, [9]. The BMS employs various circuit devices and power electronics components as well as algorithms and methods to implement various functionalities such as SOC management, overvoltage and undervoltage protection, temperature control, battery cell balancing, energy efficiency and battery life expansion [10,11]. The inefficient algorithms for the BMS in EVs can lead to a range of issues, including reduced battery performance, safety concerns, and a shorter battery lifespan. To address these issues, it is crucial to develop and implement well-designed BMS algorithms that take into account factors like data accuracy, advanced modeling techniques, sensor quality, real-time monitoring, and adaptability to different driving conditions and user behaviors.

Artificial intelligence (AI) approaches have the potential to significantly enhance the functionality and performance of BMS in EVs [12]. AI-driven BMS in EVs offers a range of benefits, including improved performance, safety, energy efficiency, and user experience, while also helping to extend the lifespan of the battery. Several state-of-the-art research articles have demonstrated the significance of the AI approach in examining the effectiveness of EV applications [13]. AI methods have several advantageous features compared to traditional approaches. For instance, AI techniques need less knowledge and require less development time to design complicated battery systems as compared with conventional model-based frameworks [14]. Moreover, AI algorithms and optimization schemes do not require comprehensive domain knowledge about battery physics, chemistry, and chemical reactions but rather a large pool of data and high computing power [15]. Additionally, they operate very effectively in the presence of sufficient data and are exceptionally efficient in dealing with the existence of uncertainties such as noise, temperature fluctuations, and aging effects. Moreover, they have self-learning operations to execute the parameterization as well as fast online execution [16].

There are two distinct ways to estimate SOC, SOH, and RUL in EV BMS technology: online measurement systems and AI algorithm-based techniques. Although they use different methods and strategies to accomplish this, both approaches intend to evaluate the performance and health of a battery. AI algorithms employ data-driven methodologies to examine both historical and current battery system data. Large datasets are used to train machine learning algorithms, like neural networks and support vector machines, to find patterns and correlations between different battery condition parameters. In addition, they need a significant volume of current and historical data to execute training and testing operation. Temperature profiles, charge–discharge cycles, and other essential operational data are examples of possible data sources [17]. On the other hand, online measurement systems use sensors and direct measurements to continuously monitor the electrical and physical characteristics of a battery. Voltage, current, temperature, and other relevant indicators may be sensed by them. The SOH is directly calculated using the data gathered from these measurements [18].

Analytical analysis is a research technique in library and information science that makes use of statistics and quantitative approaches to supply the necessary information [19]. It is an essential tool for revealing insights regarding specific and past discoveries that may be used to build future study avenues for researchers [20,21]. Universities, research organizations, corporations, and industries frequently utilize a variety of metrics, such as current status, citations, impact factors, h-index, research networks and collaboration to evaluate the capacity and expertise of researchers [22]. Numerous statistical investigations on BMS and EVs have been conducted, including bibliometric and technical evaluations of BMS [15], bibliometric analysis of optimized energy management [23], bibliometric analysis of thermal management systems [24], energy management schemes for hybrid EVs [25], recycling methods for lithium-ion batteries [26], battery storage systems integration, and renewable resources [20]. To the best of the authors' knowledge, no study has carried out a detailed investigation of AI approaches for BMS technology in EVs. Therefore, this paper utilizes a variety of statistical parameters to examine the evaluation of AI in BMS technology in the previous ten (10) years, i.e., from January 2014 to July 2023. This paper also comprehensively explains the AI algorithms used in BMS, focusing on contributions, results, merits, and demerits. Furthermore, the unresolved problems, difficulties, and potential directions for future research are provided. The significant contributions of the paper are highlighted below.

- This statistical assessment examines 78 relevant manuscripts in AI-driven BMS technology for EV applications, focusing on several vital aspects, such as keywords, the categories of manuscripts (review paper as well as original research work), the names of the journals, the names of the publishers, the year of publication, the name of the affiliated country of the authors and the overall quantity of citations.
- This survey provides a critical analysis of AI methods, algorithms, optimizations, and controllers for BMS in EVs regarding contributions, outcomes, advantages, and disadvantages.
- The study investigates the issues and concerns of AI-based BMS in EV implementations.
- Useful future research directions and opportunities are presented for the advancement of BMS in EVs.

The organization of the paper is divided into five main sections. The main findings of the study, data extraction techniques, publishing trends, and data selection criteria are covered in Section 2. Section 3 covers analytical topics such as citation analysis, distribution of highly cited articles, keyword analyses, study fields, publications, and authorship. Section 4 outlines the novel AI methods and algorithms for BMS. Section 5 narrates the future research opportunities. Section 6 presents the conclusions.

2. Survey Methods

Since the Scopus database (www.scopus.com) has more articles than other platforms and databases like the Web of Science, the Scopus database was employed as an article source in this analytical study [27]. This section describes the process used to choose 78 articles for analysis, including the criteria for inclusion and exclusion of articles, screening techniques, research methodology, data extraction, study aspects, and findings.

2.1. Criteria for Inclusion and Omission of Articles

The documents were selected using certain criteria from the Scopus record. The essential keywords used for relevant article selection in the Scopus catalogue are shown in Table 1. The top 78 articles on the subject of AI in BMS for EVs used the following standards for article inclusion and exclusion.

- The relevant articles were chosen between 2014 and 2023.
- This statistical analysis examined English-language manuscripts.
- Key indicators such as machine learning, deep learning, battery management systems, and electric vehicle applications were utilized.
- The results of a database search based on topics such as battery chemistry, material composition, electrolysis analysis, and electrochemical reactions were not taken into consideration while making the final selection.
- The information that was taken out of the 78 relevant manuscripts had the following features: (1) type of research activity (formulation and review of problems), (2) research

topic, (3) name of the publisher; (4) the name of the journal; (5) the journal impact factor; (6) the most active authors in the relevant fields, and (7) affiliated countries and universities.

Table 1. The Scopus database search for relevant manuscripts using various keyword codes.

Step	Types of Filtering	Search Code	Number of Articles
Step-1	Machine learning, Battery Management Systems, Electric Vehicle	TITLE-ABS-KEY (machine AND learning; AND battery AND management; AND electric AND vehicle)	449
Step-2	Publication Year: 2014–2023	TITLE-ABS-KEY (machine AND learning; AND battery AND management; AND electric AND vehicle) AND (LIMIT-TO (PUBYEAR , 2023) OR LIMIT-TO (PUBYEAR , 2022) OR LIMIT-TO (PUBYEAR , 2021) OR LIMIT-TO (PUBYEAR , 2020) OR LIMIT-TO (PUBYEAR , 2019) OR LIMIT-TO (PUBYEAR , 2018) OR LIMIT-TO (PUBYEAR , 2017) OR LIMIT-TO (PUBYEAR , 2016) OR LIMIT-TO (PUBYEAR , 2015) OR LIMIT-TO (PUBYEAR , 2014))	435
Step-3	Subject Areas	TITLE-ABS-KEY (machine AND learning; AND battery AND management; AND electric AND vehicle) AND (LIMIT-TO (PUBYEAR , 2023) OR LIMIT-TO (PUBYEAR , 2022) OR LIMIT-TO (PUBYEAR , 2021) OR LIMIT-TO (PUBYEAR , 2020) OR LIMIT-TO (PUBYEAR , 2019) OR LIMIT-TO (PUBYEAR , 2018) OR LIMIT-TO (PUBYEAR , 2017) OR LIMIT-TO (PUBYEAR , 2016) OR LIMIT-TO (PUBYEAR , 2015) OR LIMIT-TO (PUBYEAR , 2014)) AND (LIMIT-TO (SUBJAREA , "ENGI") OR LIMIT-TO (SUBJAREA , "ENER") OR LIMIT-TO (SUBJAREA , "COMP") OR LIMIT-TO (SUBJAREA , "MATE"))	185
Step-4	English Language	TITLE-ABS-KEY (machine AND learning; AND battery AND management; AND electric AND vehicle) AND (LIMIT-TO (PUBYEAR , 2023) OR LIMIT-TO (PUBYEAR , 2022) OR LIMIT-TO (PUBYEAR , 2021) OR LIMIT-TO (PUBYEAR , 2020) OR LIMIT-TO (PUBYEAR , 2019) OR LIMIT-TO (PUBYEAR , 2018) OR LIMIT-TO (PUBYEAR , 2017) OR LIMIT-TO (PUBYEAR , 2016) OR LIMIT-TO (PUBYEAR , 2015) OR LIMIT-TO (PUBYEAR , 2014)) AND (LIMIT-TO (SUBJAREA , "ENGI") OR LIMIT-TO (SUBJAREA , "ENER") OR LIMIT-TO (SUBJAREA , "COMP") OR LIMIT-TO (SUBJAREA , "MATE")) AND (LIMIT-TO (LANGUAGE , "English"))	150

2.2. *Screening Technique*

Because the quantity of available articles varies between different records, the following standards as well as measures were employed to choose the most relevant article from the Scopus record. The entire process was broken down into five parts, which are explained below and presented in Figure 1.

- Using the basic selection method, 449 (n = 449) manuscripts were chosen in total.

- A total of 435 (n = 435) research documents were chosen using a year constraint range of 2014 to 2023.
- By creating subject areas, 185 (n = 185) articles were chosen in total.
- The "English Language" filter was used to select a total of 150 (n = 150) items.
- The final article selection was made based on relevance. Accordingly, 78 (n = 78) manuscripts from the Scopus database were chosen for the final assessment. Table 1 shows the keywords used in searching for relevant manuscripts in the Scopus database.

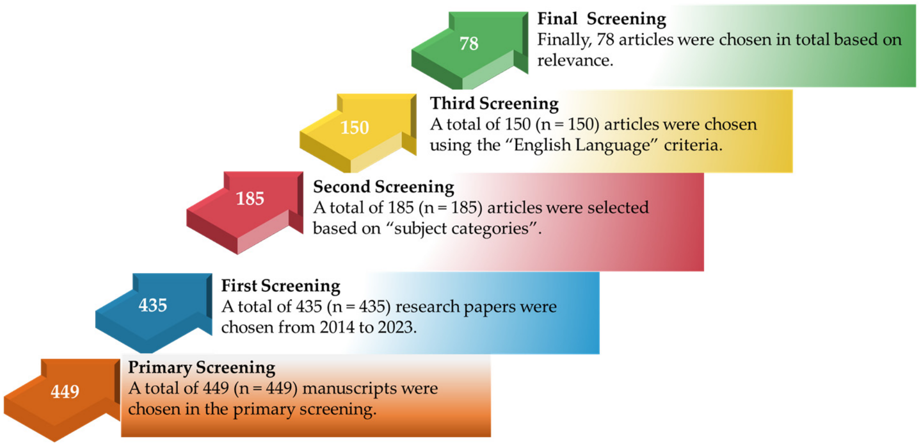

Figure 1. Methods for choosing manuscripts from the Scopus database.

2.3. Research Pattern

Scholars are heavily researching AI in order to create a more effective BMS for EV applications [25–28]. An increasing number of studies have been published in the field of ML-integrated BMS in EV implementations. To manage battery energy storage more efficiently and optimize the EV operation, researchers have been utilizing several machine learning, deep learning, and optimization and controller schemes. Figure 2 shows the upward trend in research from January 2014 to December 2023. Figure 2 shows that the number of research papers has been growing steadily, highlighting AI's importance in the BMS sector. For example, the field of BMS in EV applications saw the publication of 58, 85, and 134 articles in 2020, 2021, and 2022, respectively, that highlight the deployment of AI as an emerging research area. Between 2014 and 2023, 435 articles were published in total.

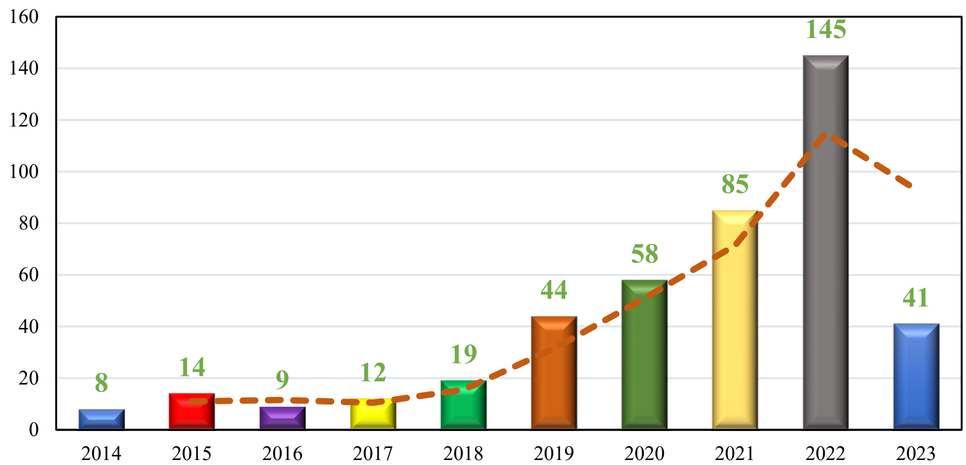

Figure 2. Number of manuscripts published in AI based BMS for EV applications between 2014 and 2023.

2.4. Data Extraction

The author's name, AI categories, shortened keywords, types of manuscripts (review papers and original research papers), objectives, targets, journal names, publisher names, publication years, names of the affiliated countries of the conforming authors, and the total number of citations were all used to mine information from the 78 manuscripts that were judged to be the most relevant. To present a thorough picture of AI-integrated BMS techniques for EV applications, statistical analysis included analysis of co-occurring keywords, research categories, distribution of article publishers, document authorship and collaboration, and network and collaboration analysis. In addition, a technical assessment of BMS in EV applications was extensively conducted, highlighting the cutting-edge AI methods, various optimization schemes, and control strategies. In line with this, the key findings, contributions, advantages, and disadvantages of the state-of-the-art AI approaches for BMS in EV applications were thoroughly discussed. Moreover, the open issues, limitations, and challenges were explored to identify the recent research gaps. Lastly, based on the statistical and technical evaluation, several useful and constructive suggestions are presented for the advancement of BMS in EV applications.

2.5. Study Structures and Key Findings

The final relevant 78 papers are shown in Table 2, which outlines the authors' names, DOI numbers, author keywords, algorithms, shortened journal names, publisher names, publication years, article types, origin countries, and citations. The selected publications had a total of 2059 citations, ranging from 0 to 350. Six papers among the 78 publications obtained more than 100 citations. The publications by Hu et al. [28] with the highest impact factor (8.162) and most citations in the 'IEEE Transactions on Industrial Electronics' journal in 2016 had 350 citations.

Table 2. Detailed explanation of the most relevant 78 articles on AI-integrated BMS in EVs.

Rank	Ref. No.	Authors	Author Keywords	AI Algorithm Used	Goal/Target	Abbreviated Source Title	Publisher	Year	Document Type	Correspondence Address	Cited by
1	[28]	Hu et al.	Bayesian Inference; EV; ESS; Health Monitoring; LIB; ML	Bayesian Inference	Health prognosis for electric vehicles.	IEEE Trans Ind Electron	IEEE	2016	Article	China	350
2	[29]	Chemali et al.	BMS; DNN; ESS; LIB; ML; SOC estimation	Deep neural networks	State-of-charge estimation of Li-ion batteries	J Power Sources	Elsevier B.V.	2018	Article	Canada	316
3	[30]	Hu et al.	BM; EV; ES; ML; state estimation	Genetic algorithm-based fuzzy C-means	Battery State Estimation in Electric Vehicles	IEEE Trans. Transp. Electrif.	IEEE	2016	Article	China	225
4	[31]	Feng et al.	Batteries; EV; ES; state estimation; SOH	Support vector machines	State-of-Health Estimation for Li-Ion Battery	IEEE Trans. Veh. Technol.	IEEE	2019	Article	China	166
5	[32]	Xiong et al.	Battery; EMS; HESS; Topologies; Ultracapacitor	Wavelet transform	HESS Topologies for EV batteries.	J. Clean. Prod.	Elsevier Ltd.	2018	Article	China	112
6	[33]	Zahid et al.	BMS; Battery state estimation; EV; ESS; ML; SOC	Fuzzy neural networks; Elman neural network	State of charge estimation for electric vehicle	Energy	Elsevier Ltd.	2018	Article	China	99
7	[34]	Hannan et al.	LIB, BMS, SOC, ML	Lightning search algorithm	State of Charge Estimation of Lithium-ion Batteries.	Sci. Rep.	Nature Research	2020	Article	Malaysia	97
8	[35]	Li et al.	ANN; data-driven modeling; EV; LIB; ML; safety standardization	Artificial neural network	Safety Envelope of Lithium-Ion Batteries.	Joule	Cell Press	2019	Article	United States	89
9	[36]	Li et al.	BES; BMS; Big data; DL; EV; Temperature-dependent model	Extreme learning machine	Big data driven lithium-ion battery modeling method	Appl. Energy	Elsevier Ltd.	2019	Article	China	70

Table 2. *Cont.*

Rank	Ref. No.	Authors	Author Keywords	AI Algorithm Used	Goal/Target	Abbreviated Source Title	Publisher	Year	Document Type	Correspondence Address	Cited by
10	[37]	Babaeiyazdi et al.	EV; Electrochemical impedance spectroscopy; LIB; ML	Gaussian process regression; Linear regression models	State of charge prediction of EV Li-ion batteries	Energy	Elsevier Ltd.	2021	Article	Canada	60
11	[38]	Li et al.	Aging-considered battery model; Battery degradation quantification; BES; BMS; DL; EV	Rain-flow cycle counting	Battery modeling and management method	Appl. Energy	Elsevier Ltd.	2020	Article	China	51
12	[39]	Tang et al.	Battery aging assessment; battery aging dataset generation; LIB management; ML	General supervised training algorithms	Recovering large-scale battery aging dataset	Patterns	Cell Press	2021	Article	United Kingdom	50
13	[40]	Sulzer et al.	applications; battery; data; knee point; lifetime; LIB; prognostics	Feature-based data-driven approach	Challenge of battery lifetime prediction	Joule	Cell Press	2021	Review	United Kingdom	49
14	[41]	Abdullah et al.	AI; EV; ML; management; smart grids	Reinforcement learning	EV Charging Management Systems	IEEE Access	IEEE	2021	Review	Qatar	34
15	[42]	Yavasoglu et al.	ANN; EV; EMS; fuel cell; HESS; ML; ultra-capacitor	Artificial neural network; convex optimization	Energy management of multi-source (battery/UC/FC) powered electric vehicle	Int. J. Energy Res.	John Wiley and Sons Ltd.	2020	Article	Turkey	30
16	[43]	Lei et al.	hybrid AC-DC microgrid; Optimal EM; Security; Sequential hypothesis testing	Whale optimization algorithm	Hybrid electric vehicle charging demand	Int J Electr Power Energy Syst	Elsevier Ltd.	2021	Article	China	25

Table 2. *Cont.*

Rank	Ref. No.	Authors	Author Keywords	AI Algorithm Used	Goal/Target	Abbreviated Source Title	Publisher	Year	Document Type	Correspondence Address	Cited by
17	[44]	Rehman et al.	EV; ESS; Experimental analysis; ML	Integer programming	Optimization of integrated photovoltaic panel, battery and electric vehicles	Energy Convers. Manage.	Elsevier Ltd.	2020	Article	Finland	14
18	[45]	Vidal et al.	ANN; batteries; BMSs; ESS; hybrid EV; HESS; ML; SOC estimation	Artificial neural network	State-Of-Charge Estimation of hybrid Energy Storage System	IEEE Transp. Electr. Conf. Expo, ITEC	IEEE	2018	Conference Paper	Canada	14
19	[46]	Zahid et al.	AI; Charging (batteries); Lead acid batteries; LIB; SOC estimations; Training and testing; BMS	Filtering algorithm	State of charge of energy storage devices	Electron. Lett.	IET	2017	Article	China	14
20	[47]	Srithapon et al.	BES system; carbon emission; DL; probabilistic power flow; transformer loss of life;	Multi-objective differential evolution; Zhao's point estimation method	Probabilistic Optimal Power Flow measurement of Electric Vehicles	IEEE Access	IEEE	2021	Article	Thailand	12
21	[48]	Sidhu et al.	AI; BMSs; Gaussian processes; Lithiumion batteries; ML	Random Forest regression	State of charge estimation of lithium-ion batteries	IECON Proc	IEEE	2019	Conference Paper	Canada	12
22	[49]	Chaoui et al.	EMS; Charging (batteries); DL; EV; Energy resources; ML; Secondary batteries	Reinforcement learning	energy management system for EV batteries.	IEEE Veh. Power Propuls. Conf., VPPC—Proc.	IEEE	2019	Conference Paper	Canada	11
23	[50]	Bansal et al.	Driving cycle uncertainties; EV; HESS; ML; Optimal sizing	Particle swarm optimization	Energy storage sizing in plug-in Electric Vehicles	J. ES	Elsevier Ltd.	2021	Article	India	10

Table 2. *Cont.*

Rank	Ref. No.	Authors	Author Keywords	AI Algorithm Used	Goal/Target	Abbreviated Source Title	Publisher	Year	Document Type	Correspondence Address	Cited by
24	[51]	Shi et al.	Driving pattern recognition; HESS; Unsupervised learning; Vehicle-to-cloud connectivity	Dynamic programming	Energy management strategy for battery	Energy	Elsevier Ltd.	2022	Article	United States	9
25	[52]	Jin et al.	BMS; LIB; ML; RUL prediction	Support vector machine	Lithium-ion battery remaining useful lifetime prediction	Electronics (Switzer-land)	MDPI	2021	Article	Denmark	9
26	[53]	Garg et al.	Energy conversion and storage; energy dispersive spectroscopy; HES; LIB; remaining life	-	Performance of Li-ion batteries	Int. J. Energy Res.	John Wiley and Sons Ltd.	2020	Article	China	9
27	[54]	Alaoui et al.	ANN; DL; EV; LIB; Supercapacitor	Deep learning (DL) model	Battery states estimation	Proc.—Int. Conf. Intell. Syst. Adv. Comput. Sci., ISACS	IEEE	2019	Conference Paper	Morocco	9
28	[55]	Jiang et al.	HESS; Parameter matching; Power allocation; Pure EV	Dynamic programming; Extreme learning machine	Power allocation for the hybrid energy storage system of pure electric vehicles	Energies	MDPI AG	2018	Article	China	9
29	[56]	Liu et al.	Climate changes by 2050; Green vehicle storage; ML; Net-zero energy community; Peer-to-peer trading; Uncertainty energy planning	Regression analysis	Uncertainty energy planning for EV	Appl. Energy	Elsevier Ltd.	2022	Article	China	8

Table 2. *Cont.*

Rank	Ref. No.	Authors	Author Keywords	AI Algorithm Used	Goal/Target	Abbreviated Source Title	Publisher	Year	Document Type	Correspondence Address	Cited by
30	[57]	Mazzi et al.	CNN; data-driven; LIB; ML; quantization; state of charge	Gated recurrent unit neural network	State of charge estimation of an electric vehicle's battery	Int. J. Energy Res.	John Wiley and Sons Ltd.	2022	Article	Morocco	7
31	[58]	Meng et al.	AI; disassembly; EV battery; ML; recycling; sustainability	Neural network	Intelligent disassembly of electric-vehicle batteries	Resour. Conserv. Recycl.	Elsevier B.V.	2022	Review	United States	6
32	[59]	Driscoll et al.	ANN; Data-driven; Estimation; LIB; ML; SOH	Artificial neural network	Lithium-ion battery state of health estimation	J. ES	Elsevier Ltd.	2022	Article	Spain	6
33	[60]	Basnet et al.	Charging (batteries); Controllers; Data acquisition; Digital storage; EV; ESS; BESS; DL	Long short-term memory	Cybersecurity issues in 5G enabled electric vehicle charging station	IET Gener. Transm. Distrib.	John Wiley and Sons Inc	2021	Article	United States	5
34	[61]	Herle et al.	data augmentation; DL; EV; LIB; ML	Coupled neural network	Battery data challenges	Int. J. Energy Res.	John Wiley and Sons Ltd.	2021	Article	India	5
35	[62]	Zhou et al.	DSM; Dynamic power Dispatch; ESS; ML; RE; Techno-economic-environmental performance	Reinforcement learning	Advances of machine learning for battery states estimation	Energy. AI.	Elsevier B.V.	2022	Review	China	4
36	[63]	Jafari et al.	EV; LIB; SOH	Extreme gradient boosting	Lithium-Ion Battery Health Prediction	Energies	MDPI	2022	Article	South Korea	4
37	[64]	Tao et al.	EV; EMS; ML; Power dispatch; Thermostatically controlled loads	Active distribution networks	Data-Driven Management Strategy of Electric Vehicles	IEEE Trans. Transp. Electrif.	IEEE	2022	Article	Australia	4

Table 2. *Cont.*

Rank	Ref. No.	Authors	Author Keywords	AI Algorithm Used	Goal/Target	Abbreviated Source Title	Publisher	Year	Document Type	Correspondence Address	Cited by
38	[65]	Bhatt et al.	Aging and regeneration; charging and discharging profile; ML model; second life battery	Back-propagation algorithm	Useful capacity prediction of second-life batteries	Int. J. Energy Res.	John Wiley and Sons Ltd.	2021	Article	Thailand	4
39	[66]	Sree et al.	DER; EV; RES gridable EV; V2G; V2H; V2L; V2V	-	Electric vehicles integration with renewable energy sources	Lect. Notes Electr. Eng.	Springer	2020	Conference Paper	Czech Republic	4
40	[67]	Al-Gabalawy et al.	DER; EV; ML; optimization; virtual power plants	Reinforcement learning	Optimization of electric vehicle virtual power plants	Int. Trans. Elecr. Energy Sys.	John Wiley and Sons Ltd.	2021	Article	Egypt	3
41	[68]	Mabuggwe et al.	DER; EV; Prosumers; Unsupervised ML	Unsupervised machine learning	unsupervised machine learning techniques for EV	IEEE Electr. Power Energy Conf., EPEC	IEEE	2020	Conference Paper	Canada	3
42	[69]	Lamprecht et al.	Automotive batteries; Balancing; EV; ESS; LIB; Active charge balancing	Decision trees; Random Forest	State of Health Estimation Method for Electric Vehicle Batteries	Int. Conf. Omni-Layer Intell. Syst., COINS	IEEE	2020	Conference Paper	Singapore	3
43	[70]	Ghalkhani et al.	AI-based monitoring systems; BMSs; EV; LIB	Convolutional neural network	Thermal Management of EV batteries	Energies	MDPI	2023	Review	Canada	2
44	[71]	Hossain Lipu et al.	EV; LIB; SOC	Random forest regression; Differential search algorithm	State of Charge Estimation of Lithium-ion Batteries	IEEE Trans. Intell. Veh.	IEEE	2023	Article	Malaysia	2

Table 2. *Cont.*

Rank	Ref. No.	Authors	Author Keywords	AI Algorithm Used	Goal/Target	Abbreviated Source Title	Publisher	Year	Document Type	Correspondence Address	Cited by
45	[72]	Eagon et al.	Charging (batteries); Digital storage; PHEV; Secondary batteries; Uncertainty analysis; Forecasting	Recurrent neural network	Electric Vehicle Range Prediction for Smart Charging Optimization	J Dyn Syst Meas Control Trans ASME	ASME	2022	Article	United States	2
46	[73]	Nguyen et al.	Automotive battery; clustering; electrical ESS; LIB; silhouette coefficient	Unsupervised segmentation model	Analyzing the driving load on electric vehicles	Int. Conf. Ecol. Veh. Renew. Energies, EVER	IEEE	2018	Conference Paper	Germany	2
47	[74]	Wang et al.	Hybrid EV; Hybrid ESS; Prediction; SOC	Bayesian extreme learning machine	SOC Prediction of HES	ICIC Express Lett Part B Appl.	ICIC Express Letters Office	2014	Article	China	2
48	[75]	Vasanthkumar et al.	BMS; DL; Hybrid EV; Internet of things; SOC estimation	Hyperparameter tuning	Battery management system hybrid electric vehicles	Sustainable Energy Technol. Assess.	Elsevier Ltd.	2022	Article	India	1
49	[76]	Kim et al.	Hybrid EV; optimal power split; real-time	Deep reinforcement learning	Real-Time Joint Optimal Power Split for Battery	Electronics (Switzerland)	MDPI	2022	Article	South Korea	1
50	[77]	Dineva et al.	BMS; Battery test and measurement; E-Mobility; EV; Estimation; LIB; ML; SOC	Genetic algorithm-based fuzzy C-means	State-of-charge prediction of Li-ion batteries	Conf. Electr. Mach., Drives Power Syst., ELMA—Proc.	IEEE	2021	Conference Paper	Hungary	1
51	[78]	Bandara et al.	FNN; LIB; LSTM; ML; SOH	Long Short-Term Memory Network	State of Health Estimation	IEEE Veh. Power Propuls. Conf., VPPC—Proc.	IEEE	2021	Conference Paper	Spain	1

Table 2. *Cont.*

Rank	Ref. No.	Authors	Author Keywords	AI Algorithm Used	Goal/Target	Abbreviated Source Title	Publisher	Year	Document Type	Correspondence Address	Cited by
52	[79]	Shimizu et al.	EV; ML; V2G	Markov model	Vehicle fleet prediction for V2G system	VEHITS—Proc. Int. Conf. Veh. Technol. Intell. Transport Syst.	SciTePress	2018	Conference Paper	Japan	1
53	[80]	Ren et al.	LIB; ML techniques; SOC; SOH	Support vector machine	State-of-charge and state-of-health estimation algorithms for lithium-ion batteries	Energy Rep.	Elsevier Ltd.	2023	Review	China	0
54	[81]	Mosayebi et al.	Charger; EV; fast charger; ML	Sliding mode control	Fast Portable Charger for Electric Vehicles	IEEE Trans. Circuits Syst. Express Briefs	IEEE	2023	Article	Denmark	0
55	[82]	Shen et al.	EV; Energy consumption; Estimation; ML; ANN; Predictive models; Roads; Transformers; Vehicles	Transformer neural network	Energy Prediction for Electric Vehicles	IEEE Trans. Transp. Electrif.	IEEE	2023	Article	United States	0
56	[83]	Liu et al.	FBG sensor; linear/nonlinear model; LIB thermal management	Fast recursive algorithm	Thermal monitoring of lithium-ion batteries	Trans Inst Meas Control	SAGE Publications Ltd.	2023	Article	United Kingdom	0
57	[84]	Wang et al.	HESS; Power battery; Power distribution; Subtractive clustering; Super-capacitor	Adaptive fuzzy neural network	Power distribution control strategy of hybrid electric vehicles	Cluster Comput.	Springer	2022	Article	China	0

Table 2. *Cont.*

Rank	Ref. No.	Authors	Author Keywords	AI Algorithm Used	Goal/Target	Abbreviated Source Title	Publisher	Year	Document Type	Correspondence Address	Cited by
58	[85]	Sukkam et al.	EV, PHEV, BTMS	-	Battery Thermal Management Systems in Electric Vehicles	AIP Conf. Proc.	AIP	2022	Conference Paper	Thailand	0
59	[69]	Joshi et al.	EV, LIB, SOH, BMS, ML	Regression analysis	Energy management in a hybrid electric vehicle	SAE Techni. Paper.	SAE International	2022	Conference Paper	India	0
60	[86]	Perumal et al.	Cost minimization; EV in hybrid; EMS; ML	Genetic algorithm	Predictions for Capacity Fade of Li-Ion Batteries	AIP Conf. Proc.	AIP	2022	Conference Paper	Ethiopia	0
61	[87]	Penjuru et al.	BMS; Digital storage; Electrochemical impedance spectroscopy; Forecasting; ML; Battery degradation; LIB	Support vector regression	Capacity State-of-Health Estimation of Electric Vehicle Batteries	J Electrochem Soc	Institute of Physics	2022	Article	India	0
62	[88]	Barragán-Moreno et al.	Battery aging; battery impedance; BMS; capacity degradation; EV; LIB; ML; SOH	neural networks	State-of-Health Estimation of Electric Vehicle Batteries	Electronics (Switzer-land)	MDPI	2022	Article	Denmark	0
63	[89]	Wen et al.	FESS; EV; ML; PCA; RUL	Empirical mode decomposition	Safety risk analysis in flywheel-battery	J. ES	Elsevier Ltd.	2022	Article	Poland	0
64	[90]	Rippstein et al.	BEV; ML; optimization; V2H	Ad-hoc machine learning approach	Optimization for smart home energy systems with V2X	IEEE Veh. Power Propuls. Conf., VPPC—Proc.	IEEE	2022	Conference Paper	Germany	0

Table 2. *Cont.*

Rank	Ref. No.	Authors	Author Keywords	AI Algorithm Used	Goal/Target	Abbreviated Source Title	Publisher	Year	Document Type	Correspondence Address	Cited by
65	[91]	Benlamine et al.	EV; LIB; ML; SOH	Predictive prognostics	Sate of Health optimization of EV batteries	IEEE Veh. Power Propuls. Conf., VPPC—Proc.	IEEE	2022	Conference Paper	France	0
66	[92]	Khezri et al.	Batteries; Costs; Degradation; DER; EV; fast-charging; Load modeling; ML; optimal sizing	Supervised learning	Sizing of a Renewable-Battery System	IEEE Trans. Sustainable Energy	IEEE	2022	Article	Germany	0
67	[93]	Babaeiyazdi et al.	BES Systems; Power Systems; SOC; SOH	Gaussian process regression	State-of-Charge Prediction of Degrading Li-ion Batteries	IEEE Power Energy Soc. Gen. Meet.	IEEE	2022	Conference Paper	Canada	0
68	[94]	Fouka et al.	BMS; battery state prediction; data analytics; EV; ML	Computer programming	Li-Ion Battery Lifetime Prognostics	Int. Conf. Inf., Intell., Syst. Appl., IISA	IEEE	2022	Conference Paper	Greece	0
69	[95]	Chen et al.	Autonomous vehicle; EV; project-based learning; zero-emission vehicles	-	Energy-Harvesting Electric Vehicles	IEEE Eurasian Conf. Educ. Innov., ECEI	IEEE	2022	Conference Paper	China	0
70	[96]	Li et al.	EV; Electrochemical Impedance Spectroscopy; LIB; ML; SOH;	Gaussian process regression	State of Health Indicator Modeling of Lithium-ion Batteries	IEEE Int. Conf. Electro Inform. Technol.	IEEE	2022	Conference Paper	United States	0

Table 2. *Cont.*

Rank	Ref. No.	Authors	Author Keywords	AI Algorithm Used	Goal/Target	Abbreviated Source Title	Publisher	Year	Document Type	Correspondence Address	Cited by
71	[97]	Liu et al.	Electrochemical impedance spectroscopy; LIB; Electrochemical-impedance spectroscopies; SOH; SVM	Deep neural networks	online state-of-charge estimation for lithium-ion batteries	IEEE Int. Conf. Electro Inform. Technol.	IEEE	2022	Conference Paper	China	0
72	[98]	Showers et al.	Adaptive boosting; BMSs; Charging (batteries); Digital storage; EV; PSO; SOC; SOH;	Particle swarm optimization	Hybrid electric vehicle energy management systems	Proc SPIE Int Soc Opt Eng	SPIE	2022	Conference Paper	China	0
73	[99]	Mehta et al.	EMS; Fuel storage; HEV; LIB; Power distributions; Fuel cells	Metaheuristic search methods	Estimating State of Charge for Li-ion Battery	AIMS Energy	AIMS Press	2022	Article	South Africa	0
74	[100]	Hasib et al.	Charging (batteries); Digital storage; EV; Ions; Learning algorithms; LIB; ML; BES; SOC	-	Prediction of SOC for Electric Vehicles	Proc.—IEEE Int. Conf. Artif. Intell. Mach. Vis., AIMV	IEEE	2021	Conference Paper	India	0
75	[101]	Hossain Lipu et al.	ML; Secondary batteries; Vehicles; Driving range; Green energy technologies; Rapid transitions; Storage capacity; Forecasting	Linear regression	State of Charge Estimation in Electric Vehicle Batteries	Int. Conf. Electr. Eng. Inf. Commun. Technol., ICEEICT	IEEE	2021	Conference Paper	Bangladesh	0

Table 2. *Cont.*

Rank	Ref. No.	Authors	Author Keywords	AI Algorithm Used	Goal/Target	Abbreviated Source Title	Publisher	Year	Document Type	Correspondence Address	Cited by
76	[102]	Mahajan et al.	BMSs; Charging (batteries); Digital storage; EV; LIB; ML; SOC	Decision trees; Differential search algorithm; Random Forest regression	Energy Management Strategy for Electric Vehicle Battery	Conf Rec IAS Annu Meet	IEEE	2021	Conference Paper	Malaysia	0
77	[103]	Singh et al.	Battery life; EMS; ML; Range of vehicle; Regenerative braking; Ultracapacitors	Regenerative braking control algorithm	State of Charge Estimation for EV	Lect. Notes Mech. Eng.	Springer	2021	Conference Paper	India	0
78	[104]	Herle et al.	Charging (batteries); EV; ML; Secondary batteries; Turing machines; Virtual storage; SOC	Support vector data descriptor	State of charge estimation for li-ion batteries on various drive cycles	Adv. Intell. Sys. Comput.	Springer	2021	Conference Paper	India	0

Table 2 information encompasses a wide spectrum of research efforts directed at enhancing EV battery management by leveraging various AI and ML techniques. Numerous studies target crucial aspects of battery management, such as state estimation, encompassing SOC and SOH estimation, vital for understanding and optimizing battery performance. For instance, Chemali et al. focus on employing Deep Neural Networks (DNN) for precise SOC estimation of Li-ion batteries, highlighting the trend of utilizing complex neural network architectures for accurate parameter predictions [45]. Additionally, various studies utilize diverse AI algorithms, including Bayesian Inference (Hu et al., 2016), Genetic Algorithm-based fuzzy C-means (Hu et al., 2016), Support Vector Machines (Feng et al., 2019), Wavelet Transform (Xiong et al., 2018), Extreme Learning Machine (Li et al., 2019), and Reinforcement Learning (Abdullah et al., 2021), among others, showcasing the versatility in methodologies adopted for addressing battery-related challenges [30–32,105–107].

Furthermore, the geographical distribution of these studies across different countries—China, Canada, the United States, the United Kingdom, Qatar, Turkey, Finland, and Thailand—underscores the global interest and collaboration in advancing EV battery management technologies. This collective research effort signifies the multi-faceted approaches adopted to improve the performance, reliability, and longevity of EV batteries, essential for the evolution of sustainable and efficient electric transportation systems worldwide. The amalgamation of AI/ML/DL algorithms, diverse target objectives, and international collaborations in these studies reflects the comprehensive and interdisciplinary nature of the quest to optimize EV battery performance and management.

3. Statistical Analysis

Statistical analysis is essential for identifying and understanding current research trends as well as investigating the most influential articles on a specific topic. Through this analytical discussion, readers will gain a thorough understanding of the most significant papers, present research trends, conclusions, and critical debate relating to AI-integrated BMS in EV applications.

3.1. Distribution of the Papers

Figure 2 displays the distribution of the 78 papers in AI-integrated BMS for EV applications that were selected for the time period between 2014 and 2023. Figure 3 shows that 2022 had the highest rate of article publishing (27 research papers), while 2014 and 2017 had the lowest rates (1 research article each). There were nearly identical numbers of papers published in 2018, 2019, and 2020, with 7, 6, and 9 publications, respectively. The trend in the number of papers published from 2014 to 2023 generally exhibited exponential growth, with few deviations.

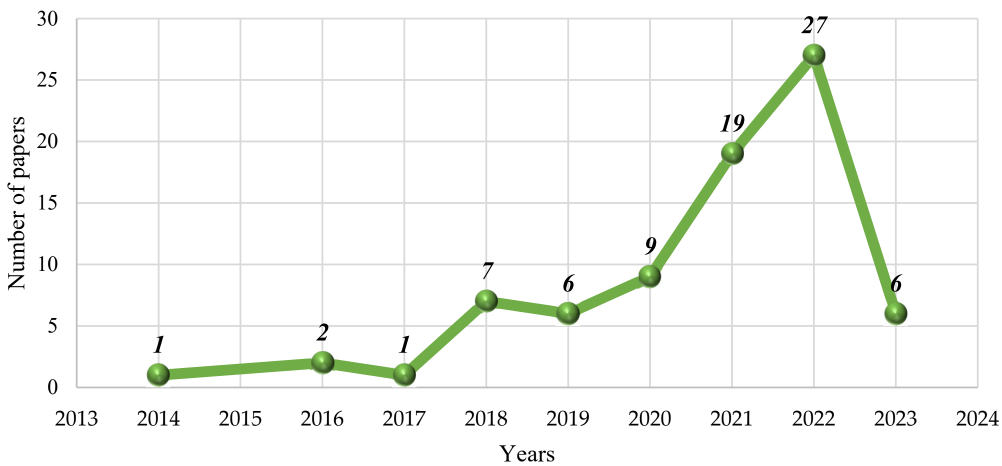

Figure 3. Number of relevant manuscripts in AI- integrated BMS for EV applications between 2014 and 2023.

3.2. Analysis of Co-Occurring Keywords

The coincidence keyword breakdown from the 78 most pertinent articles using the Scopus platform is shown in Figure 4. The top 15 most frequent keywords used in a variety of articles between 2014 and 2023 were selected from the Scopus database. "Machine Learning", "Digital Storage", "Charging (batteries)", and "Battery Management Systems" were the four most frequently used keywords. The total for "Machine Learning" was 57, while "Digital Storage", "Charging (batteries)", and "Battery Management Systems" had numbers of 46, 42, and 41, respectively. The most common phrases in recent years have also included "Electric Vehicles", "Energy Storage", and "Secondary Batteries", which reflects the rising need for AI-integrated BMS in EV applications.

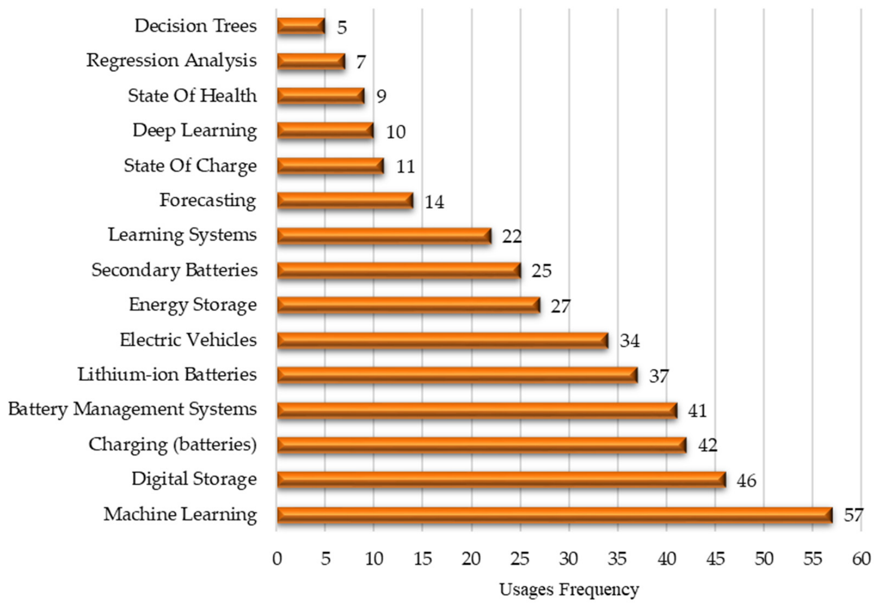

Figure 4. The analysis of keywords for BMS in EVs using the Scopus database.

3.3. Research Categories in the Most Relevant 78 Papers

The research classifications of the papers that were chosen as being the most pertinent are shown in Table 3 and Figure 5. Additionally, the relationships among research styles, time periods, and citation ranges are demonstrated. Experimental work, development, and performance assessment made up the majority of publications (45%), followed by conference papers (35%) and state-of-the-art technical overviews (8%). In the fourth slot, reviews (systematic and nonsystematic) and observational papers were combined, with 5 manuscripts each, with citation ranges of 3–232 and 20–171, respectively. With the broadest range of citations (1–355), experimental work, development, and performance assessment had the most publications (40%). The majority of articles from 2014 to 2023 fell under the issue formulation and original research work categories (modelling, simulation, and performance assessment).

Table 3. Research articles categories of the most relevant 78 articles on AI-driven BMS in EVs.

Categories of Articles	Publications Rate	Year Range	Citation
Experimental work, development, and performance assessment	35	2014–2023	1–355
Conference paper	27	2015–2019	0–14
State-of-the-art technical overview	6	2014–2022	9–191
Review (systematic/nonsystematic)	5	2016–2020	3–49
Observational papers	5	2017–2021	20–171

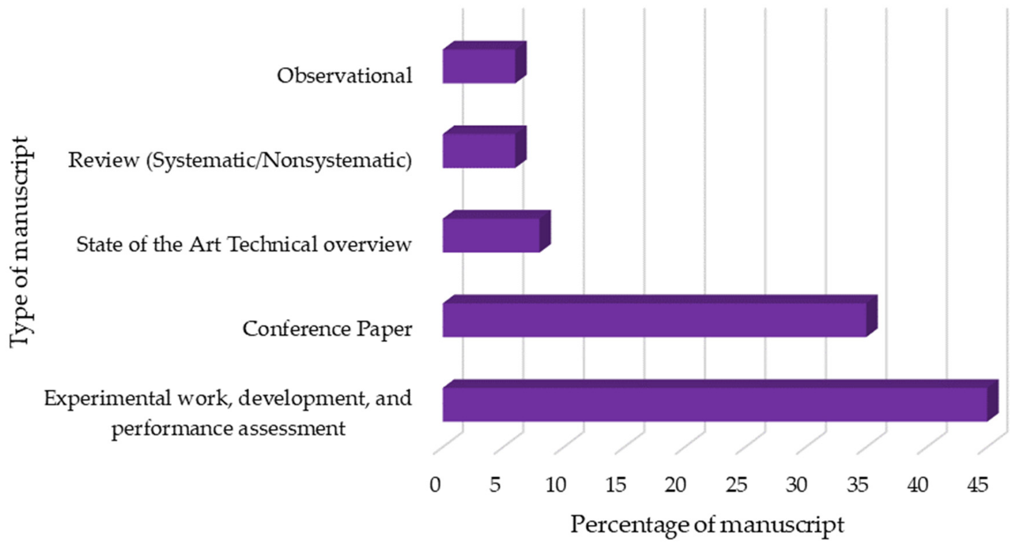

Figure 5. The proportions of different manuscript types among the 78 most important papers.

3.4. Distribution of Article Publishers

Figure 6 reveals that the top 78 pertinent articles were released by 14 different publishers. Out of the 78 publications, the Institute of Electrical and Electronics Engineers (IEEE) issued the most (37%). Elsevier came in second with 21% of the publications, followed by John Wiley & Sons, Inc. (9%), and MDPI AG (8%). The rest of the publishers were Springer (5%), Cell Press (3%), American Institute of Physics Inc. (2%), SAGE Publishing (1%), Nature Research (1%), IET (1%), ASME (1%), ICIC Express Letters Office (1%), SciTePress (1%), SAE International (1%), Institute of Physics (1%), AIMS Press (1%), etc.

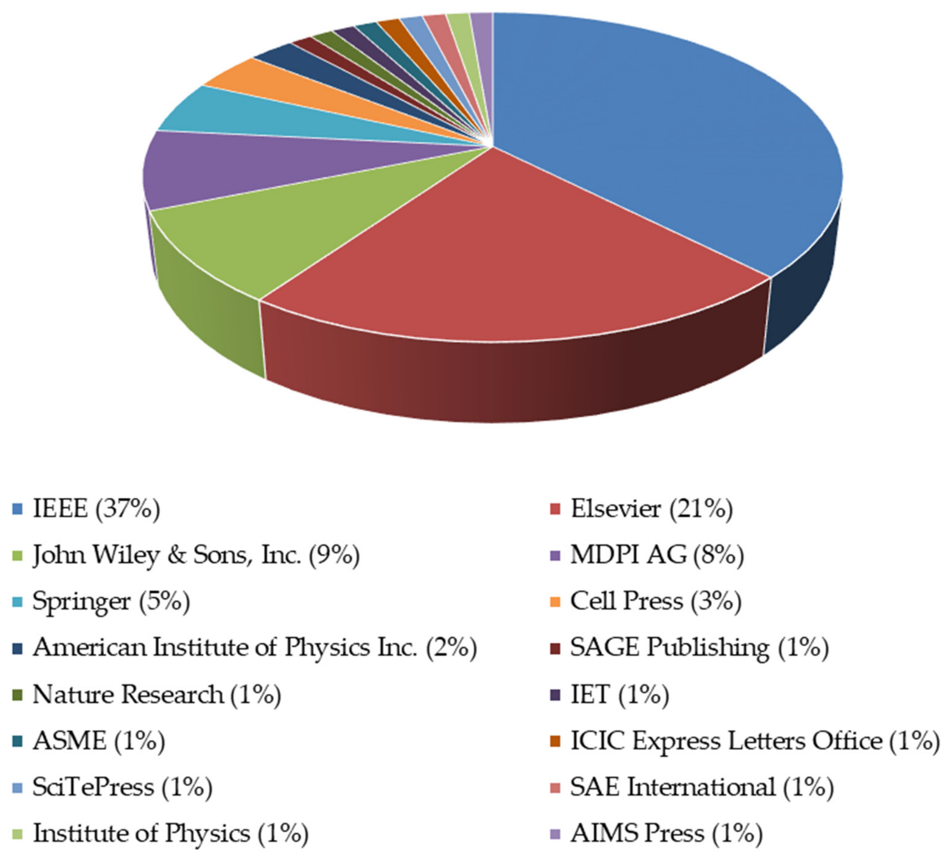

Figure 6. Percentage of top 78 manuscripts between the different publishers.

Figure 7 shows the number of papers published in various journals, together with the impact factor for each journal. The top seven journals produced 29% of the 78 papers that were chosen, and their impact factors varied from 2.6 to 11.4. The "International Journal of Energy Research" journals published the most papers, with five manuscripts. "Applied Energy", "Electronics Switzerland", "Energies", "Energy", "IEEE Transactions on Transportation Electrification", and "Journal of Energy Storage" journals each published three articles. "IEEE Access" and "Joule" each published two articles. Less than two articles from the chosen database were published by the remaining journals and conferences, and only a small number of them were Electronics Letters, Energy And AI, Energy Conversion And Management, Energy Reports, IECON Proceedings Industrial Electronics Conference, IEEE International Conference On Electro Information Technology, IEEE Power And Energy Society General Meeting, IEEE Transactions On Circuits And Systems II Express Briefs, IEEE Transactions On Industrial Electronics, IEEE Transactions On Intelligent Vehicles, IEEE Transactions On Sustainable Energy, IEEE Transactions On Vehicular Technology, ICIC Express Letters Part B Applications, IET Generation Transmission And Distribution, International Journal Of Electrical Power And Energy Systems, International Transactions On Electrical Energy Systems, Journal Of Cleaner Production, Journal Of Dynamic Systems Measurement And Control Transactions Of The ASME, Journal Of Power Sources, Journal Of The Electrochemical Society, Patterns, Scientific Reports, and Sustainable Energy Technologies And Assessments.

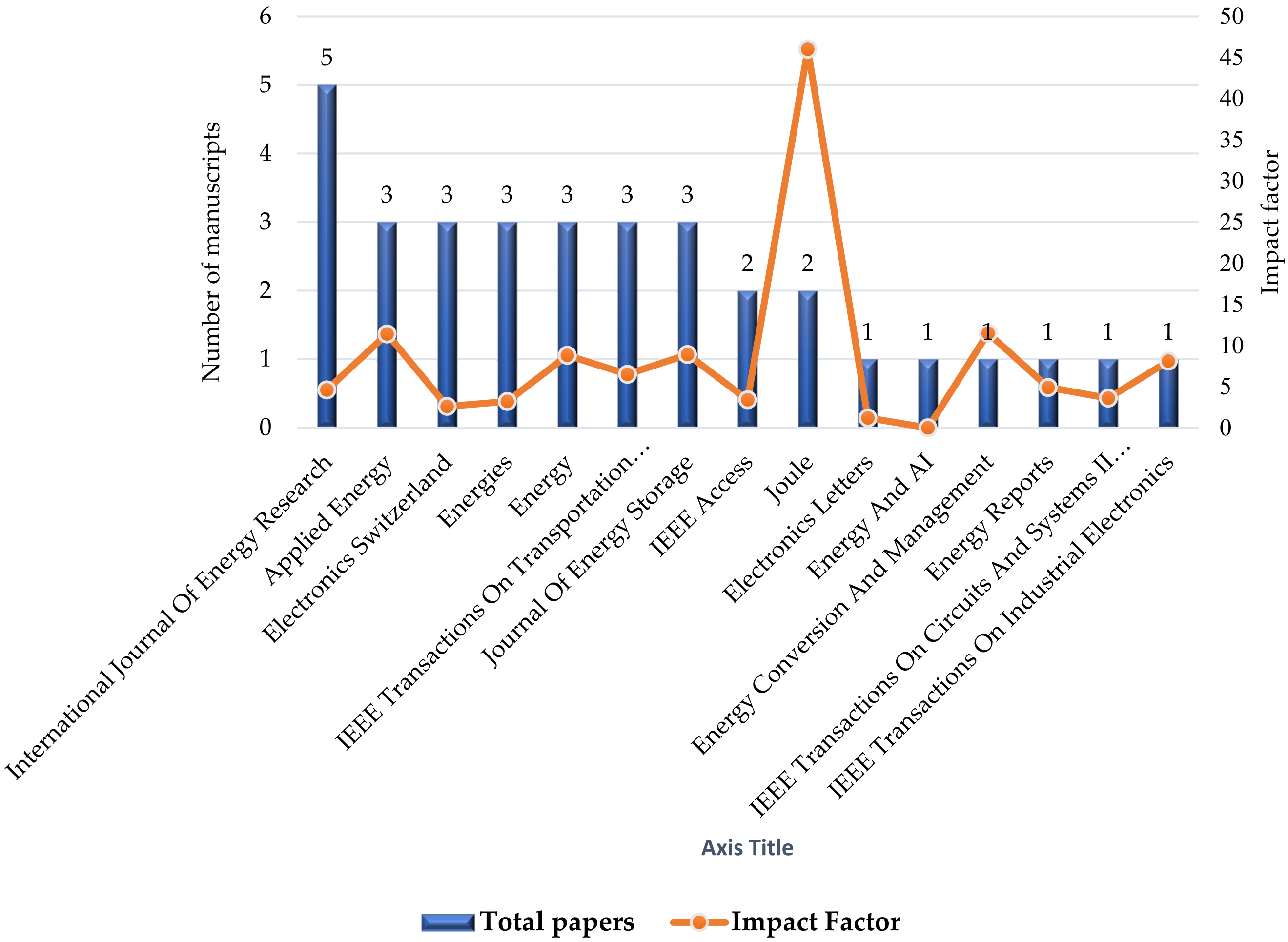

Figure 7. Distribution of the 78 manuscripts between the different publishers.

3.5. Document Authorship and Collaboration

The research contours of the well-known writers who have written three or more of the 78 documents are shown in Table 4. Ten different authors contributed to the top 78 pertinent articles. M. A. Hannan from Malaysia's Universiti Tenaga Nasional was the primary author of three publications. With a comparable number of publications, Aini Hussain from the Universiti Kebangsaan Malaysia came in second. With two submissions, Ali N. Emadi, a reputed international researcher at McMaster University in Canada, came in third. The remaining top 10 authors each released two articles during the same time period. With 24,867 citations and an h-index of 69, Ali N. Emadi of McMaster University in Canada was in the lead, followed by Xiaosong Hu of Chongqing University in China, who had 18,566 citations and an h-index of 78.

Table 4. Manuscript authorship and collaboration of the most relevant 78 articles on BMS in EVs using AI technology.

Rank	Author	Affiliation	Country	Articles	Citations	h-Index	Author's Position
1	Hannan, M. A.	Universiti Tenaga Nasional	Malaysia	3	11,890	52	1-1st author 2-Co-author
2	Hussain, Aini	Universiti Kebangsaan Malaysia	Malaysia	3	8526	40	3-Co-author
3	Emadi, Ali N.	McMaster University	Canada	2	24,867	69	2-Senior author
4	He, Hongwen	Beijing Institute of Technology	China	2	12,998	54	2-Co-author
5	Hu, Xiaosong	Chongqing University	China	2	18,566	78	2-1st author
6	Khooban, Mohammad Hassan	Aarhus Universitet	Denmark	2	5639	45	2-Senior author
7	Hossain Lipu, Molla Shahadat	Green University of Bangladesh	Bangladesh	2	3780	25	2-1st author
8	Babaeiyazdi, Iman	York University	Canada	2	71	2	2-1st author
9	Channegowda, Janamejaya	Ramaiah Institute of Technology	India	2	98	5	2-Co-author

3.6. Network and Collaboration Analysis of the Most Relevant 78 Papers

The top 10 nations and co-occurring countries that dominate the AI-integrated BMS in EV applications are depicted graphically in Figures 8 and 9. After China, which had 23 published manuscripts, the United States came in second with 13 manuscripts. India was in third place with 12 articles. Figure 9 depicts the network of co-occurrences among all of the countries that contributed to the production of the 78 articles that were selected. Figure 9 also demonstrates that, after India and the United States, China had the greatest number of foreign connections. "National Natural Science Foundation of China" is the guarantor of the most manuscripts out of the 78 that were determined to be the most pertinent, with 7, followed by "Ministry of Higher Education, Malaysia", which placed second.

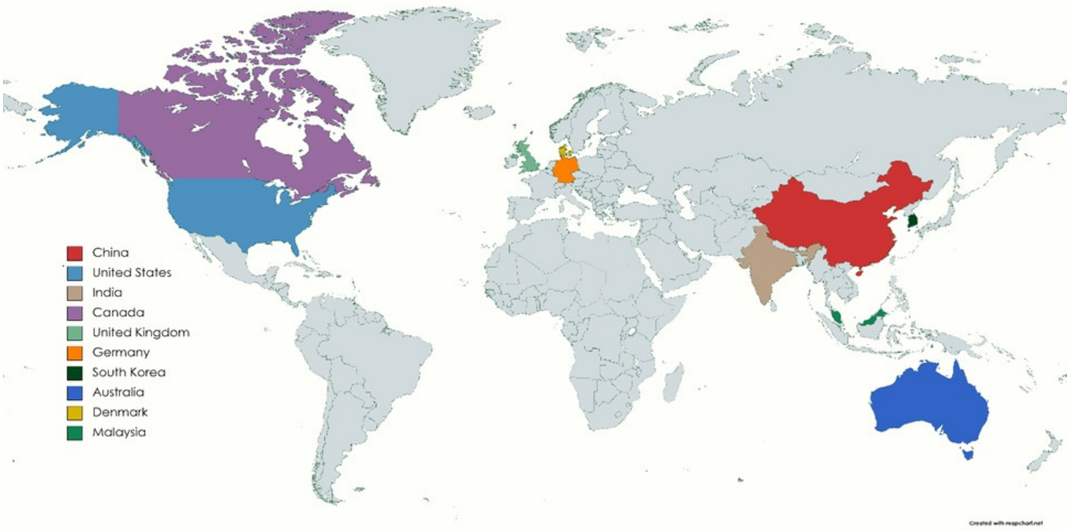

Figure 8. A graphic showing the top 10 nations in applications for AI-integrated BMS for EVs.

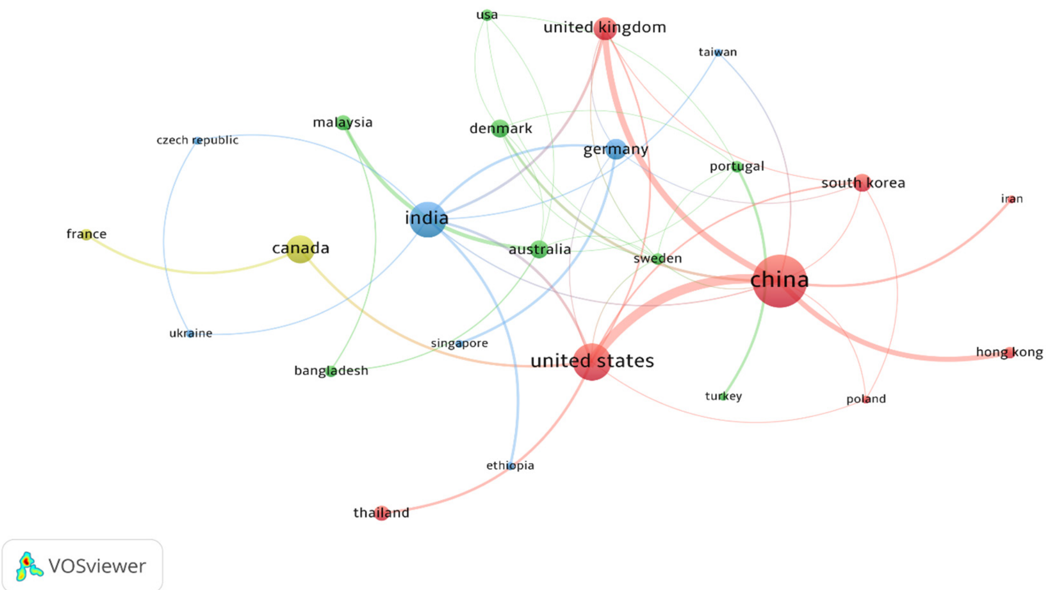

Figure 9. Analysis of co-occurrence countries in the Scopus database using VOSviewer.

4. Technical Assessment of AI Approaches in BMS of EVs

This section covers a technical assessment of the state-of-the-art AI approaches for BMS in EV applications. The AI methods and algorithms were categorized into machine learning, deep learning, optimization and rule-based approaches. Battery parameters are pivotal in determining the SOC, SOH, and RUL of a battery, with ML methods harnessing a diverse range of these parameters for more precise estimations. Primary parameters like voltage provide insights into SOC, yet may lack accuracy in dynamic scenarios or aging batteries. Incorporating current measurements enhances SOC estimation accuracy by evaluating the battery's current flow. Temperature influences internal resistance and capacity, impacting performance and lifespan, thus adjusting SOC estimations. Monitoring internal resistance reveals a battery's health, guiding ML algorithms to estimate SOH and RUL based on resistance changes. Capacity fade, derived from historical data, predicts degradation trends, vital in determining SOH. ML algorithms scrutinize cycling behavior, electrochemical impedance spectroscopy (EIS) data, calendar aging factors, and operating conditions to develop models accurately predicting SOC, SOH, and RUL. These ML techniques, employing regression, neural networks, or other sophisticated algorithms, integrate parameters' dynamic relationships to enhance accuracy, although the significance of parameter selection varies based on battery type, application, and estimation goals. The amalgamation of multiple parameters via ML amplifies estimation precision and reliability.

Machine learning involves the use of algorithms and statistical models that enable computer systems to progressively improve their performance on a specific task without explicit programming. When applied to EV battery management, machine learning algorithms analyze data from various sensors and historical patterns to predict battery performance, estimate degradation, and optimize charging strategies. Deep learning, a subset of machine learning, involves neural networks with multiple layers capable of learning complex patterns in data. In EV battery management, deep learning models can provide more sophisticated insights by extracting intricate patterns from vast datasets, enabling more accurate predictions and optimal control strategies. Optimization algorithms, on the other hand, focus on finding the best possible solution among a set of feasible alternatives. These algorithms are used in EV battery management to fine-tune charging and discharging schedules, maximizing battery lifespan and performance. Neural-based networks encompass a broader category that includes deep learning models but also covers other architectures and paradigms inspired by the structure and functionality of the human brain. In EV battery management, neural-based networks encompass various approaches, including deep learning, reinforcement learning, and other network architectures, utilized to optimize thermal management, predict battery degradation, and enhance overall battery efficiency and safety. Each of these methodologies plays a crucial role in leveraging data-driven insights and computational techniques to enhance EV battery performance, longevity, and reliability.

4.1. Machine Learning Approaches

4.1.1. Backpropagation Neural Networks (BPNN)

Backpropagation Neural Network is a type of ANN that utilizes a supervised learning technique for training. It is a foundational concept in the field of deep learning and machine learning. The basic idea behind backpropagation is to train a neural network by adjusting its weights and biases in order to minimize the difference between its predicted output and the actual output for a given set of training examples. The network learns by continuously adjusting these weights through multiple iterations, gradually reducing the error or the difference between predicted and actual outputs.

The BPNN algorithm, which is structured with an input layer, a hidden layer, and an output layer, has been widely used in SOC estimation for BMS applications. It is executed using an appropriate training algorithm and activation function. For instance, Ma et al. [108] developed a model for estimating SOH and RUL for lithium-ion BMS. Particle swarm optimization (PSO) was integrated with BPNN to find the optimal parameters and improve the outcomes. The results showed that the root mean squared error (RMSE) and average absolute error were 0.78% and 1.01%, respectively. A BPNN is excellent at modelling complicated relationships in battery data, which makes it appropriate for SOC estimation. Moreover, BPNNs can handle non-linear patterns and adjust to shifting battery conditions. Nonetheless, they have several limitations, such as the requirement for a sizable quantity of labelled data for training, vulnerability to overfitting, and processing requirements that might not be appropriate for real-time applications. To successfully use BPNN advantages in battery management, proper data preparation, model tuning, and careful consideration of computing resources are important. Vidal et al. [45] used the BPNN method to estimate SOC for lithium iron phosphate (LFP) and lead acid (LA) batteries. The proposed model was tested using five light vehicle test cycles. The RMSE was calculated to be 0.33% and 0.84% for the LFP and the LA batteries, respectively. Driscoll et al. [59] predicted SOH with the BPNN model based on the NASA Ames PCoE Battery data set. A feature-based SOH model was developed using the current, voltage, and temperature profiles during the charging process. High accuracy of SOH prediction was obtained under varying conditions with coefficients of determination between 0.896 and 0.992. Barragán-

Moreno et al. [88] applied the BPNN model to predict the maximum capacity of EV batteries. The performance of the proposed model was verified using diverse degradation data from real EV batteries. According to the findings, the suggested model produced mean absolute errors as low as 0.9%.

The contributions of BPNN are fundamental in predicting battery states, optimizing energy management, and ensuring efficient utilization of battery power. Through continuous learning, BPNNs enable BMS to accurately forecast battery life, anticipate failures, and regulate charging/discharging processes. This predictive capability enhances battery safety, prolongs lifespan, and maximizes performance. The advantages of BPNN in BMS for EVs include their adaptability to nonlinearities in battery behavior, capability to handle complex data patterns, and potential for real-time decision-making. However, drawbacks include the need for substantial data for effective training, vulnerability to overfitting, and challenges in interpreting the decision-making process due to their inherent black-box nature. Nonetheless, BPNN remains a cornerstone technology in optimizing BMS for EVs, significantly improving their efficiency and reliability.

4.1.2. Radial Basis Function Neural Network (RBFNN)

RBFNN is a type of artificial neural network that uses radial basis functions as activation functions. It is a three-layered network consisting of an input layer, a hidden layer with radial basis function neurons, and an output layer.

RBFNN is used in a variety of tasks, including pattern recognition, function approximation, and clustering. An input layer, a hidden layer made up of radial basis function neurons, and an output layer are the three main layers of an RBFNN. The hidden layer of RBFNN is where each neuron computes its output as a radial basis function of the distance between the input data and a center point specific to that neuron. RBFNN has been demonstrated to be appreciated in battery SOC estimation. For example, Wu et al. [109] proposed an improved RBFNN-based method for SOH estimation of lithium-ion batteries, and the results showed that this method can accurately estimate the SOH within a maximum $\pm4\%$ estimation error. Zhang et al. [110] developed a PSO-based RBFNN hybrid model for lithium-ion battery SOH prediction. The experimental results reported that this hybrid model was able to reduce average absolute error (AAE) and RMSE by 0.23% and 0.34%, respectively. RBFNN performs satisfactorily in complex and nonlinear battery applications due to its greater ability to efficiently estimate complex functions utilizing radial basis functions. Despite their advantages, RBFNNs may need careful parameter adjustment to work at their best, including adjusting the locations of the radial basis functions. However, because of their ability to recognize complicated patterns and nonlinearity, they are a helpful tool in the study of neural networks and machine learning.

RBFNNs excel in capturing nonlinear relationships within battery data, enabling accurate state estimation and enhancing overall BMS performance. Their outcomes include improved battery lifespan through better charge management, increased safety by predicting faults or anomalies, and enhanced energy utilization in EVs. The advantages of RBFNN in BMS for EVs encompass their ability to handle complex data patterns, faster convergence during training, and their relatively simpler architecture compared to other neural networks. However, challenges arise in determining the appropriate number of radial basis functions, which can impact model accuracy, and in interpreting the reasoning behind the network's decisions due to its inherent complexity. Despite these challenges, RBFNNs continue to play a crucial role in optimizing BMS for EVs, contributing significantly to their efficiency, reliability, and longevity.

4.1.3. Extreme Learning Machines (ELM)

ELM is a type of machine learning algorithm used for supervised learning tasks, particularly in the realm of neural networks. They were proposed as an alternative to traditional gradient-based learning methods for training neural networks. The core principle of ELM is to minimize the computational burden associated with training neural networks, especially in terms of the time required for training. Unlike traditional neural networks like feedforward neural networks (FNN) or BPNN, where both the input-to-hidden and hidden-to-output connections are subject to training, ELM follows a unique approach.

A set of machine learning algorithms called Extreme Learning Machines was created to effectively and quickly train artificial neural networks. ELM is particularly well known for its proficiency in managing huge datasets and challenging issues. The primary principle of ELM is to use hidden neurons with straightforward activation functions, such as the sigmoid or radial basis functions, to randomly set the weights between the input and hidden layers of a neural network, often in a single hidden layer configuration. ELM is applied in BMS applications due to its improved scalability, greater training speed, and generalization performance. Pan et al. [111] presented a model of SOH estimation using the ELM algorithm. This model has shown excellent performance in terms of speed and accuracy. The results indicated that the maximum estimation error is less than 2.5%. ELM has benefits in terms of training speed and ease of use, but it might not be as adaptable as other DL approaches when it comes to managing incredibly complicated hierarchical data structures. Li et al. [36] used the ELM algorithm to develop a cloud-based BMS with a new training method combined with a data preprocessing approach. The proposed model achieved satisfactory outcomes with SOC and terminal voltage errors of 3% and 2%, respectively. Jinag et al. [55] established a novel ELM controller-based hybrid energy storage system. The effectiveness of the ELM controller was verified with the rule-based controller, and reports illustrated the superiority of the ELM over the rule-based controller, indicating a reduction in electricity consumption and battery life loss of 3.78% and 6.51%, respectively.

ELMs contribute by swiftly and accurately predicting battery states, optimizing charging and discharging strategies, and enhancing overall energy management in EVs. Their outcomes include improved efficiency in battery utilization, prolonged battery lifespan, and heightened safety by predicting potential faults or irregularities. The advantages of ELMs in BMS for EVs lie in their rapid training process, requiring minimal tuning of parameters compared to traditional neural networks. Additionally, ELMs exhibit robustness against overfitting, making them suitable for handling large volumes of data efficiently. However, drawbacks include their reliance on randomly generated hidden layer parameters, leading to less interpretability and potential challenges in fine-tuning model performance. Nevertheless, ELMs remain instrumental in optimizing BMS for EVs, contributing significantly to their reliability, performance, and effective energy management.

4.1.4. Random Forest (RF)

Random Forest is a versatile and popular machine learning algorithm used for both classification and regression tasks. It operates by constructing a multitude of decision trees during training and outputs the mode (for classification) or average prediction (for regression) of the individual tree.

The application of RF in the field of BMS has been demonstrated to be quite advantageous. In comparison to some other algorithms, RF is strong against overfitting and requires less hyperparameter adjustment. However, the computational complexity of RF models may be a drawback for real-time applications with strict reaction-time constraints. To exploit the advantages of RF in battery management, careful evaluation of computing resources and post-model interpretation approaches may be required. Wang et al. [112] used an RF model to predict both SOH and RUL of a lithium-ion battery. The mean error of the calculated SOH, according to the authors, was 1.8152%, which is lower than that of other, traditional models. The authors in [71] applied the RF approach to estimate SOC using different materials of lithium-ion batteries. The validation was performed under experimental tests at room temperature and EV drive cycles at varying temperature conditions. RF illustrated satisfactory outcomes with RMSE of 0.382% in the HPPC test and mean absolute error (MAE) of 0.193% in the DST drive cycle at 25 °C.

RF models contribute by accurately predicting battery performance, enabling efficient charge and discharge control, and aiding in fault detection within EV batteries. The outcomes include improved battery lifespan, enhanced safety by detecting anomalies or potential failures, and optimized energy utilization in EVs. The advantages of using RF models in BMS for EVs encompass their ability to handle large datasets, mitigate overfitting, and provide feature importance rankings for better interpretability. Additionally, RF models are less prone to outliers and noise in the data compared to other machine learning methods. However, challenges associated with RF include longer computational time for training with extensive datasets and potential complexities in parameter tuning for optimal performance.

4.1.5. Recurrent Neural Network (RNN)

An artificial neural network type called the recurrent neural network (RNN) is made to process sequential data by keeping an internal state or memory. Relational RNNs display dynamic temporal activity because they feature connections that form directed cycles, in contrast to standard feedforward neural networks, where information flows in one direction (from input to output).

The use of RNN in BMS has recently become more popular. RNNs are especially adept at processing time-series data, making them very useful for assessing and enhancing battery performance. RNNs are able to capture temporal dependencies and sequential patterns, which is critical for comprehending how batteries deteriorate over time. RNNs present a possible path for more precise and adaptable battery management solutions, which will increase performance, sustainability, and cost-effectiveness as battery technology develops. Tao et al. [113] presented a study about the SOC estimation for EVs by the RNN model, where the authors mentioned that the three most important features of the RNN compared to others are accuracy, robustness against measurement uncertainties, and adaptability against different battery aging cycles, which make this model more efficient than other models. In order to optimize smart charging, Eagon et al. [72] proposed RNN-based EV range prediction. Despite daily route unpredictability, the suggested technique displayed remarkable accuracy, with an RMSE of less than 6%.

Their primary contribution lies in their ability to model sequential data, making them adept at predicting battery states over time, optimizing charging and discharging strategies, and enabling accurate forecasting of battery health. The outcomes of employing RNNs in BMS for EVs include improved efficiency in managing battery resources, better estimation of battery degradation, and enhanced safety by identifying patterns associated with potential faults or anomalies. The advantages of RNNs in this domain include their capacity to handle sequential data effectively and learn temporal dependencies, and their suitability for time-series prediction tasks. However, RNNs are prone to vanishing or exploding gradient problems, which can hinder learning over longer sequences, and they might require substantial computational resources, especially with deep architectures or extensive datasets.

4.1.6. Gaussian Process Regression (GPR)

GPR is a probabilistic non-parametric approach used for regression tasks, particularly in machine learning and statistics. It is a powerful method that allows for flexible modeling of complex relationships between input variables and their corresponding outputs.

In the field of BMS, GPR has shown to be an invaluable tool by providing a probabilistic and data-driven strategy for forecasting battery behavior and enhancing its efficiency. GPR has found applications in various domains, from EVs to renewable energy storage, where accurate predictions of battery degradation and remaining lifespan are essential for efficient and cost-effective operations. In essence, GPR offers a robust and versatile approach to battery management, enabling precise monitoring and optimization of battery performance while considering the uncertainties inherent in real-world conditions. Meng et al. [114] proposed a GPR-based end-of-life (EOL) prediction model. The authors found that compared to the other popular model, the mean EOL cycle predicted by the GPR base technique was more accurate and had a narrower range of prediction uncertainty. Deng et al. [115] presented a model of GPR for estimating the SOC of a lithium-ion battery.

The authors reported three strong superiorities of the GPR method: the ability to approximate nonlinearity accurately, nonparametric modeling, and probabilistic predictions. The experimental results showed that the estimation error was less than 3.9% in different dynamic cycles, temperatures and ageing conditions. Li et al. [96] utilized GPR based on electrochemical impedance spectroscopy (EIS) and the cycle number to predict the SOH of lithium-ion batteries. The effectiveness of the proposed model was verified using publicly available battery datasets. The suggested GPR model achieved an increased accuracy rate if the discharging and cycle number of charging were added as a new feature in addition to the impedance measured by the EIS measurement. Babaeiyazdi et al. [37] used EIS and linear regression model-based GPR to estimate SOC for lithium-ion batteries. The results demonstrated that SOC error was less than 3.8%. Another study by Babaeiyazdi et al. [93] employed GPR using lithium-ion battery degradation profiles. The GPR was compared with RF, in which GPR outperformed RF with an MAE of 0.0204.

GPR helps by precisely estimating battery health and performance, helping to optimize charge and discharge procedures, and accurately modeling and predicting battery behavior. Using GPR in BMS for EVs leads to better assessment of battery deterioration, increased safety by spotting possible faults or anomalies, and more efficiency in managing battery resources. One of GPR's benefits is that it may provide estimates of uncertainty in addition to predictions, which enables better decision-making. GPR can also handle tiny datasets well and provides flexibility in selecting several kernel functions to capture various relationships in the data. But because GPR depends on the full training dataset, it has drawbacks such as higher computing cost for large datasets and trouble scaling to high-dimensional data.

4.1.7. Support Vector Machine (SVM)

SVM is a supervised learning algorithm used for classification and regression tasks. It is primarily utilized for classification problems, where the goal is to separate data points into different classes by finding an optimal decision boundary.

In BMS applications, SVMs have several advantages, including high accuracy in classification and regression tasks, robustness to noise and outliers, adaptability, and efficiency in handling high-dimensional data. Nonetheless, they do have limitations, including computational complexity, sensitivity to parameter adjustment, interpretability issues, and difficulties dealing with unbalanced data. Feng et al. [31] designed an online-based SOH estimation model with a partial charging segment. Two commercial Li-ion batteries were employed to execute training, validation, and testing, and reports indicated SOH with less than 2% error. Jiang et al. [87] applied support vector regression (SVR) and principal component analysis to predict the capacity fade of lithium-ion batteries. The results demonstrated that SVR has better accuracy than GPR, with an R2 score of 0.9194. Hu et al. [28] evaluated the performance and complexity of SOH prediction using the SVM technique under temperature effects, where the authors demonstrated the superiority of SVM over conventional approaches. Patil et al. [116] used a novel multistage SVM approach for prediction of lithium-ion battery RUL, considering voltage and temperature profiles and cycling data under different operational settings. The results indicated faster computations that are potentially suitable for real-time RUL estimation. In another study, Yan [117] presented an SOC estimation technique using the SVM method. In this model, voltage current and temperature were used as the input parameters of the training model, and SOC was considered as the output of this model. The experimental results showed that the maximum relative error was less than 3%, and average relative error was less than 2.5%, which indicated the high accuracy of the SVM model. SVMs may be an effective tool for optimizing battery performance and health when set up and used correctly, but their appropriateness relies on the unique use cases and data properties.

SVM contributes by effectively modeling battery behavior, aiding in predicting battery states, and facilitating fault detection within EV batteries. The outcomes of employing SVM in BMS for EVs include improved efficiency in managing battery resources, enhanced safety by identifying anomalies or potential failures, and accurate estimation of battery degradation. The advantages of SVM lie in its ability to handle high-dimensional data efficiently, effective performance with smaller datasets, and its robustness against overfitting. Additionally, SVM allows for the use of different kernel functions to capture nonlinear relationships within the data. However, SVM can be computationally intensive, especially with larger datasets, and its performance might be impacted by the choice of kernel and the need for appropriate parameter tuning. Despite these challenges, SVM remains a valuable and widely used tool in optimizing BMS for EVs, contributing significantly to their reliability, performance, and overall battery health management.

4.1.8. Reinforcement Learning (RL)

RL is a type of machine learning paradigm in which an agent learns to make sequences of decisions by interacting with an environment in order to achieve a particular goal or maximize a cumulative reward. It is inspired by the way humans and animals learn through trial and error, by taking actions in an environment and learning from the consequences of those actions.

RL can provide dynamic and adaptive control schemes suitable for operating various functionalities of BMS. Heba et al. [41] presented a comprehensive reinforcement learning-based EV charging management system review. In comparison to conventional BPNN and RBFNN approaches, which have shortcomings, including the need for a large amount of training data and real-time feasibility uncertainty, RL has demonstrated considerable advantages such as in energy utilization and extending battery life. Jin et al. [41] conducted a critical survey on EV charging management systems based on RL. Chaoui [49] suggested a resource allocation scheme-based RL framework to develop an energy management scheme for EVs. Multiple energy storage systems were used to validate the proposed approach, achieving SOC equalization across all batteries and extending battery life. The RL approach was used by Gabalawy [67] to optimize EV virtual power plants. The outcomes showed that RL can enhance robustness, shorten convergence times, and enable smart grid VPP optimization. RL reduced the fleet's charging costs by 25% while increasing balancing power by 48% to 82%. Minho et al. [118] presented an RL-based model to estimate SOC for lithium-ion batteries. The authors found that the training accuracy of RL for SOC estimation can increase with large amounts of data. The proposed model was verified by simulation with battery charge/discharge data. RL can optimize battery management under dynamic and uncertain environments, making it well-suited for applications where the optimal strategy may change over time. It can learn from experience and adapt to various battery states and usage patterns, potentially leading to efficient energy utilization and prolonging battery life. The necessity for a large quantity of training data, which can be problematic or expensive in battery management circumstances, is one of RL's drawbacks. It also requires careful design and exploration strategies. Moreover, RL algorithms can be computationally demanding, limiting their real-time feasibility in EV applications. A summary of ML techniques used in BMS is depicted in Table 5.

RL contributes by optimizing charging and discharging strategies, dynamically adapting to varying driving conditions, and maximizing the efficiency of energy usage in EVs. The outcomes of employing RL in BMS for EVs include improved adaptability to diverse driving patterns, enhanced energy management leading to increased range, and the potential for real-time decision-making to optimize battery usage. The advantages of RL in this context involve its ability to learn from interactions with the environment without requiring a labeled dataset, adapt to changing conditions, and find optimal strategies through trial and error. However, challenges with RL in BMS for EVs include the time-consuming training process, complexities in reward design, and the need for careful fine-tuning of hyperparameters. RL's application in BMS for EVs shows promise in revolutionizing energy management strategies, although it currently necessitates further research and development to address its challenges and harness its full potential in enhancing the efficiency and longevity of EV batteries.

Table 5. ML techniques used for advanced BMS applications.

Refs.	ML Method	Target	Key Findings	Advantages	Disadvantages
[117]	SVM	SOC	– Maximum Relative error less than 3%. – Average relative error less than 2.5%.	– High Accuracy – Robustness against noisy data. – Flexibility for non-linear data.	– Computational Intensity. – Difficulties with large data set. – Model complexity and interpretability.
[108]	BPNN	RUL and SOH	– RMSE is 0.78%. – AAE is 1.01%	– Nonlinear Modeling. – Automatically feature Modeling. – Adaptability.	– Complexity and overfitting. – Lengthy training time. – Lack of interpretability.
[110]	RBFNN	SOH	– The average absolute error and route mean square error may be decreased by 0.23% and 0.34%, respectively, using this hybrid model.	– Nonlinearity and function approximation. – Local learning and generalization. – Interpretability.	– Selection of Radial Basis Function. – Limited scalability. – Lack of sequential learning.
[111]	ELM	SOH	– Maximum estimation error is less than 2.5%.	– Fast training. – Simple implementation. – Scalability.	– Limited control over model complexity. – Overfitting in noisy data. – Lack of interpretability.
[112]	RF	SOH and RUL	– The calculated SOH's average inaccuracy is 1.8152%.	– Higher Accuracy – Robustness to noisy data.	– Lack of interpretability. – Overfitting potential. – Expensive memory and computational resources.
[119]	RNN	SOC	– Estimation error is less than 3%.	– Sequential Modeling – Adaptability of varying time intervals – Online based real-time control	– Complexity and training time – Required Huge amount of data. – Lack of Interpretability.
[115]	GPR	SOC	– The estimation error of this model is less than 3.9%.	– Flexible Modeling – Able to predict uncertainty – Interpretability.	– Sensitive to noise. – Computational complexity. – Limited Scalability.
[118]	RL	SOC	The error of estimation depends on the training of RL with a sufficient amount of data.	– Autonomous learning – Generalization of Algorithms – Flexibility and adaptability.	– Required Significant amount of data – Training complexity – Interpretability issues

4.2. Deep Learning

4.2.1. Deep Neural Network (DNN)

DNN is a type of ANN that is composed of multiple layers of interconnected nodes or neurons, typically arranged in an input layer, one or more hidden layers, and an output layer. Chemali et al. [29] used DNN to estimate SOC under diverse EV drive cycles and varying temperature conditions. The DNN obtained an MAE of 1.10% over a dataset at 25 °C after being validated across numerous datasets. Lipu et al. [14] presented a comprehensive review of the methods, implementation issues and prospects of DNN for battery management systems, where the authors clearly demonstrated that DNN is able to achieve precise efficiency estimation of SOC, SOH, and RUL for BMS, which can improve battery reliability, safety and longevity. However, one of the major drawbacks of this model is that it requires a huge amount of data. Zafar et al. [120] presented a three-layer DNN model for estimation of lithium-ion battery SOC. This module used a large dataset of real-world EV batteries with different temperatures. The experimental results showed that MSE and RMSE were 0.1% and 0.3%, respectively. DNN is adaptable and may be used for a variety of BMS activities. However, since large datasets are frequently required, DNN in BMS confronts issues linked to data needs. Due to their complexity, they may experience overfitting and be difficult to design and optimize. Additionally, DNN's lack of interpretability in safety-critical BMS applications might be troublesome. It is crucial to provide resilience across a variety of scenarios in order to preserve safety and dependability.

The outcomes of employing DNNs in BMS for EVs include improved efficiency in managing battery resources, enhanced safety by identifying anomalies or potential failures, and precise estimation of battery degradation. The advantages of DNNs lie in their capability to learn complex patterns from data, handle large datasets efficiently, and offer high prediction accuracy. Additionally, DNNs can automatically extract features, reducing the need for manual feature engineering. However, challenges with DNNs in BMS for EVs involve the need for substantial computational resources during training and the risk of overfitting with complex architectures or insufficient data. Despite these challenges, DNNs remain a pivotal technology in optimizing BMS for EVs, significantly contributing to their reliability, performance, and overall battery health management.

4.2.2. Long Short-Term Memory (LSTM)

LSTM is a type of RNN architecture designed to address the vanishing and exploding gradient problems often encountered in standard RNNs. LSTMs are well-suited for processing and making predictions based on sequential data, such as time series, natural language, speech, and more.

LSTM networks are extremely useful for state estimation, fault detection, and optimization in BMS since they are excellent at precisely simulating and predicting the complicated temporal behavior of batteries. The accuracy of decision-making is increased by their capacity to collect long-term dependencies in battery data, thus enhancing battery performance and longevity. On the other hand, the data appetite of LSTM networks is their primary flaw when it comes to battery management. Effectively training LSTM often requires substantial battery data, which can be difficult and resource-intensive to gather, particularly for certain battery chemistries or uncommon fault circumstances. This need for data may restrict their application in circumstances when there is a dearth of data. Basnet and Ali [60] explored cybersecurity concerns on the 5G platform for EV charging stations based on LSTM. This model had approximately 100% detection accuracy when it came to identifying cyberattacks in the monitoring system. En and Du [80] compared LTSM, SVM, and GPR to predict SOH for lithium-ion batteries. The assessment was carried out using various performance indicators, such as datasets, input features, hyperparameter adjustments, benefits, and drawbacks. Ren et al. [121] proposed a method of SOC estimation using LSTM where the PSO algorithm was employed to optimize the hyperparameters of LSTM. The proposed PSO-based LSTM adaptability was assessed using random noise and EV drive cycles. The outcomes were satisfactory, with an SOC error of 0.5%.

The outcomes of employing LSTMs in BMS for EVs include improved accuracy in predicting battery health, enhanced efficiency in managing battery resources, and the ability to capture long-term dependencies crucial for forecasting battery behavior. The advantages of LSTMs lie in their ability to handle sequential data, mitigate vanishing or exploding gradient problems encountered in traditional recurrent neural networks, and retain memory over extended time intervals. Additionally, LSTMs can learn from and adapt to sequences of variable lengths. However, challenges with LSTMs in BMS for EVs include their increased computational complexity, potential difficulties in interpreting the learned representations due to their complex architecture, and the need for substantial amounts of data for effective training. Despite these challenges, LSTM networks remain a valuable tool in optimizing BMS for EVs, significantly contributing to their reliability, performance, and overall battery health management.

4.2.3. Gated Recurrent Units (GRU)

GRU is a type of RNN architecture, similar to LSTM networks, designed to capture and model dependencies in sequential data. GRUs were introduced as a more computationally efficient alternative to LSTM while retaining similar performance in modeling long-range dependencies.

GRU is a type of RNN architecture that can be employed in BMS for various purposes. Zhang et al. [122] proposed an SOH model based on GRU whose learning rate is enhanced by a sparrow search algorithm to capture the hidden relationship between SOH and input features. The relevant experimental tests were conducted to check the performance and adaptability of the proposed approach using a single battery and a battery pack. Duan et al. [123] suggested an activation function layer-based GRU network that exhibited more consistent and precise SOC prediction performance when compared to LSTM and conventional GRU models. The experimental results demonstrated that the SOC prediction accuracy of the GRU-ATL model was 0.1–0.4% more accurate than that of the conventional GRU model and 0.3–0.7% better than that of the LSTM model when the measurement data contained noise. The RMSE and MAE of the SOC predicted by the GRU-ATL model were both stable in the range of 0.7–1.4% and 1.2–1.9%, respectively. GRU is computationally efficient and ideal for real-time applications in resource-constrained BMS because it requires fewer parameters than LSTM. Although GRUs have advantages in terms of efficiency, they could have trouble capturing the entire complexity of battery activity, which can be very nonlinear. Like other RNNs, they continue to need a sizable quantity of labelled data for training, which might be a drawback in circumstances when data are scarce. GRU may also be difficult to comprehend, similarly to LSTM, which is problematic for safety-critical BMS applications where understanding model choices is essential.

GRUs contribute by effectively modeling temporal dependencies in battery data, enabling precise predictions of battery states, optimizing charging and discharging strategies, and aiding in fault detection within EV batteries. The outcomes of employing GRUs in BMS for EVs include improved accuracy in estimating battery health, enhanced efficiency in managing battery resources, and the capacity to capture long-range dependencies crucial for forecasting battery behavior. The advantages of GRUs lie in their ability to handle sequential data efficiently, similarly to LSTMs, yet with a simpler architecture involving fewer parameters, resulting in faster training times. GRUs also mitigate vanishing gradient problems and demonstrate competitive performance while requiring less computational resources. However, challenges with GRUs in BMS for EVs include potential limitations in capturing long-term dependencies compared to LSTMs and difficulties in interpreting the learned representations due to their abstract nature. Despite these challenges, GRUs remain a valuable and efficient tool in optimizing BMS for EVs, contributing significantly to their reliability, performance, and overall battery health management.

4.2.4. Convolutional Neural Network (CNN)

Convolutional Neural Networks (CNNs or ConvNets) are a class of deep neural networks primarily designed for processing and analyzing structured grid-like data, especially images and videos. They are highly effective in computer vision tasks but have also found applications in areas like natural language processing and speech recognition.

CNNs are a family of deep learning models that are frequently employed in computer vision applications, including image analysis and recognition. Although CNNs are not often linked with BMS, these networks have potential uses in this area, notably when it comes to estimating SOC and SOH and regulating the temperature conditions of batteries in EVs. The successful deployment of CNNs in BMS depends on the data quality and quantity, the neural network's architecture, and the specific requirements of the BMS. Mazzi et al. [57] applied the CNN model to estimate SOC for EV batteries. The performance was compared with GRU. The report indicated that the 1D CNN is more accurate than the GRU-based model, with an RMSE of 2.33% and MAE of 1.62%. A summary of DL methods applied in BMS is depicted in Table 6.

Table 6. DL methods applied for advanced BMS applications.

Refs.	DL Method	Target	Key Findings	Advantages	Disadvantages
[120]	DNN	SOC	Normalized mean square error and root mean square error are 0.1% and 0.3% respectively.	– High Accuracy. – Enhance Fault detection.	– Required huge amount of data – Robustness to environmental variability. – Real-time processing challenge.
[121]	LSTM	SOC	Estimation error 0.5%.	– High Accuracy. – Able to handle irregular samples. – Missing data imputation.	– Required long data training time. – Computational Complexity – Struggle to handle imbalance data
[123]	GRU	SOC	– The mean absolute error between 0.7 – RMSE in between 1.2–1.9%.	– Efficient to train data. – Effective for short to medium sequences. – Ease to implement.	– Limited memory capacity. – Limited use for complex sequence – Hyper parameter sensitivity.
[57]	CNN	SOC	– RMSE 2.33% – MAE 1.62%	– High accuracy. – Better outcomes than GRU under large data features.	– Data requirements. – Complexity – Computational resources. – Real-Time processing.

CNNs contribute by efficiently processing spatial and temporal information from battery sensor data, aiding in accurate state estimation, optimizing charging and discharging strategies, and facilitating fault detection within EV batteries. The outcomes of employing CNNs in BMS for EVs include improved accuracy in predicting battery health, enhanced efficiency in managing battery resources, and the ability to extract and learn hierarchical features crucial for identifying patterns in battery behavior. The advantages of CNNs lie in their ability to automatically extract relevant features from raw sensor data, reducing the need for handcrafted feature engineering, and their effectiveness in handling image-like or multidimensional data. Additionally, CNNs can capture local patterns and exhibit translational invariance, making them well-suited for analyzing spatial and sequential data. However, challenges with CNNs in BMS for EVs involve increased computational complexity, especially with larger and more complex architectures, and potential limitations in interpretability due to their hierarchical nature. Despite these challenges, CNNs remain a powerful and promising tool in optimizing BMS for EVs, significantly contributing to their reliability, performance, and overall battery health management.

4.3. Optimization Algorithms

4.3.1. Genetic Algorithm (GA)

GAs are an optimization and search technique inspired by the processes of natural selection and genetics. They belong to the class of evolutionary algorithms and are used to find approximate solutions to optimization and search problems by mimicking the principles of natural selection, crossover, mutation, and survival of the fittest.

GAs can be employed in BMS for various tasks, including optimization, state estimation, and control. Hu et al. [30] proposed a new method of battery state estimation using GA, where a clustering technique was used to learn the topology of the model. The outcome demonstrates that the estimator beats those created using traditional modeling techniques and displays adequate accuracy. Ma et al. [113] provided a lithium-ion battery SOC calculation model via GA optimization in different research. A BPNN optimized by GA was suggested to mitigate the nonlinear errors induced by Kalman filter (KF) in the process of linearization. The results indicate that the accuracy range of the proposed algorithm is less than 0.0121 in the dynamic stress test (DST) drive cycle, and the maximum error and average error are small. GAs offer significant advantages for BMS by providing versatile optimization and control solutions. GAs can optimize battery charging and discharging strategies, estimate critical battery parameters, and enhance fault detection algorithms, contributing to improved battery performance and longevity. They excel in exploring complex search spaces, making them suitable for multidimensional battery optimization tasks. However, GAs has some challenges, including the need for computationally intensive evaluations, convergence issues, and sensitivity to parameter settings. Careful algorithm design and integration are essential to harnessing the advantages of GAs effectively while addressing their limitations in BMS applications.

GAs contribute by optimizing charging and discharging strategies, identifying optimal configurations for battery systems, and facilitating the efficient allocation of resources within EVs. The outcomes of employing GAs in BMS for EVs include improved efficiency in managing battery resources, enhanced battery lifespan, and the ability to search for solutions within a large and complex solution space. The advantages of GAs lie in their ability to handle nonlinear and complex optimization problems without requiring explicit mathematical formulations, allowing them to find near-optimal solutions in multi-dimensional and non-convex search spaces. Additionally, GAs are robust and flexible in exploring various potential solutions. However, challenges with GAs in BMS for EVs involve the computational burden, especially with larger search spaces, and the potential for premature convergence or suboptimal solutions based on parameter settings. Despite these challenges, GAs remain a valuable tool in optimizing BMS for EVs, contributing significantly to their reliability, performance, and overall battery health management.

4.3.2. Particle Swarm Optimization (PSO)

PSO is a population-based metaheuristic optimization technique inspired by the social behavior of bird flocking or fish schooling. It is used to find optimal solutions to optimization problems by simulating the movement and interaction of individuals (particles) within a multidimensional search space.

PSO has been widely employed in BMS applications. Li et al. [124] proposed a model for online SOC and SOH estimation for lithium-ion batteries using PSO. PSO was utilized to enhance the SVM's kernel operation. The tests such as the DST demonstrated high flexibility and viability. Lipu et al. [125] developed a PSO-based nonlinear autoregressive network with exogenous inputs (NARX) model for SOC estimation of lithium-ion batteries. The robustness of this model was analyzed at three different temperatures under diverse EV drive cycles. The results indicated that the proposed model has higher estimation speed and achieves higher accuracy by reducing RMSE and MAE by 53% and 50% compared to a single NARX algorithm. PSO presents advantages in BMS by efficiently optimizing charging and discharging strategies, estimating battery parameters, and handling multi-objective trade-offs. However, PSO may struggle with noisy sensor data, convergence to suboptimal solutions, and sensitivity to parameter tuning. Proper noise handling, diversity maintenance, and constraint management are vital when applying PSO to BMS, as these challenges can affect its effectiveness in optimizing battery performance and lifespan while ensuring safety and efficiency.

PSO contributes by optimizing charging and discharging strategies, identifying optimal parameters for battery management, and facilitating efficient energy utilization within EVs. The outcomes of employing PSO in BMS for EVs include improved efficiency in managing battery resources, enhanced battery lifespan, and the ability to explore and exploit solutions in a diverse search space. The advantages of PSO lie in its simplicity, ease of implementation, and ability to efficiently search for solutions in high-dimensional spaces without relying on gradient information. Additionally, PSO can handle non-linear and non-convex optimization problems effectively. However, challenges with PSO in BMS for EVs include the potential for premature convergence to suboptimal solutions, sensitivity to parameter settings, and limitations in handling complex optimization landscapes. Despite these challenges, PSO remains a valuable optimization technique in optimizing BMS for EVs, contributing significantly to their reliability, performance, and overall battery health management.

4.3.3. Lightning Search Algorithm (LSA)

LSA is a meta-heuristic method that takes inspiration from the lightning phenomena. Hannan et al. [34] proposed an SOC estimation model using the LSA optimization technique for lithium-ion batteries. The results reported that the method outperformed several state-of-the-art methods in terms of accuracy, flexibility, and resilience under various operating situations. LSA has the advantage of quickly converging to optimal or nearly optimal solutions, which makes it particularly useful for issues where achieving quick solutions is crucial. It performs consistently across a range of optimization tasks and effectively manages high-dimensional search areas. Nevertheless, LSA has some limitations, particularly in complicated, multimodal issues. Furthermore, LSA's exploration–exploitation balance might not be as well-balanced.

4.3.4. Whale Optimization Algorithm (WOA)

The social behavior of humpback whales serves as the basis for the relatively new WOA that draws inspiration from nature. It is used to solve a variety of optimization issues in an optimum or nearly optimal manner. Wu et al. [126] proposed a model of SOC estimation where the authors used WOA to determine the optimal battery parameters, leading to enhanced estimation accuracy. The Whale Optimization Algorithm offers both advantages and disadvantages. WOA is known for its simplicity and ease of implementation. It effectively balances exploration and exploitation, making it suitable for a wide range of optimization problems. WOA can handle both continuous and discrete optimization problems and is less likely to get stuck in local optima due to its exploration strategy, making it robust in finding global optima. It also has a low number of control parameters, reducing the need for extensive tuning. However, WOA has some drawbacks, such as sensitivity to the choice of certain parameters, which can affect its performance. It may not always outperform other state-of-the-art optimization algorithms, especially in complex and high-dimensional problems. Additionally, the convergence speed of WOA can be slower in some cases compared to more sophisticated algorithms. Overall, the effectiveness of the Whale Optimization Algorithm depends on the specific problem at hand and the careful selection of its parameters. The different optimization approaches used by BMS are presented in Table 7.

Table 7. Optimization approaches used for advanced BMS applications.

Refs.	Optimization Technique	Target	Advantage	Disadvantage
[30]	GA	SOC, SOH	– Effective at global optimization. – Robustness to the noisy data. – Versatility.	– Computational. -Complexity. – Difficulty in handling constraints.
[28]	PSO	SOC, SOH	– Multi objective optimization. – Interpretable results. – Adaptability.	– Parameter sensitivity. – Struggle to handle noisy data. – Limited multimodal search.
[34]	LSA	SOC	– Adaptability. – Interpretability. – Robustness.	– Tuning complexity. – Low convergence speed. – Parameter dependency.
[126]	WOA	SOH	– Potential for novel solution. – Parallel processing. – Balance exploration.	– Lack of widespread adaptation. – Complex implementation. – Limited extensive research.

4.4. Rules-Based Approaches

4.4.1. Fuzzy Neural Network (FNN)

An FNN is a hybrid computational model that combines elements of fuzzy logic and neural networks. It merges the learning capabilities of neural networks with the reasoning and decision-making abilities of fuzzy logic, aiming to address complex problems that involve uncertainty, imprecision, and incomplete information.

Fuzzy neural networks, which combine fuzzy logic and artificial neural networks, offer several advantages and disadvantages. They excel at handling uncertain and imprecise data, making them suitable for applications in fields like pattern recognition, control systems, and decision support. Fuzzy neural networks can capture complex relationships in data and adapt their models over time, enabling them to handle non-linear and dynamic systems effectively. Additionally, they can integrate human-like reasoning, allowing for more interpretable and explainable results, which is crucial in applications where transparency is essential. However, there are also downsides to fuzzy neural networks. They can be computationally intensive, requiring significant computational resources for training and inference. Tuning the fuzzy membership functions and neural network parameters can be challenging, making them less straightforward to implement than conventional machine learning approaches. Furthermore, their interpretability might diminish due to the increase in the model complexity, making it difficult to understand the reasoning behind their decisions in highly complex systems. Fuzzy Neural Networks are a strong hybrid model that incorporates aspects of fuzzy logic with neural networks. Zahid et al. [33] designed an SOC estimation model utilizing a subtractive clustering-based neuro-fuzzy system. The proposed model was simulated using an advanced car simulator. Current temperature, real power loss, available and requested power, cooling air temperature, and battery thermal factor were the input factors to model to calculate SOC. The training and testing verification were conducted using 10 distinct EV drive cycles. According to experimental findings, the suggested model performs better than BPNN and ELM.

4.4.2. Fuzzy C-Mean (FCM)

FCM is a clustering algorithm that extends the traditional K-Means clustering method to handle fuzzy or soft clustering, where data points can belong to multiple clusters with varying degrees of membership. It is a popular technique used for partitioning data into clusters based on similarity.

Hu et al. [30] presented a genetic algorithm-based fuzzy C-means clustering technique. The clustering outcome is used to determine the model parameters and topology. Then, the recursive least-squares approach is used to extract the parameters. The backpropagation learning method is eventually used to optimize the previous data and consequent sections to provide excellent accuracy and robustness. Results from experiments show that the suggested technique performed better than those created using traditional fuzzy modeling techniques in terms of accuracy.

5. Open Issues and Limitations

5.1. Algorithms and Method Issues

One of the important difficulties in developing a BMS is selecting the structure for AI approaches. Many different hyperparameters, such as weights, biases, hidden layers, hidden neurons, time steps, batch sizes, learning rates, etc., are frequently used to frame complicated AI algorithms. Using the best hyperparameters, training algorithms and activation functions can reduce the computational complexity of overfitting and underfitting issues. Additionally, using hit-and-trial procedures to find suitable parameters requires more time and human expertise. Thus, a precise and reliable framework needs to be established in order for hyperparameter adjustment to deliver the advanced BMS outcomes.

5.2. Data Abundance and Variety

The diversity and availability of data are the biggest obstacles to the practical use of AI algorithms. Having enough data of high enough quality is necessary for AI algorithms to work accurately. However, it requires time and effort to compile a substantial volume of diverse, large-scale data. Typically, trials with a 1 Hz sample frequency are used to collect data. The data duration between EV driving cycles varies with different voltage and current levels [127]. For instance, one EV drive cycle is predicted to take 1372 s, 360 s, 916 s, and 600 s, respectively, by the federal urban driving schedule (FUDS), dynamic stress test (DST), Beijing dynamic stress test (BJDST), and US06 drive cycle [128]. Since efficient algorithms require a sizable data set for training purposes, several EV driving cycle repeats are required to prepare data [129]. Better outcomes may be achieved with more data, but this can also slow down the computer's learning process and make it work harder, which may result in overfitting problems [130]. As a result, issues with data quantity and diversity require special attention.

5.3. Optimization Technique Integration

Different AI methods may be combined with a variety of optimization techniques, but the results vary in terms of execution time and convergence speed. Generally, it takes a lot of time and effort to integrate optimization techniques into AI methods. Additionally, initializing parameters and running the operational loop require in-depth expertise when creating an optimization framework. Although the integration of optimization techniques with an AI algorithm has substantially improved the accuracy, prediction efficiency, and durability of BMS, there are still a number of issues with complex calculations and prolonged processing times. Predictions may be incorrect due to poor searching capabilities and parameter selections. Therefore, further research works are needed to address integration concerns with optimization.

5.4. Data Integrity

Data integrity is another barrier to applying AI strategies in practical situations. A top-notch battery dataset has been created by a few well-known automotive research teams and is openly available to the public [131]. The charge/discharge current pattern in this dataset is stable and guarantees the different EV driving cycle methods. Studies are carried out in a lab environment with the recommended temperature and charge/discharge current rates to collect data on the various EV drive cycles. The simulation-derived current and voltage profiles of EV driving cycles do not match the data that were actually collected in the field. Therefore, further study is needed to validate intelligent algorithms in practical settings.

5.5. Battery Material Concerns

Although lithium-ion batteries exhibit remarkable qualities, the positive and negative electrode operational differences significantly impact SOC estimates. Lithium cobalt oxide (LCO) is rare, costly and has a limited capacity. The lithium nickel manganese cobalt oxide (LNMC) and lithium nickel cobalt aluminum oxide (LNCA) batteries perform satisfactorily in terms of high capacity and extended lifespan; however, there is a scarcity of nickel and cobalt resources. Although lithium manganese oxide (LMO) batteries have a high voltage and adequate sources of manganese exist, they have a constrained capacity and an extended lifespan [132,133]. Lithium titanate (LTO) and lithium iron phosphate ($LiFePO_4$) are two different lithium-ion battery chemistries that were used in [124] to test the precision of the SOC assessment technique. Validation was carried by using a test bench platform and an ageing cycle test. First, experiments were conducted with fresh lithium-ion battery cells. When compared to LTO, a $LiFePO_4$ battery had better accuracy, with an RMSE of 0.5305% at 25 °C. The LTO battery, however, performed well in the ageing cycle test, with an estimated RMSE of 0.00334% after 1000 age cycles.

5.6. Hardware Development and Real-Time Implementation

The use of AI techniques in real-time BMS with low memory storage and processing costs has not received significant investigation. Thus, in-depth examination is mandatory to create an embedded prototype system for real-time BMS operation and management. Research in [6] used the hardware-in-the-loop (HIL) experimental platform to evaluate the real-time machine learning-based SOC estimation technique. The HIL test bench was built using a DC supply, current sensor, battery monitoring device, host computer, battery management unit, and CAN analyzer. The findings indicated that the SOC estimation error and capacity faults were 2% and 19.7%, respectively. The adaptive network-based fuzzy inference system (ANFIS)-based SOC estimation was tested in real-time utilizing the HIL experiment setup [130]. The HIL outcomes showed that the optional model is suitable for real-time EV applications because they were quite comparable to the simulated results.

5.7. IoT Integration and Cloud Computing Technology

The accuracy and robustness of AI algorithms and controllers of BMSs in real-world situations may be greatly enhanced by cloud storage, cloud computing, and big data platforms. Big data technology allows combining intelligent methods with massive memory devices, processing, and analysis. The valuation of the battery states such as SOC, SOH an d RUL, thermal runway, and fault identification may be tracked and stored in the cloud throughout the battery's lifespan. The battery monitoring and control center will then pre-process the data, carry out the investigation, and offer valuable recommendations for future improvement. Nonetheless, integration of the Internet of Things (IoT) and cloud computing has several concerns, including security and privacy, interoperability, scalability, data management, standards and protocols, and regulatory and legal issues. Hence, extensive study is necessary to address the aforesaid problems.

5.8. Thermal Management of EV Batteries

Battery thermal management systems are integral for maintaining optimal operating conditions, ensuring safety, and extending the lifespan of batteries. ML techniques have emerged as valuable tools in enhancing battery thermal management strategies. ML algorithms can process a myriad of data inputs such as ambient temperature, current, voltage, and internal battery temperature to predict and optimize the thermal behavior of batteries. By analyzing historical thermal data and correlating it with battery performance and degradation patterns, ML models can predict heat generation, manage thermal runaway risks, and optimize cooling or heating strategies in real time. These models can adapt to varying operating conditions and usage patterns, enabling proactive thermal management interventions to maintain the battery within a safe and efficient temperature range. Pagani et al. [134] provided an overview of many research projects that aim to employ ML approaches for power and thermal control on single-core and multicore CPUs. Conventional approaches to power and thermal management depend on information about the workloads and applications to be performed (such as average and transient power consumption) as well as some a priori understanding about the chip's thermal model. A thorough examination of all of the experimental and numerical studies was carried out on several battery thermal management system (BTMS) procedures for electric and hybrid cars, where Tete et al. [135] addressed battery cooling systems with air, liquid, phase-change material, heat pipe, and refrigeration cooling methods. A thorough overview was conducted of the major discoveries and results of the current experimental, simulation, and modelling work on BTMS. In addition, this research presented a comprehensive review of hybrid battery cooling systems. Wang and Du provided a detailed summary and categorization of the battery cooling and preheating system research progress based on heat transfer media [136]. Numerous factors were taken into consideration while evaluating different thermal management systems, such as the cost of manufacturing and maintenance, the simplicity of the system, the effectiveness of the heating or cooling process, internal temperature gradients, safety, and flexibility. ML-driven thermal management not only ensures better battery performance but also helps in extending battery life by mitigating thermal stress, thus making it a promising approach for the efficient operation of diverse battery systems across different applications. Nevertheless, several issues and challenges affect the performance of EVs, such as temperature control, heat generation, uniform thermal distribution, cooling and heating systems, energy consumption, fast charging and high power outputs.

6. Future Research Opportunities

This section provides several effective, insightful recommendations for the advancement of BMS in EV applications.

- The key to the transportation sector's long-term, sustainable growth is the development of smart BMS technology, particularly for EVs. However, there are a number of problems with BMS in EV applications, including inefficient BMS operations, long charging times, high starting prices, and limited battery life. More research is required in order to develop accurate BMS technology that can provide better control mechanisms, advantageous market policies, global cooperation, and sustainable development for improved EV performance.
- To operate BMS accurately, it is essential to suitably estimate various battery states, such as SOC, SOH, and RUL. Problems with overheating, overcharging, and over-discharging would result from an incorrect SOC prediction. Additionally, incorrect predictions of a battery's SOH and RUL would force users to either replace the battery before it explicitly fails or wait until it does, which would raise the capital cost. Therefore, more research activities involving DL algorithms should be implemented to increase the accuracy, robustness, and reliability of BMS in EV applications. In order to maximize operational effectiveness and reduce BMS computational complexity,

multi-scale and co-estimations can be used to improve the estimation of battery SOC, SOH, and RUL.
- In order to guarantee the secure and effective operation of BMS in EVs, it is crucial to use the appropriate controller approaches for battery temperature control, fault diagnosis and charge equalization. Battery inconsistency issues can be caused by a variety of factors, such as battery ageing and temperature variation, by altering internal properties such as internal resistance and capacitance. Identification of faults is essential to preventing issues like thermal runway, battery swelling, short circuits, overheating, electrolyte leakage, and over-discharge. Therefore, it is essential to employ resilience controller techniques to ensure the secure and dependable operation of BMS in EV applications.
- It has been proven that using AI algorithms, when combined with BMSs, yields better results than relying solely on non-hybrid algorithms. However, AI integrated with an optimization model might necessitate difficult mathematical calculations, powerful processing, and human expertise, all of which could produce unfavorable results. Therefore, future research should cover practicality issues to develop an effective hybrid model for BMSs.
- Proper disposal and recycling of lithium-ion batteries are crucial for environmental sustainability. Research is currently underway to create new battery chemistries that are more sustainable and environmentally friendly, in addition to reusing and recycling batteries. For instance, some companies are investigating the use of sodium-ion batteries, which use a more plentiful and less hazardous substance than lithium. Overall, a holistic approach to sustainability that considers the entire life cycle of batteries, from manufacturing to disposal, is necessary for achieving the Sustainable Development Goals (SDGs).
- To verify AI algorithms, experimental tests have often been used. However, AI algorithm execution with minimal resource and memory usage has not yet been accomplished. Therefore, additional study is needed to develop a better battery testing system and set up an embedded prototyping system or hardware-in-the-loop system to implement, manage, and assess real-time algorithms in BMS.
- The effectiveness of AI algorithm-based BMS can be significantly increased by combining big data platforms and cloud-based technologies. Voltage, current, temperature, and other measurements obtained from EVs in real time may be used to assess the performance and precision of the AI algorithms. For examining the estimated battery health condition and performance over time, real-time monitoring is essential for collecting information, which is subsequently preserved in a cloud-based database. With this knowledge, various actions could be taken to improve the battery system's performance in the future, such as data extraction, data analysis, and future prediction. Therefore, big data, cloud-based technologies, and real-time monitoring could significantly increase BMS effectiveness.

BMSs in EVs present a spectrum of potential areas for exploration and development. One significant avenue is the enhancement of BMS algorithms to optimize battery performance, ensuring efficient energy utilization and prolonged battery life. Exploring advanced predictive analytics could aid in accurately forecasting battery degradation, facilitating proactive maintenance schedules. Additionally, there is a need to delve deeper into cybersecurity measures to safeguard BMS against potential cyber threats, ensuring the integrity and safety of the vehicle's power system. Further research into BMS hardware design, such as the development of innovative sensors and controllers, could lead to more precise monitoring and control of the battery, consequently improving overall EV performance. Comprehensive exploration in these areas holds the promise of revolutionizing EV technology, fostering increased reliability, safety, and longevity, ultimately accelerating the widespread adoption of electric vehicles while advancing the sustainability goals of the automotive industry.

7. Conclusions

This study offers a thorough analysis of the statistical evaluation of BMS for EV-based AI technology, encompassing a range of AI methods, results, problems, and potential future prospects for advancement. Accordingly, the study used 78 relevant publications published between 2014 and 2023 in the Scopus database to thoroughly review advanced BMS technology in EV applications. The analysis included current trends in publication, citation analysis, examination of keywords, publication trends, research categories, influential authors, networking, and collaboration. Furthermore, the report covered important approaches and algorithms found in highly influential literature and outlined key findings, contributions, advantages, and disadvantages. The study concluded with recommendations for future research and development in the field.

The statistical analysis of the 78 appropriate publications will provide guidelines and suggestions for academicians, researchers, and engineers for potential research collaboration around the world. In addition, this statistical investigation will enable potential reviewers, journal editors and other prominent scholars to evaluate the contributions and knowledge gaps of the 78 influential papers. Moreover, the statistical study can help policymakers and public/private officials create an effective long-term plan and policy for meeting global decarbonization targets by 2050. The key finding of this study are:

- Scope of Analysis: Evaluation of 78 relevant publications from 2014 to 2023 in the Scopus database, providing a comprehensive overview of advanced BMS technology in EV applications.
- Comprehensive Examination: Analysis encompassed diverse facets such as publication trends, citation analysis, keywords, research categories, influential authors, networking, and collaboration, offering a holistic understanding of the field.
- In-depth Coverage of the Literature: Exploration of influential literature highlighted important approaches, algorithms, key findings, contributions, and associated advantages and disadvantages related to BMS in EVs.
- Guidelines for Collaboration: Statistical analysis poised to offer guidelines and suggestions for global research collaboration among academicians, researchers, and engineers in the realm of BMS for EVs.
- Evaluation Tool for Influential Papers: Provides a framework for potential reviewers, journal editors, and prominent scholars to assess contributions and identify knowledge gaps within the 78 influential publications.
- Contribution to Policy-making: Potential to aid policymakers and public/private officials in formulating effective long-term plans and policies aligned with global decarbonization targets by 2050 through the insights derived from the statistical study.
- Support for Sustainable BMS Management: Anticipated support for sustainable BMS management in EVs, leading to extended battery lifecycles, improved EV performance, and alignment with SDGs related to clean energy, employment opportunities, sustainable cities, and emission reduction.

In conclusion, the statistical examination is anticipated to support the sustainable management of BMS in EVs. Therefore, further research into advanced BMS will extend battery lifecycles and enhance EV performance, paving the way for the achievement of the SDGs for SDG 7: clean energy, SDG 8: employment opportunities and economic development, SDG 11: sustainable cities, and SDG 13: emission reduction.

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Abbreviations

AAE	Average Absolute Error
AI	Artificial intelligence
ANFIS	Adaptive Network-Based Fuzzy Inference System
ANN	Artificial Neural Network
BES	Battery Energy Storage
BJDST	Beijing Dynamic Stress Test
BMS	Battery Management System
BPNN	Backpropagation Neural Networks
BTMS	Battery Thermal Management System
CNN	Convolution Neural Network
DER	Distributed Energy Resources
DL	Deep Learning
DNN	Deep Neural Network
DSM	Demand Side Management
DST	Dynamic Stress Test
EIS	Electrochemical Impedance Spectroscopy
ELM	Extreme Learning Machines
EMS	Energy Management System
EOL	End of Life
ESS	Energy Storage System
EV	Electric Vehicle
FBG	Fiber Bragg Grating
FCM	Fuzzy C-Mean
FESS	Flywheel Energy Storage System
FNN	Feedforward Neural Network
FNN	Fuzzy Neural Network
FUDS	Federal Urban Driving Schedule
GA	Genetic Algorithm
GHG	Greenhouse Gas
GPR	Gaussian Process Regression
GRU	Gated Recurrent Unit
HESS	Hybrid Energy Storage System
HIL	Hardware-in-the-loop
IoT	Internet of Things
KF	Kalman Filter
LA	Lead Acid
LCO	Lithium Cobalt Oxide
LFP	Lithium Iron Phosphate
LIB	Lithium-ion Battery
LMO	Lithium Manganese Oxide
LNCA	Lithium Nickel Cobalt Aluminum Oxide
LSA	Lightning Search Algorithm
LSTM	Long Short Term Memory
LTO	Lithium Titanate
MAE	Mean Absolute Error
ML	Machine Learning

NARX	Nonlinear Autoregressive Network With Exogenous Inputs
PCA	Principle Component Analysis
PHEV	Plug in Hybrid Electric Vehicle
PSO	Particle Swarm Optimization
RBFNN	Radial Basis Function Neural Network
RF	Random Forest
RL	Reinforcement Learning
RMSE	Root Mean Squared Error
RNN	Recurrent Neural Network
RUL	Remaining Useful Life
SDG	Sustainable Development Goal
SOC	State of Charge
SOH	State of Health
SVM	Support Vector Machine
SVR	Support Vector Regression
V2G	Vehicle to Grid
WOA	Whale Optimization Algorithm

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