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Review article

Scientometric research and critical analysis of battery state-of-charge estimation

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ABSTRACT

With the advent of lithium-ion batteries (LIBs) and electric vehicle (EV) technology, the research on the battery State-of-Charge (*SoC*) estimation has begun to rise and develop rapidly. In order to objectively understand the current research status and development trends in the field of battery *SoC* estimation, this work uses an advanced search method to analyse the literature in the field of battery *SoC* estimation from 2004 to 2020 in the Web of Science (WoS) database. We employed bibliometrics analysis methods to make statistics on the publication year, the number of publications, discipline distribution, journal distribution, research institutions, application fields, test methods, analysis theories, and influencing factors in the field of battery *SoC* estimation. With using the Citespace software, a total of 2946 relevant research literature in the field of battery *SoC* estimation are analyzed. The research results show that the publication of relevant research documents keeps increasing from 2004 to 2020 in the field of battery *SoC* estimation. The research topics focus on battery model, management system, LIB, and EV. The research contents mainly involve Kalman filtering, wavelet neural network, impedance, and model predictive control. The main research approaches include model simulation, charging and discharging data recording, algorithm improvement, and environmental test. The research direction is shown to be more and more closely related to computer science and even artificial intelligence (AI). Intelligence, visualization, and multi-method collaboration are the future research trends of battery *SoC* estimation.

1. Introduction

The environmental pollution caused by traditional energy is becoming more and more serious, accompanied by the issue of energy crisis [1]. Many countries have developed novel energy technologies to slow down global warming [1]. Battery technology has developed rapidly because of the capability of reducing carbon dioxide (CO_2) emission to a certain extent [2–7]. The State-of-Charge (*SoC*) of the battery is an important indicator in the process of battery use [8–10]. It is essential to ensure the reasonable energy distribution and safety of the battery [11–13]. Therefore, the research on the *SoC* estimation of battery is significant for the long-term effective battery operation and the prevention of catastrophic accidents [14–18]. The accurate estimation of *SoC* is important for battery safety [19,20]. As an essential index of the performance, the battery *SoC* estimation is defined as the available state of the charge remaining in the battery [8–10].

The battery *SoC* estimation has become a new research hotspot and continued to develop rapidly since 2004 [21,22]. The applications and expansion based on the battery *SoC* estimation are diverse and complex [6,23–26]. However, few existing publications show a detailed analysis of the current research status of battery *SoC* estimation from the year 2004 to 2020. Therefore, scientometric research is needed to analyse the

Abbreviations: AEKF, Adaptive extended Kalman filter; AKF, Adaptive Kalman filter; ANN, Artificial neural network; ANFIS, Adaptive neuro-fuzzy inference system; BECM, Battery equivalent circuit model; BMS, Battery managemenet system; CATC, China automotive test cycle; EKF, Extended Kalman filtering; EV, Electric vehicle; FFRLS, Forgetting factor recursive least square; HEV, Hybrid-electric-vehicle; LIB, Lithium-ion battery; LLR, Log-likelihood rate; OCV, Open-circuit-voltage; NEDC, New European driving cycle; PNGV, Partnership for a new generation of vehicles; RBFNN, Radial basis function neural network; RC, Resistance-capacitance; RSMO, Robust sliding mode observer; SEI, Solid electrolyte interphase; SMO, Sliding mode observer; SoC, State-of-Charge; SoH, State-of-Health; UDDS, Urban dynamometer driving schedule; WoS, Web of Science.

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trend and state-of-the-art research work on the battery *SoC* estimation.

Chang W.Y. concluded four categories of mathematical methods for *SoC* estimation, which focused on summarizing and explaining the mathematical principles but ignored the influence of the battery model and environment [27]. Zhou et al. summarized the battery models and research progress of *SoC* estimation in which different *SoC* estimation methods were distinguished based on the battery model. Wang et al. introduced the details of battery model and *SoC* estimation method, while Po et al. gave a more unique summary on commercial *SoC* estimation systems [15,28,29]. These papers intensively investigate the battery models for *SoC* estimation, however, various *SoC* algorithms and battery research are not comprehensively covered but focused too much on the role of *SoC* estimation in battery management system (BMS). Xiong et al. comprehensively described the *SoC* estimation methods and the classification of battery models especially on the inconsistency issue in battery packs and the approaches to resolve the problem [30]. The lack of scientific statistical methods could lead to more subjective conclusions, which may miss emerging research hotspots due to the huge amount of literature. Meng et al. provided a review and classification of methods for online *SoC* estimation only, but no comprehensive and systematic approach on *SoC* offline estimation [31]. Muhammad et al. mainly explained the working principle of lithium-ion battery (LIB) and the estimation algorithm of *SoC*, Rivera-Barrera et al. introduced the strengths and weaknesses of *SoC* estimation methods for online BMS, while Hannan et al. systematically evaluated different *SoC* estimation methods [29,32,33]. Hu et al. made a systematic analysis of state-of-the-art estimations for the first time but did not mention the *SoC* estimation method [34]. How et al. uniquely reviewed the strengths and weaknesses of *SoC* estimation from the model-based and data-driven perspectives [35], but the *SoC* algorithms were not well presented. Espedal et al. mainly described the challenges of modeling and *SoC* estimation caused by internal changes in LIBs [36]. Nevertheless, most aforementioned work only focused on the LIBs. Adaikkappa et al. presented various battery models and their corresponding characteristics, but the summary of the *SoC* estimation algorithm is not detailed enough [37]. Cui et al. reviewed the methods on the neural network estimation of *SoC* [38].

For the research on the battery *SoC* estimation, reviewing the research progress and the status of *SoC* estimation by counting all the literature to analyse the characteristics still needs the scientific approach to achieve. The scientific statistics on the literature in the field of *SoC* estimation is employed for the first time in this paper, and the relevant content such as literature keywords and subject distribution are used for realizing the development summary and trend prediction of *SoC* estimation. Compared with the reviews published in the past, the present work achieves much rigorous and objective summary and accurate predictions for battery *SoC* estimation, and cover the application fields and descriptions of *SoC* estimation in a much comprehensive way through scientometric research and critical analysis.

The reported work involved in this paper are scientific journals and conference articles of battery *SoC* estimation in the academic database Web of Science (WoS) from the year 2004 to 2020. The present work uses Citespace software to perform statistical analysis on trends in academic journals, discipline distribution, journal distribution, research institution distribution, and research methods. It aims to review the publications that show the detailed analysis of battery *SoC* estimation research and provide research hotspots and development trends for researchers in the field of battery *SoC* estimation, which could provide a detailed and comprehensive understanding on the current research status of battery *SoC* estimation.

The review is organized into the following parts: Section 2 describes the methodology. Section 3 mainly analyzes core journals and conferences from WoS, dominant source countries and organizations, core authors, and keywords by Citespace. Section 4 analyzes the experimental methods and battery models used for *SoC* estimation research from the year 2004 to 2020. Section 5 derives the research content of battery *SoC* estimation based on the research objectives and technologies. The last Section summarizes the analytical results.

2. Research methodology

WoS is applied as the database in this work according to the authoritative and high-impact academic journals. The strategy of searching and analyzing relevant documents is critical due to multitudinous academic publications on the battery *SoC* estimation. To ensure the quality of the searched literature and quick visualization, the search conditions were set as peer-reviewed English-language journals and conferences. The frame of the present work is shown in Fig. 1, in which Citespace was employed to analyse the reported work from WoS.

3. Scientometric analysis

3.1. Yearly quantitative analysis of academic publications

2946 academic publications including journal articles and conference proceedings on battery *SoC* estimation from the year 2004 to 2020 are analyzed as shown in Fig. 2.

The result shows that the number of academic publications in battery *SoC* estimation has been steadily growing from 2004 to 2020, reflecting the genuine continuous need in the community. There are three main explode years of academic publications with an increment of 52.63 %, 51.78 % and 78.82 % in 2008, 2012 and 2013, respectively. The launching of the world's first mass-produced plug-in hybrid vehicle based on lithium iron phosphate batteries in 2008 drove the development of *SoC* technologies. In 2012 and 2013, the successful commercialization of LIBs led to an increase in demand for battery *SoC* estimation. Since then, Kalman filter and neural network algorithms have started to be much widely applied to *SoC* estimation.

3.2. Leading journals and conference proceedings

The leading journals and conference proceedings could give a rapid understanding of the domain research. Table 1 and Table 2 show the leading journals and conference proceedings on the *SoC* estimation aspect from 2004 to 2021, respectively. The top three journals are JOURNAL OF POWER SOURCES, ENERGIES, and APPLIED ENERGY, while the top three conference proceedings are IEEE INDUSTRIAL ELECTRONICS SOCIETY, PROCEEDINGS OF THE AMERICAN CONTROL CONFERENCE, and ENERGY PROCEDIA. The results show that the publications of the battery *SoC* estimation research were mostly related to the power, energy, and control system. The lack of research content in this subsection will be supplemented later by keyword analysis.

3.3. Timeline

In the long history of battery *SoC* estimation, many scientists and researchers have contributed to the development of methods, models and algorithms. Some parts with important contributions to *SoC* estimation are described as follows.

In 1992, Aylor et al. introduced a lead-acid battery *SoC* indicator on electric wheelchairs, which combined the Open-Circuit-Voltage (OCV) method and the coulometric technique [13]. The study pointed out the direction in which *SoC* is needed to integrate into the battery monitoring system as a core part.

In 2001, Pang et al. proposed the lead-acid *SoC* estimation algorithm based on an accurate battery model, minimizing undesired errors in *SoC* estimation when the current changes [11]. Besides, the estimation method for battery internal parameters was described in detail [11]. This was the first comprehensive introduction to the combination of model estimation and battery *SoC* algorithm.

In 2003, Cai et al. proposed to integrate the artificial neural network

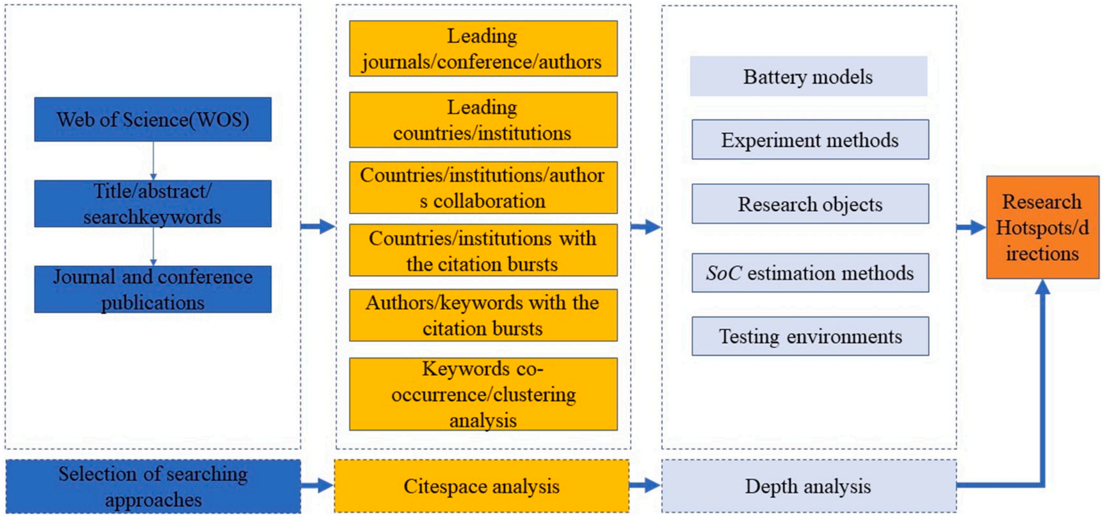

Fig. 1. Research approach for the battery *SoC* estimation.

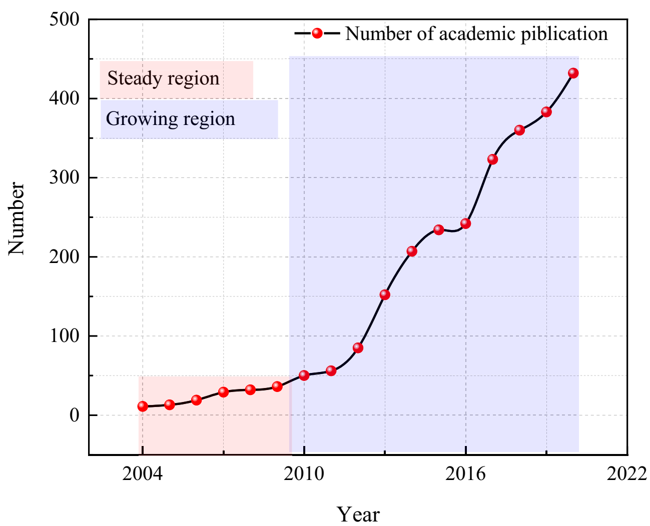

Fig. 2. Variation of number of publication in battery *SoC* estimation from 2004 to 2020.

(ANN) and the fuzzy logic for the first time, presenting an adaptive neuro-fuzzy inference system (ANFIS) model to estimate the *SoC* of a high-power Ni-MH rechargeable battery. The study showed that the results were better than those acquired using the ANN when interpolating [39].

In 2004, Plett et al. introduced that extended Kalman filtering (EKF) could fill the algorithmic requirements of a BMS for a hybrid-electric-vehicle (HEV) [40,41]. The principle of EKF for state and parameter estimations was interpreted and verified [40,41].

In 2005, Plett et al. also proposed the dual and joint EKF for estimating *SoC* and State-of-Health (*SoH*) simultaneously, which proved that the capacity estimation can be well achieved by the dual EKF method [42].

In 2008, Lee et al. combined the dual EKF with the modified OCV method for *SoC* and capacity estimations for the first time, which overcame the variations in the conventional OCV method [10].

In 2009, Han et al. proposed an adaptive Kalman filter (AKF) for the *SoC* estimation of lead-acid batteries, which could reduce the *SoC* estimation error compared the EKF method [43]. Then, Wang et al. proved that the AEKF for *SoC* estimation of a Ni/MH battery pack was effective, which could correct the initial *SoC* value by Ampere-hour (Ah) method and avoid filtering divergence [44].

In 2010, Hu et al. proposed an adaptive Luenberger observer for *SoC* estimation of a lithium-ion battery pack for EVs, which could converge the *SoC* estimation error into a favorable range such as within 2.5 % [45].

In 2011, He et al. proposed an adaptive extended Kalman filter (AEKF) based on an improved Thevenin model for battery *SoC* estimation. The proposed method reduced the maximum *SoC* estimation error from 14.96 % to 2.54 %, and the mean *SoC* estimation error from 3.19 % to 1.06 % [46].

In 2012, Dai et al. proposed a dual time-scale Kalman filtering algorithm to estimate the *SoC* of each cell of lithium-ion battery packs in a series-connected battery system, which could perform well even without the requirements of large-memory and high-quality CPU for the BMS [47].

In 2013, He et al. applied an unscented particle filter to the new working model for *SoC* estimation of LIBs, which provided better robustness with the considerations of temperature, charge-discharge rate, and running mileage [48].

In 2014, Kang et al. proposed a new model based on the radial basis function neural network (RBFNN) and cycle life model to estimate the *SoC* of an 6-Ah LIB, which controlled the mean absolute error (MAE) of *SoC* estimation to be under 5 % at different temperatures [20].

In 2015, Chen et al. integrated the robust sliding mode observer (RSMO) with the online parameter identification for a battery equivalent circuit model (BECM) via applying the forgetting factor recursive least square (FFRLS) algorithm and the learning capability of RBFNN, in which the proposed RSMO is superior to conventional SMO for the *SoC* estimation in terms of accuracy and tracking capability [49].

In 2016, Sun et al. proposed a systematic *SoC* estimation framework for a multi-cell series-connected battery pack of EVs using the bias correction technique, which reduced the maximum absolute *SoC* estimation error of all cells in the battery pack to be less than 2 % [50].

In 2018, Chen et al. found that multi-scale dual H infinity filters have better robustness and higher estimation accuracy than single/multi-scale dual Kalman filters [51].

In 2019, they proposed an improved neural battery model in which the *SoC* estimation errors could be maintained below 2 % after convergence by the EKF method [52].

In 2020, Deng et al. proposed that the data-driven methods were much superior to estimate the *SoC* of the battery pack. The estimation error based on the data-driven methods under different dynamic cycles, temperatures, aging conditions, and even extreme conditions could be lower than 3.9 % [53].

Table 1
Journals publications in battery *SoC* estimation from 2004 to 2021.

Journal title	Number of articles	%Total publications
JOURNAL OF POWER SOURCES	215	12.04 %
ENERGIES	186	10.41 %
APPLIED ENERGY	105	5.88 %
JOURNAL OF ENERGY STORAGE	91	5.10 %
ENERGY	79	4.42 %
IEEE ACCESS	76	4.26 %
IEEE TRANSACTIONS ON VEHICULAR TECHNOLOGY	56	3.14 %
INTERNATIONAL JOURNAL OF ENERGY RESEARCH	56	3.14 %
IEEE TRANSACTIONS ON INDUSTRIAL ELECTRONICS	51	2.86 %
IEEE TRANSACTIONS ON POWER ELECTRONICS	37	2.07 %
ELECTROCHIMICA ACTA	35	1.96 %
IEEE TRANSACTIONS ON CONTROL SYSTEM TECHNOLOGY	32	1.80 %
JOURNAL OF THE ELECTROCHEMICAL SOCIETY	32	1.80 %
APPLIED SCIENCES BASEL	25	1.40 %
INTERNATIONAL JOURNAL OF ELECTROCHEMICAL SCIENCE	25	1.40 %
JOURNAL OF POWER ELECTRONICS	24	1.18 %
IEEE TRANSACTIONS ON INDUSTRY APPLICATIONS	21	1.00 %
JOURNAL OF RENEWABLE AND SUSTAINABLE ENERGY	18	0.95 %
BATTERIES BASEL	17	0.95 %
ELECTRONICS	17	0.95 %
IEEE TRANSACTIONS ON ENERGY CONVERSION	17	0.95 %
ENERGY CONVERSION AND MANAGEMENT	15	0.84 %
IEEE TRANSACTIONS ON TRANSPORTATION ELECTRIFICATION	15	0.84 %
INTERNATIONAL JOURNAL OF ELECTRICAL POWER ENERGY SYSTEMS	15	0.84 %
JOURNAL OF CLEANER PRODUCTION	14	0.78 %
MATHEMATICAL PROBLEMS IN ENGINEERING	14	0.78 %
CONTROL ENGINEERING PRACTICE	12	0.67 %
IET POWER ELECTRONICS	12	0.67 %
IEEE TRANSACTIONS ON INDUSTRIAL INFORMATICS	11	0.62 %
IEEE TRANSACTIONS ON SMART GRID	10	0.56 %
IET ELECTRICAL SYSTEMS IN TRANSPORTATION	9	0.50 %
JOURNAL OF DYNAMIC SYSTEMS MEASUREMENT AND CONTROL TRANSACTIONS OF THE ASME	9	0.50 %
JOURNAL OF ELECTRICAL ENGINEERING TECHNOLOGY	8	0.45 %
INTERNATIONAL JOURNAL OF HYDROGEN ENERGY	7	0.39 %
MICROELECTRONICS RELIABILITY	7	0.39 %
SUSTAINABILITY	7	0.39 %
ELECTRIC POWER SYSTEMS RESEARCH	6	0.34 %
ELECTRICAL ENGINEERING	6	0.34 %
ENERGY STORAGE	6	0.34 %
IONICS	6	0.34 %
CHINESE JOURNAL OF MECHANICAL ENGINEERING	5	0.28 %
ELECTRONICS LETTERS	5	0.28 %
ENERGY SCIENCE ENGINEERING	5	0.28 %
IEEE TRANSACTIONS ON SUSTAINABLE ENERGY	5	0.28 %
INTERNATIONAL JOURNAL OF AUTOMOTIVE TECHNOLOGY	5	0.28 %
JOURNAL OF ENGINEERING JOE	5	0.28 %

The timeline summary of landmark research on battery *SoC* estimation shows that the accuracy has kept enhanced via developing novel methods and models throughout the years. As the chronological summary is lack of objective statistics of important research content, the analysis of keywords will be performed to demonstrate the details in the next Section.

Table 2
Conference proceedings in battery *SoC* estimation from 2004 to 2021.

Conference title	Number of articles	%Total publications
IEEE INDUSTRIAL ELECTRONICS SOCIETY	52	4.20 %
PROCEEDINGS OF THE AMERICAN CONTROL CONFERENCE	50	4.04 %
ENERGY PROCEDIA	40	3.23 %
IEEE VEHICLE POWER AND PROPULSION CONFERENCE	37	2.99 %
IEEE ENERGY CONVERSION CONGRESS AND EXPOSITION	35	2.82 %
IEEE CONFERENCE ON INDUSTRIAL ELECTRONICS AND APPLICATIONS	27	2.18 %
IEEE TRANSPORTATION ELECTRIFICATION CONFERENCE AND EXPO	26	2.10 %
IFAC PAPERSONLINE	24	1.94 %
ANNUAL IEEE APPLIED POWER ELECTRONICS CONFERENCE AND EXPOSITION APEC	20	1.61 %
CHINESE AUTOMATION CONGRESS	20	1.61 %
CHINESE CONTROL CONFERENCE	20	1.61 %
ADVANCED MATERIALS RESEARCH	19	1.53 %
IEEE TRANSATIONS ON INDUSTRY APPLICATIONS	16	1.29 %
APPLIED ENERGY	15	1.21 %
APPLIED MECHANICS AND MATERIALS	14	1.13 %
ASIA PACIFIC POWER AND ENERGY ENGINEERING CONFERENCE	14	1.13 %
IEEE TRANSPORTATION ELECTRIFICATION CONFERENCE AND EXPO ASIA PACIFIC	14	1.13 %
PROCEEDINGS OF THE IEEE INTERNATIONAL SYMPOSIUM ON INDUSTRAL ELECTRONICS	13	1.05 %
2014 IEEE TRANSPORTATION ELECTRIFICATION CONFERENCE AND EXPO ASIA PACIFIC 2014	11	0.89 %
8TH INTERNATIONAL CONFERENCE ON APPLIED ENERGY ICAE 2016	11	0.89 %
DESTECH TRANSACTIONS ON ENVIRONMENT ENERGY AND EARTH SCIENCES	11	0.89 %
IEEE CONFERENCE ON DECISION AND CONTROL	11	0.89 %
INTERNATIONAL TELECOMMUNICATIONS ENERGY CONFERENCE INTELEC	11	0.89 %
2017 CHINESE AUTOMATION CONGRESS CAC	10	0.81 %
CHINESE CONTROL AND DECISION CONFERENCE	10	0.81 %
2016 AMERICAN CONTROL CONFERENCE ACC	9	0.73 %
EUROPEAN CONFERENCE ON POWER ELECTRONICS AND APPLICATIONS	9	0.73 %
JOINT INTERNATIONAL CONFERENCE ON ENERGY ECOLOGY AND ENVIRONMENT ICEE 2018 AND ELECTRIC AND INTELLIGENT VEHICLES ICEIV 2018	9	0.73 %
JOURNAL OF POWER SOURCES	9	0.73 %
2020 IEEE TRANSPORTATION ELECTRIFICATION CONFERENCE EXPO ITEC	8	0.65 %
IECON 2015 41ST ANNUAL CONFERENCE OF THE IEEE INDUSTRIAL ELECTRONICS SOCIETY	8	0.65 %
IECON 2020 THE 46TH ANNUAL CONFERENCE OF THE IEEE INDUSTRIAL ELECTRONICS SOCIETY	8	0.65 %

3.4. Keywords

To have more comprehensive and accurate understanding on the key points and trends of research and development of battery *SoC* estimation, keywords are analyzed as shown in Fig. 3. It is found that “model”, “management system”, “pack” and “lithium-ion battery” are with the highest co-occurrence frequency, which means that those keywords have strong correlations with the study of battery *SoC* estimation. Among those 4 keywords, “model” appears most frequently, which was the earliest research area in the community. The study of the model is classified into the construction of battery model and the determination of system model. The battery model is mainly constructed for “lithium-ion batteries”, “$LiFePo_4$ batteries”, etc. The system model is mainly determined using “the extended Kalman filter method”, “neural network algorithm”, “genetic algorithm”, etc. It shows that “model predictive

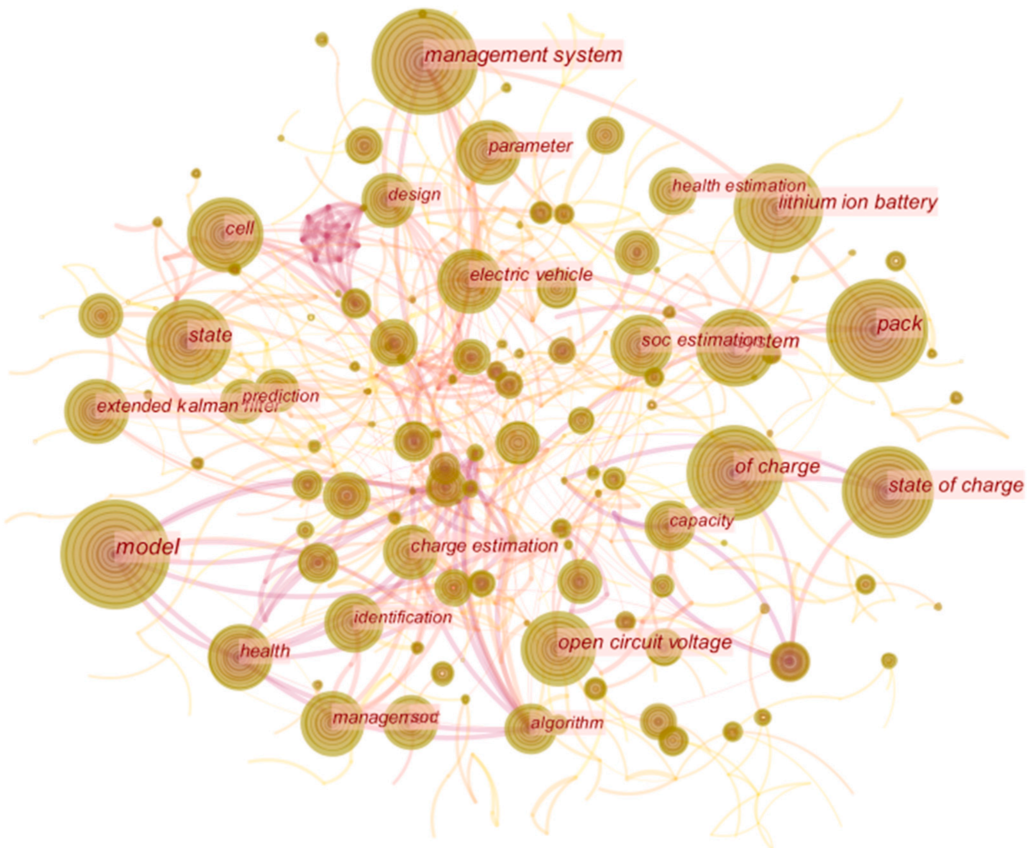

Fig. 3. Scientific distribution map for keywords.

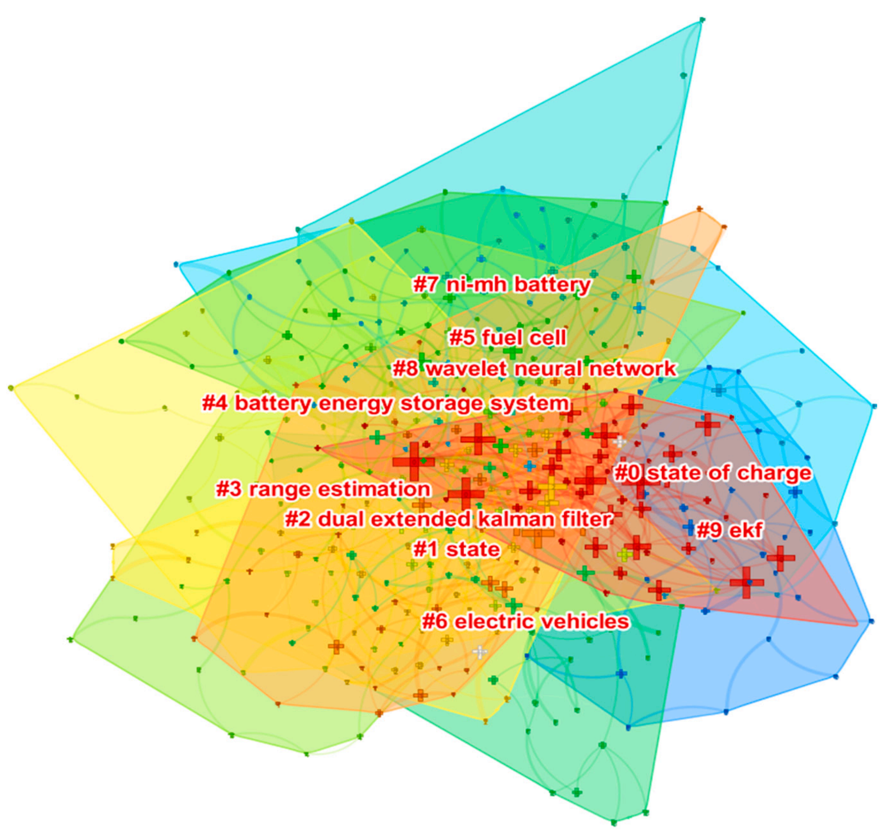

Fig. 4. Keyword clustering analysis.

control" is the recent research hotspot, which indicates the future trend in model research.

To further investigate the keywords in the research of *SoC* estimation, top 10 of 26 clusters in total with the highest frequency are displayed in areas of different colors as shown in Fig. 4. The clustering is capable of analyzing research directions and hotspots in the field accurately. The algorithm for cluster analysis is Log-Likelihood Rate (LLR).

The modularity and silhouette are two indicators to judge the effectiveness of cluster analysis. The structure of cluster analysis is considered as reasonable when the index exceeds 0.3. The modularity and silhouette are 0.6183 and 0.8211 in Fig. 4, respectively, showing the high reliability of cluster analysis. The first 10 categories are State of charge, State, Dual extended Kalman filter, Range estimation, Battery energy storage system, Fuel cell, EVs, Ni-MH battery, Wavelet neural network, and EKF. The number #0 - #9 represent that the number of keywords ranked from high to low. The Cluster #0 State of charge is the core research component and the year of starting this research is 1992, which belongs to the early research stage. It mainly focuses on the topics of EV, pack, management system, and parameter estimation. The Cluster #1 State includes the topics about the state of charge, state of health, impedance, and simulation. The Cluster #2 Dual extended Kalman filter involves the topics of OCV, degradation, capacity fade, and estimation. There is also the latest trend to combine the artificial neural network with this Cluster. The Cluster #3 Range estimation mainly focuses on the equivalent circuit, online estimation, and time constant. The equivalent circuit establishment is crucial to provide the battery parameters for *SoC* estimation. The online estimation takes into account the impact of temperature changes on the battery, while the time constant is the important indicator of the internal characteristics of battery. The Cluster #4 Battery energy storage system includes renewable energy, cycle life, and estimation algorithm, in which the average year is mainly in 2016. The Cluster #5 Fuel cell research involves optimization, strategy, and prognostics. The average year is 2015, which is the early stage. The Cluster #6 Electric vehicles (EVs) mainly includes filter research, electrochemical model, energy, and observer. The filter is mainly used to better estimate the state of the EV such as position, *SoC*, etc., while the observer is mainly used to estimate the *SoC*. The Cluster #7 Ni-MH battery research mainly focuses on parameter identification, equivalent circuit model, and diagnosis, in which the parameter identification is used to build accurate battery models. The Cluster #8 Wavelet neural network is the recent research hotspot, which contains particle filter, sliding mode observer, polymer battery, and health estimation. Particle filter is a generalized method of Kalman filter, which is mainly used to estimate the battery *SoC* in this field. The wavelet neural method is mainly used to estimate the state of the polymer battery. The Cluster #9 EKF is an algorithm for the battery *SoC* estimation, which includes an unscented Kalman filter, adaptive Kalman filter, and the combination of the neural network. The frequency of the neural network reaches 67, which is the highest one in the EKF research, showing the research trend in this area.

The cluster naming in Citespace is determined by the nominal terms extracted from the cited publications, which can be regarded as the future trend of the research. Research frontier is embodied in the documents forming the co-citation matrix and the clustering of keywords emerging in the cited documents. Therefore, the emerging clustering of research keywords is applied to determine the research frontiers in the field of battery *SoC* estimation. In order to identify and predict the latest evolution and development trend of battery *SoC* estimation research, the keywords with the strongest citation bursts are selected for analysis. Compared with high-frequency keywords in safe evacuation, keywords with the strongest citation bursts are much suitable for detecting emerging trends and sudden changes in the development of battery *SoC* estimation. Table 3 shows the top 30 keywords with the strongest citation bursts detected by the burst detection algorithm.

Table 3 shows the keywords burst from 2004 to 2021, and the order of arrangement is sorted by the strength of the burst. Lead-acid battery, EV, Pack, Online state, Degradation, Management system, Sliding mode observer, Optimization, Particle filter, Lead-acid, and Capacity estimation are the top 10 keywords with the strongest burst indicator. In the early stage, the research on the battery *SoC* estimation was mainly for lead-acid batteries, in which the burst is from 2004 to 2014. In the future, optimization, degradation, and unscented Kalman filter will be the new trend for battery *SoC* estimation because those keywords burst in recent three years. The online state is also an interesting topic with high burst in 2018 and 2019, in which the online state estimation could be useful for considering the environmental parameters in the field of

Table 3
Top 30 keywords with the strongest citation bursts (Red boxes represent the burst time from the beginning into the end while blue ones represent the time without burst).

Keywords	Year	Burst Strength	Begin	End	2004-2021
Lead acid battery	2004	16.93	2004	2014	
Electric vehicle	2004	15.51	2017	2018	
Pack	2004	11.31	2013	2014	
Online state	2004	8.91	2018	2019	
Degradation	2004	8.52	2019	2021	
Management system	2004	7.06	2013	2015	
Sliding mode observer	2004	6.98	2017	2018	
Optimization	2004	6.59	2019	2021	
Particle filter	2004	6.48	2016	2018	
Lead acid	2004	6.38	2010	2015	
Capacity Estimation	2004	6.17	2012	2017	
Parameter estimation	2004	5.86	2010	2018	
Polymer battery	2004	5.76	2014	2016	
Battery management system	2004	5.37	2006	2015	
Framework	2004	5.01	2017	2018	
$LiFeO_4$ battery	2004	4.83	2016	2018	
Impedance	2004	4.64	2007	2016	
Li-ion battery	2004	4.6	2016	2017	
Predicting state	2004	4.15	2010	2013	
Nickel metal hydride	2004	4.07	2006	2013	
Cycle life	2004	3.94	2015	2016	
Intercalation	2004	3.91	2014	2015	
Capacity fade	2004	3.65	2006	2014	
Unscented kalman filter	2004	3.62	2018	2021	
Vehicle	2004	3.49	2015	2017	
Equivalent circuit	2004	3.41	2014	2017	
Adaptive state	2004	3.37	2014	2016	
Electrode	2004	3.19	2009	2014	
Discharge	2004	3.17	2004	2010	
Behavior	2004	2.96	2015	2016	

battery *SoC* estimation. In 2013, the research about the pack had a burst, which indicates that the *SoC* estimation of the battery pack has become a new research trend based on its high capacity, low cost, and other advantages. Besides, the impedance and parameter identification had long burst periods of 9 and 8 years from 2007 to 2016, and from 2010 to 2018, respectively, which means that both are always the Research frontier. Based on the aforementioned analysis, the optimization, degradation, and unscented Kalman filter would become the future research frontier of battery *SoC* estimation, while the capacity estimation and parameter identification would be the research focus of the unscented Kalman filter, and the impedance would be the focus of optimization and degradation.

3.5. Countries

Fig. 5 shows the distribution of published literature on battery *SoC* estimation research in various countries. There are 84 nodes in the graph, representing 84 countries, and the circular radius of the nodes represents the number of publications. In terms of the number of publications, China ranks the first globally with 890 articles in total. The USA (300 articles), South Korea (103 articles), and England (79 articles) also made a significant contribution to the field of battery *SoC* estimation.

The burst index of citations indicates the frequency of publications in a particular country during a specific period, which could provide a reference for the trends and changes of countries/institutions/keywords in the field of battery *SoC* estimation. The top 25 countries with the strongest citation bursts are shown in Table 4.

The top 10 countries with the strongest citation burst index would affect the direction of battery *SoC* research based on the high-frequency published articles.

Taiwan, Iran, and South Korea have been working on battery *SoC* estimation research for longer time compared to other countries. The USA has the strongest citation burst index (17.83), showing that the research has been highly recognized by other countries. Since 2018, Pakistan, Algeria, Jordan, U Arab Emirates, and Sweden have begun to participate in the field of battery *SoC* estimation. Sweden ranks 8th with a citation burst index of 3, showing its strong competitiveness and great research potential in the field of battery *SoC* estimation. The country-wise analysis of the *SoC* estimation research combined with the information of timeline and burst strength is conducive to academic communication and cooperation among researchers.

4. Research approaches for battery *SoC* estimation

Many experimental studies focus on the battery *SoC* estimation because the accurate prediction could allocate battery energy effectively and ensure battery safety [54–58]. The research approaches for investigating the battery *SoC* estimation mainly include battery model, algorithm improvement, and experimental verification. The purpose of building a battery model is to simulate and predict the characteristics of the battery during the charging and discharging processes. Various algorithms are developed to accurately calculate the *SoC* at a specific time through the external characteristics of the battery, such as current and voltage. The experimental method could verify and improve the developed battery model and algorithm, which is usually verified by dynamic charging and discharging tests.

4.1. Battery models

There are many approaches to classify the battery models. Here, the battery models are classified into 3 types: Equivalent circuit models [59–69], Black-box models [70–72], and Electrochemical models [73–82].

The Equivalent circuit models mainly include the internal resistance battery model (Rint), the resistance-capacitance battery model (RC), the Thevenin model, and the Partnership for a new generation of vehicles (PNGV model) [61,83]. The feature of the equivalent circuit models is to estimate battery *SoC* through the resistance, capacitance, and voltage characteristics. For example, Fig. 6 is a schematic diagram of the Rint model in which the voltage and current can be calculated by Eq. (1). Although the equivalent circuit model only simply simulates the internal changes of the battery through the parameters such as current, voltage and resistance, it is still widely used in *SoC* estimation due to its simplicity and accuracy.

$$U_L = U_{OC} - I_L R_0 \tag{1}$$

Fuller et al. developed an electrochemical model for LIBs, which is based on the chemical processes that take place in the battery [84]. The models describe the chemical processes of battery with great details, however, the user has to set many battery-related parameters such as the electrodes thickness and the initial salt concentration in the overall heat capacity [81]. It is not user-friendly due to the complexity of parameter setting. Electrochemical impedance spectroscopy (EIS) is a non-destructive effective method to measure the parameters and dynamic

Fig. 5. The network of countries.

Table 4
Top 25 Countries with the strongest citation bursts.

Countries	Year	Strength	Begin	End	2004 - 2021
USA	2004	**17.83**	2010	2015	
TAIWAN	2004	**6.43**	2005	2013	
FRANCE	2004	**5.93**	2016	2017	
JAPAN	2004	**5.58**	2014	2015	
SOUTH KOREA	2004	**5.48**	2007	2012	
SINGAPORE	2004	**4.06**	2014	2018	
IRAN	2004	**3.75**	2007	2013	
SWEDEN	2004	**3**	2018	2019	
AUSTRIA	2004	**2.51**	2012	2015	
EGYPT	2004	**2.05**	2015	2017	
PEOPLES R CHINA	2004	**2.04**	2005	2007	
TURKEY	2004	**2.03**	2004	2007	
BELGIUM	2004	**2.01**	2011	2012	
DENMARK	2004	**2**	2019	2021	
SOUTH KOREA	2004	**1.99**	2006	2010	
BANGLADESH	2004	**1.85**	2017	2018	
JORDAN	2004	**1.69**	2018	2019	
NETHERLAND	2004	**1.42**	2015	2016	
FRANCE	2004	**1.36**	2006	2007	
JAPAN	2004	**1.36**	2006	2007	
U ARAB EMIRATES	2004	**1.3**	2016	2019	
ARGENTINA	2004	**1.2**	2009	2012	
PAKISTAN	2004	**1.03**	2018	2019	
ALGERIA	2004	**1**	2018	2019	
U ARAB EMIRATES	2004	**0.9**	2018	2020	

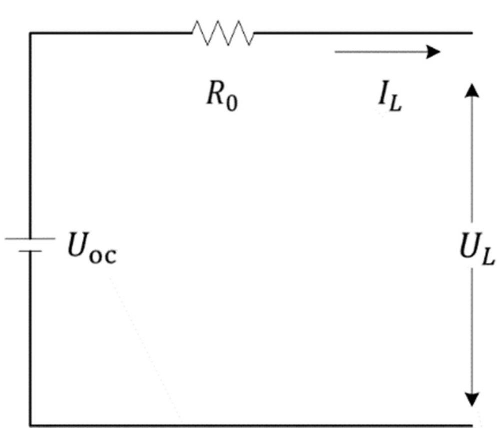

Fig. 6. Equivalent circuit of Rint model.

behavior of battery [85]. At present, research on EIS mainly focuses on *SoC* prediction, electrode material analysis, lithium-ion deintercalation process, and solid electrolyte interphase (SEI) research, etc. [78,85].

Black-box models are developed with the advancement of computer software technology, which can be treated as data-driven approaches to estimate the battery parameters [20,86]. The techniques for black-box modeling can be divided into fuzzy-based estimation, fuzzy-based neural network, bio-inspired algorithm, and support vector machines. The input variables of the model can be selected from the elements that affect the battery performance, while the model output variables are the state characteristics such as *SoC*, capacity, etc. [14,87]. Fig. 7 shows the process for black-box modeling. The Black-box model can accurately describe the changes inside the battery in real-time through data training. Although there are still issues in the data acquisition and the fusion of algorithms, the black-box model is still the popular battery model in the research community. Its goal is to accurately reflect the changes inside the battery in real-time regardless of the type of battery and the level of battery power.

The process of building the battery model is mainly divided into two types: offline and online. The main difference between them is the capability of reflecting the changes of battery internal parameters caused by the environmental factors to the model in real-time. It is tedious and costly to calibrate the parameters at every moment during the use of the battery [88–96]. Besides the high cost of online parameter identification and the high identification failure rate, the results of online parameter identification are required to verify and compare with offline parameters [97–100]. Therefore, it is widely accepted to establish a battery model offline to simulate the behavior of the battery before charging and discharging [97,101–104]. Fotouhi et al. aimed at the issue of online parameter identification and focused on the cost and proper trade-offs between different methods and models with a unique perspective, and the proposed framework validated the key role of speed during the online parameter identification process [105]. A promising battery model could simulate changes of the internal characteristics in the battery to estimate the battery *SoC* [106–108], while the combination of simulation and battery model could simplify the process of investigation [109,110].

There are some software available to investigate and establish the battery models. ANSYS is good at performing module thermal simulation and analysis of modules in battery packs. Zview is usually used to analyse and study the impedance of the battery to build an equivalent circuit model. Matlab Simulink is generally used to study the input current and output voltage of the circuit model.

4.2. *Algorithm and experimental verification*

It is necessary to combine algorithms with the developed battery model to estimate the *SoC* of the battery [111–113]. Currently, the approaches for estimating the *SoC* of batteries mainly include the OCV method, Coulomb counting method, Kalman filtering method, and neural network algorithm [113–115].

The OCV method is capable of estimating the *SoC* value from the measured OCV of the battery [26,114,116–120]. Since a long period of time is required to obtain a stable OCV value, the OCV method is not suitable for the *SoC* estimation when the battery current changes drastically [121,122]. Nowadays, the Coulomb counting method is commonly used to estimate the *SoC* by integrating the load current against time [123–126]. However, the drawback origins from the difficulty of automatic determination of the initial value of *SoC*, resulting in a large cumulative error [127]. The Kalman filtering method obtains the minimum variance estimation by a recursive algorithm according to the collected voltage and current [47,128–133]. Thus, this method exhibits the merits of avoiding the inaccurate estimation of the initial value of *SoC* and eliminating the cumulative error [129]. At present, the main trend of the Kalman filter algorithm is the in-depth study of unscented Kalman filters and the combination of the neural network model and the EKF method. [134–137].

The neural network method relies on a large number of samples for data training to achieve high accuracy [128,138–140]. With the advanced development of computing power and artificial intelligence,

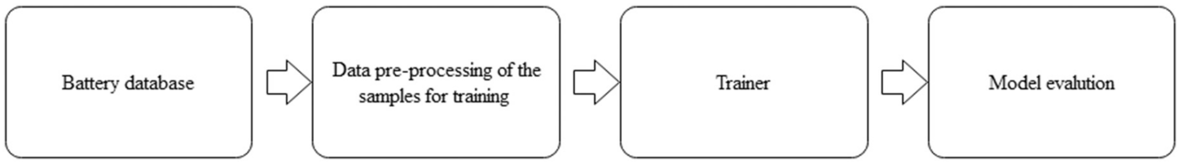

Fig. 7. Process flow of black-box modeling.

the shortcoming of neural network algorithms has been resolved. At the same time, the neural network algorithm can reduce the battery model error to a certain extent with strong fault tolerance [87,141]. The integration of neural network algorithms with other algorithms will become a new trend in the future research of battery *SoC* estimation.

At present, the experimental verification of battery *SoC* estimation is mainly realized by emulating the actual conditions of charging and discharging processes of the battery. In the research field of high-power batteries of EVs, according to road conditions of the country, it can be divided into New European Driving Cycle (NEDC), China Automotive Test Cycle (CATC), Urban Dynamometer Driving Schedule (UDDS), etc. There are no standardized conditions for the low-power battery *SoC* experimental verification, which is only divided into constant current charging and discharging and non-constant current charging and discharging. The goal of performing the experiments is to verify the accuracy and stability of *SoC* estimation under different conditions.

5. Research contents of battery *SoC* estimation

5.1. Research objects

The types of battery can be divided into primary battery and rechargeable battery. The research of battery *SoC* estimation are mainly based on rechargeable type that is roughly classified into lead-acid batteries [43,142,143], nickel-metal hydride batteries [144,145], lithium cobalt-acid batteries [146,147], lithium manganate batteries [148], lithium iron phosphate batteries [149], lithium-sulfur (Li—S) batteries [150–152], ternary LIBs (nickel cobalt manganese lithium-ion batteries) [153–155], etc.

In addition to the type of battery, there is a certain difference between the *SoC* estimation of the battery pack and the battery cell. The battery parameters of different batteries vary, which is called battery inconsistency. This would cause the modeling of the battery pack different from that of the battery cell, resulting in the derivation of capacity and *SoC* estimations [156,157]. As the *SoC* estimation is based on the accurate estimation of the battery capacity, the battery capacity estimation is also a key research content of the *SoC* estimation.

5.2. Environments

The main environmental factor affecting the battery *SoC* estimation is temperature [158]. In the battery management systems on mobile devices, EVs, and other devices, overheating or low temperature would cause adverse impacts on battery *SoC* estimation, resulting in serious security risks.

The electrochemical reaction at the electrode/electrolyte interface is dependent of the ambient temperature [148]. For LIBs, the reaction rate of the electrode decreases along with the temperature [159]. This is because the viscosity of electrolytes increases and even partially solidifies at low temperatures, leading to the increase of the charge transfer impedance and the decrease of the electrical conductivity of LIBs [159,160]. Provided that the battery voltage remains constant, the discharge current and the power output would reduce. The chain reactions would lead to the change in battery capacity at low temperatures, making the battery *SoC* estimation much difficult.

The high-temperature effect on the capacity is relatively complex, which depends on the types of batteries [161]. For example, lithium-ion migration speeds up at high temperatures such that the capacity of LIBs is slightly higher than that at the normal temperature [161]. For nickel-metal hydride batteries, the charging efficiency and battery life would greatly reduce as hydrogen storage electrodes decompose at high temperatures [162]. No matter how the battery changes at high temperatures, the estimation of battery *SoC* would be affected. The thermal runaway also leads to battery explosion.

In light of the thermal effect, the influence of temperature on the battery is needed to consider in the process of battery *SoC* estimation. Currently, there are two main approaches: (1) Set the temperature as a regulating factor on the estimation of battery capacity because the accurate battery capacity is a prerequisite for accurate estimation of *SoC* [148]; (2) add the influence of temperature into the process of battery model establishment, while the influence of temperature on the battery can also be involved through the online parameter identification [110]. In the future, the influence of temperature on battery *SoC* estimation will tend to be adjusted and simplified online.

6. Conclusion

The battery *SoC* estimation is of great significance for rationally distributing battery energy and ensuring battery safety. For example, with the rise of EVs, as a core component of the BMS, accurate and stable estimation of battery *SoC* ensure the safety of vehicles and drivers. This paper analyzes the knowledge base, research frontiers, and application trends of battery *SoC* estimation based on the WoS database. The research method is to conduct correlation analysis and processing of the literature using the Citespace. The research hotspots of battery *SoC* estimation is analyzed through co-citation theory and burst detection analysis. Through the visualization of research and analysis, the development path and research trend of battery *SoC* estimation can be clearly and intuitively observed.

1) The model, the model predictive control, and the neural network model are the research hotspot in the future. The management system is the next popular topic, in which the core algorithm is the Kalman filter.
2) In the battery *SoC* research field, the optimization, degradation, and unscented Kalman filter will be the future research frontier based on the burst detection analysis. For the unscented Kalman filter, capacity estimation and online parameter identification are the research focus. For the optimization and degradation, the impedance of the battery is critical for the model optimization and battery degradation.
3) As shown in Fig. 4, dual EKF and EKF rank second and ninth among top 10 clusters, which indicates that EKF is critical in the battery *SoC* estimation. The future trend of the Kalman filter will be with multiple algorithms.
4) The experimental verification of the battery *SoC* is divided into battery model verification and *SoC* estimation algorithm verification. The verification of the battery model tends to be intelligent by inputting the charging and discharging data into the simulation software. The verification of the battery *SoC* estimation algorithm depends on the type of battery, but the overall trend would be intelligent charging and discharging verifications combined with environmental factors.

Though various models and algorithms have been developed, the online status of the battery is still required to further investigate with effective and accurate ways. Besides, the errors induced by current and voltage measurements and estimations, and the variation of capacity are still high, which could be further reduced by optimizing the data-driven method with machine learning involving data training and algorithm fusion. Improving the speed and accuracy of online parameter identification based on artificial intelligence algorithms would also definitely become a research hotspot of battery modeling. Regarding the algorithm level of *SoC* estimation, the unscented Kalman filter, the dual Kalman filter, and the extended Kalman filter combined with the artificial intelligence (AI) neural network would be the other research hotspot. Improving and modifying the Kalman filter algorithms and combining them with AI neural networks are expected to improve the robustness and accuracy in the battery *SoC* estimation. Besides, a joint estimation algorithm for the battery status will be one of the future directions. Less research focus should be put on the *SoC* estimation for lead-acid batteries and discharging conditions of batteries.

Research on the *SoC* estimation will remain promising with high demands in the future. The challenge comes from the difficulty of the battery model describing the internal changes of the battery accurately and timely, which could be alleviated by combining the machine learning model with the online parameter identification. The combination of *SoC* estimation with other disciplines should also be an alternative promising pathway, such as the emerging ultrasonic detection of *SoC* of LIBs, which would be beneficial to developing sensor-based BMS. Overall, there are still rooms for further improvement on the research in the *SoC* estimation especially the real-time performance, accuracy, and burden of algorithm on the computer.

Declaration of competing interest

All co-authors have seen and agreed with the content of the manuscript and there is no financial interest to report. We declare that the manuscript is original, which has not been published before or submitted elsewhere for the consideration of publication. We know of no conflicts of interest associated with this work, and there has been no significant financial support for this work that could have influenced its outcome.

Data availability

Data will be made available on request.

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