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Review

A Systematic Literature Review of State of Health and State of Charge Estimation Methods for Batteries Used in Electric Vehicle Applications

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Abstract: In recent years, artificial intelligence and machine learning have captured the attention of researchers and industrialists in order to estimate and predict the state of batteries. The quality of data must be good, and the source of data must be the same for different models' performance comparisons. The lithium-ion battery is popularly used because of its high energy density and its compact size. Due to the non-linear and complex characteristics of lithium-ion batteries, electric vehicle users have to know about battery health conditions. Different types of state estimation methods are used, namely, electrochemical-based, equivalent circuit model (ECM) based, and data-driven approaches. This paper is a survey of electric vehicle history, different battery chemistries, battery management system (BMS) basics and key challenges and solutions in BMS, and in-depth discussions about other battery state of charge and state of health estimation methods. Research trend analysis, critical analysis of this work, limitations, and future directions of existing works are discussed. This paper also provides information on the open-access available datasets of different battery chemistry for a data-driven approach. This paper highlights the key challenges of state estimation techniques. Knowledge of accurate battery state of charge (SOC) provides critical information about remaining available energy. In comparison, battery state of health (SOH) indicates its current health condition, remaining lifetime, performance, and proper energy management of the electric vehicles.

Keywords: battery management system; state-of-charge; state-of-health; machine learning; data-driven approach

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1. Introduction

In order to reduce Green House Gas (GHG) emissions, the use of clean and green energy needs to be promoted. Renewable energy sources such as solar, wind, and tidal are abundant in nature. Combustion engine vehicles take crude oil such as petrol or diesel as fuel. These internal combustion (IC) engine vehicles pollute the environment and release harmful gases. Meanwhile, a pure electric vehicle (EV) takes electrical charges as input fuel.

The battery of the EV is charged by a grid mains supply or by the solar panel. To promote EV manufacturing, in 2015, the Indian government launched the phase-I Fast Adoption and Manufacturer of Electric Vehicles (FAME) program; however, due to the lack of charging infrastructure and the high capital cost of EV batteries, the EV market capture became slow-paced. Some countries are developing their existing technology to enhance, modify, and equip themselves with the emerging technology for EVs [1]. Original Equipment Manufacturers (OEMs) have started developing their existing technology to enhance, modify, and equip themselves with emerging technology to fulfill the end-user's requirements.

In the early days, lead–acid batteries were preferred for domestic stationary uses due to their low cost and operation safety. Even now, there is a high demand for compact electronic appliances with high-capacity storage for mobile applications. Considering this requirement, lithium-ion batteries are used because of their high energy density and compact size. Lithium-ion batteries are used in mobile phones, electric vehicles (EVs), aircraft engines, battery-operated scooters, etc. Figure 1 shows the history and invention of electric vehicle batteries. Electric vehicles came into the picture in early 1832, and Robert Anderson invented the first crude electric carriage. Previously, non-rechargeable primary battery cells were used in EVs. After the invention of the first rechargeable lead–acid battery in 1859, the capability to store electricity onboard a vehicle came into the picture for usage. The first human-carrying tricycle was invented in 1881. In 1901, the first hybrid electric car was invented. These hybrid cars were powered by gasoline and batteries. In 1912, experiments with lithium-ion batteries started, and in 1970, these batteries became available in the market for commercial use. After that, in 1971, NASA's first lunar rover electric manned vehicle was sent to the moon. Between 1920 and 1980, smooth roads were constructed, and the transportation of fuel rapidly grew so that the fuel prices for gasoline vehicles were reduced and fuel became abundantly available compared to electric vehicle battery costs; therefore, the electric vehicle market faded. Again, in 1990, revisions on EV policies, regulations, and the availability of different models attracted customers' attention, and there developed a renewed interest for EVs. From 2009 onwards, charging infrastructure for EVs has started to be built. Battery cost is almost 60–70% that of the cost of the EV, but in 2013, battery costs were reduced by 50% compared to the previous four years and made EV purchases affordable to customers. Different charging–discharging strategies of EVs are discussed in [2–4].

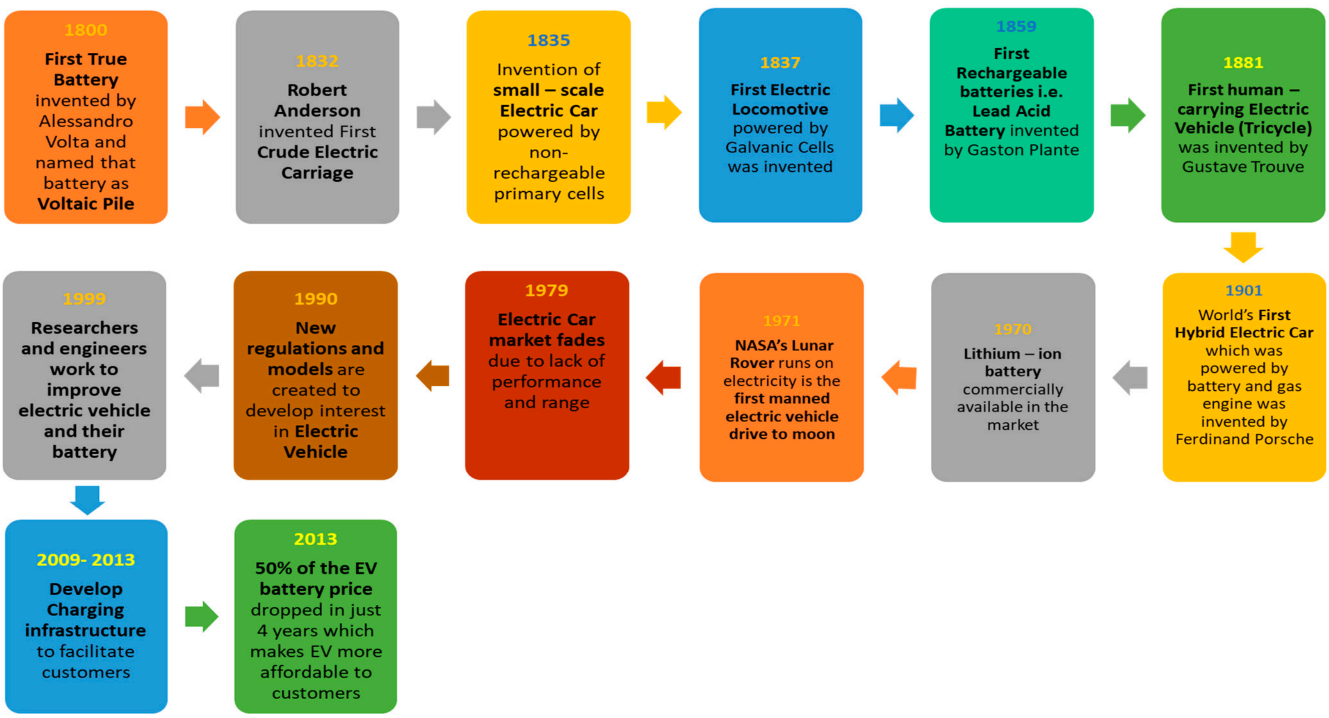

Figure 1. History of electric vehicles and batteries [5,6] accessed on 19 January 2022.

According to [7], however, the cumulative output of power batteries in China in 2020 was 83.4 GWh. In the transportation sector, EVs play a significant role in reducing CO_2 and SOx gases from the environment and also require less maintenance. EVs can be powered by batteries, solar power, electric generators, or a combination of batteries and gasoline [8]. Types of EVs include battery electric vehicles (BEVs), hybrid electric vehicles (HEVs), and plug-in hybrid electric vehicles (PHEVs). The average battery capacity for a BEV is 55 kWh, and for a PHEV it is 14 kWh. Globally, 10 million electric cars had been sold up to 2020, of which 2.1 million were sold in 2019, which had surpassed the 2018-year record [9]. China has the world's largest market for EV cars. China sold about 1.06 million EV cars in 2019, followed by Europe with 560,000 EV car sales, and then the US with 326,000 EV car sales. In 2020, electric car registration increased by 41%, and global car sales dropped by 16%. Around 3 million electric cars were registered globally in 2020. For the first time, Europe significantly captured the largest EV market, with 1.4 million new registrations, overtaking China with 1.2 million registrations. Different new models of EVs with new features provide customers with a great deal of variety to choose from. Encrypting information fetched from the vehicle is critical as it is the owner's or driver's personal data. Cyber security plays a significant role in Plug-in Hybrid Electric Vehicles, Hybrid electric vehicles, Battery Electric vehicles (xEVs), automated vehicles, and self-driving vehicles. Sport Utility Vehicle (SUV) car models cover half of all the available EV car models in the market with the aim of enticing customers. To boost EV sales and increase the purchase of BEVs and PHEVs, some national subsidies have been granted by some countries like France, Germany, Italy, and China. During the pandemic, China curtailed the subsidy at the year-end of 2020 and postponed it till 2022. According to (the International Energy Agency) the IEA report of 2020, to achieve the global mass adoption of EV stock as a transport mode for light-duty passenger vehicles, the government must also focus on commercial vehicles like buses, cars, trucks, and fast-charging infrastructure. Some advantages of EVs are their low operating cost, low maintenance cost, simple design, and no harmful gas emission. EVs can capture energy during braking through regeneration, and EVs are more efficient in terms of not having a complex Internal Combustion engine. Therefore, EVs are treated as eco-friendly.

Many countries, such as the USA, Norway, China, France, Japan, the U.K., and the Netherlands, are the futuristic global stakeholders in faster EV adoption. Initiatives have been taken to promote and expedite EV adoption globally. The USA has started numerous incentive programs, income tax credit rebates, separate EV charging tariffs, discounts in parking allowance, shared e-mobility, and awareness campaigns. The Department of Energy has initialized a program called "EV Everywhere," which focuses on research and development and consumer awareness to market EVs and achieve parity in cost till 2022. California is targeting to convert 100% of its municipal fleet to run on alternative fuel by 2022. Some incredible awareness campaigns like "Best Ride Ever" and "National Drive Electric Week" have been organized in California. France started zero parking costs, a 15% subsidy for converting IC engine vehicles into electric vehicles, and a 25% purchase subsidy on low-emission vehicles, such as e-bikes [4]. In the United Kingdom, one would be exempted from congestion charges, car tax, and annual circulation tax upon purchase of an EV car. Shanghai recorded the greatest level of EV adoption in the country. It ranks as the leading city globally in terms of EV sales. The "Ten Cities, Thousand Vehicles" program has been launched in 25 cities in China. Shenzhen is the headquarters of Build Your Dreams (BYD), one of the leading suppliers of lithium-ion batteries and EV manufacturing companies. Oslo, Norway, has implemented low taxes, free parking, discounts on road toll fares, and exemption from public charging fares. Norway is further planning to ban gas and diesel vehicles by 2025, India is also planning to ban gas and diesel vehicles by 2030, and France and Britain plan to ban gas-diesel cars by 2040 [4]. In this paper [10], the authors have discussed different ways to predict charging duration time, which will be helpful for researchers to estimate SOH.

Our contributions are summarized as follows:

- Research trends in state estimation, key challenges, and solutions related to BMS are discussed;
- Literature review on SOC and SOH estimation techniques is discussed;
- Publicly available dataset details for Machine Learning/Deep Learning (ML/DL) methods are listed;
- Critical analysis, limitations, and research gaps in existing work are discussed;
- Future direction and unmapped areas are discussed;

- These contributions will help researchers choose the algorithm suited to their research problem.

1.1. Different EV Lithium-Ion Battery Chemistry Comparison

Different low-temperature lithium-ion batteries are required based on specific applications [11]. An application-based lithium-ion battery low-temperature operating range is shown in Figure 2. At low temperatures, below 0 °C, battery capacity starts to decrease, and at below −20 °C, battery operation is highly not recommended. Maintaining individual internal cell temperature is difficult, practically impossible, and also not feasible. Therefore, external thermal management through the use of heating elements, hot liquid, or air heat transfer is applied in practice in order to maintain thermal stability.

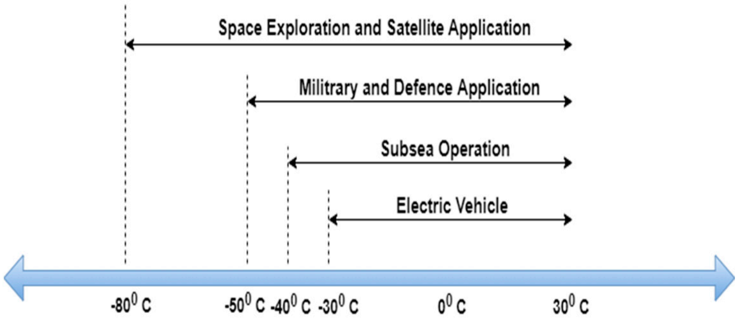

Figure 2. Low-temperature operating range of lithium-ion batteries for specific applications.

In 2019, the Nobel Prize in Chemistry for research contributions to the development of lithium-ion batteries was awarded to John Goodenough, Stanley Whittingham, and Akira Yoshino. There are various types of batteries available on the market, but for EV or automotive purposes, lead–acid and lithium-ion batteries are mainly used. Nowadays, lithium-ion batteries are popular in terms of EV applications due to their high energy density, high volumetric density, low self-discharge rate, long life, and also because they operate at high voltages. There are different categories of lithium-ion batteries available on the market, and some popular lithium-ion battery chemistries used for EVs are shown in Table 1 [8]. The nominal voltage mentioned in Table 1 is referenced to a standard graphite anode. Nickel–manganese–cobalt (NMC) dominates lithium-ion battery chemistry, with a 71% sales share the rest comprising nickel–cobalt–aluminum (NCA) batteries. Lithium–iron–phosphate (LFP) batteries still have a less than 4% sales share in the electric car market [9]. LFP batteries can operate up to 40 °C, whereas NMC and NCA batteries can function up to 35 °C. The prices of LFP, NMC, and NCA batteries range from USD 200 to 250 per kWh (according to 2019 prices) [4]. Globally, China leads 75% of the total battery manufacturing capacity, followed by the USA with 9% and South Korea with 7%. Some battery manufacturing organizations include Exide Leclanche, Panasonic, LG Chem, CATL, Samsung SDI, Tesla, BYD, and TATA Chemicals (Group 2021). Some of the major disadvantages of lithium-ion batteries are that they have non-linear characteristics, are costly, are explosive in nature, and are complex. The non-linearity of lithium-ion batteries can be seen when the battery temperature is near freezing point and above 60 °C when operating at high Depth Of Discharge (DOD), high/low SOC, and high C-rates. Due to the expensive and explosive nature of lithium-ion batteries, battery management system (BMSs) play a major role in managing the battery state and protecting electronic devices from danger, improving the performance and efficiency of xEV. Key technologies in the BMS includes battery modeling, diagnosis, indication, controlling, communication, and protection. A well-designed BMS strategy will protect the battery from any internal fault, temperature variation, over-charge/over-discharge, and control current flow. The proper design of BMS software can precisely perform state of charge (SOC) and state of health (SOH) diagnostics and prognostics. Battery state cannot be measured directly, while voltage, current, and temperature are measured directly from the battery. Knowledge of the battery state plays a significant role in the battery's smooth functioning in working conditions. Battery states can be monitored by using proper estimation techniques. Table 2 shows some of the publicly available battery datasets focused on different papers. The results of these datasets were achieved under different conditions using different chemistries and capacities. In the data-driven technique, most of the literature uses one set of data and compares results with different data present in another piece of literature; this way of comparison of results is vague. For the different data-driven approach results comparison, the data must be obtained from the same source. There is a lack of research interest and literature publications focusing on SOC and SOH estimation or battery prediction using different ML techniques. There are few papers that discuss both SOC and SOH for EV applications [12–15]. This paper fills the literature gap by providing an overview of BMS functioning and different techniques used to estimate and predict battery state. This paper compares the advantages, disadvantages, research gaps, and future trends of different state estimation and prediction techniques. This paper also discusses the online open-access dataset used by different authors in their paper for study. Useful and meaningful data gathering is an important and basic task for working on data-driven models. Most of the time is spent gathering accurate data. Some free open-access public data sets are available for synthesis and comparison. In EVs, SOC is a replacement for a fuel gauge in conventional vehicles, whereas SOH is a replacement for an odometer [13].

Table 1. Some popular lithium-ion battery chemistries available on the market used in EV applications.

Battery Chemistry Names	Nominal Voltage (V)	Energy Density	Life Cycle	Safety	Cost	Battery Manufacturing Capacity in the World
LFP	3.2	low	Long life	Safest to use	expensive	17%
NMC	3.6	high	Average life	Safe to use	expensive	55%
LCO	3.6	high	Average life	Requires safety measures	cheaper	18% (LCO and including other chemistries)
LMO	3.7	low	Short life	Safe to use	expensive	2%
NCA	3.6	high	Average life	Require safety	expensive	7%

Table 2. Open access online datasets used in different papers.

Dataset Category	Description	Cell Chemistry/No. of Cells	Variables
NASA data set [16,17]	NASA provides six experimental datasets at various DODs, discharge current rates, and temperatures.	18650 NCA (2 Ah)/34 cells	V, I, T, IR, Q
CALCE data set [16,17]	CALCE provides a dataset of the aging cycle at different CC-CV charges and CC discharges.	Prismatic LCO (1.35 Ah)/12 cells	V, I, T, IR, Q, E
A123 System data set [16]	This dataset is used for comparative study.	LFP	Q, V, I, T, IR
CALCE, NASA, Oxford [18]	The dataset is divided into groups based on charging protocol.	Oxford -Pouch cell (740 mAh)/8 cells	V, I, T
Lithium-ion Panasonic NCR 18650 PF [19]	Six drive dataset is used for training purposes and another three drive cycle dataset is used for testing.	NMC (2.9 Ah)	V, I, T
Battery Archive dataset [20]	This dataset is taken from various institutions and converted into a standard format.	LFP, NMC, NCA, LCO, NMC-LCO	Q, Form Factor, T, SOC, C-rate during charge/discharge
Automotive Lithium-ion Cell Usage dataset [21]	This dataset is generated from a programmable battery cycler simulation using a cell in an electric car using a Federal drive cycle.	lithium polymer cell (15 Ah)	T, V, I, SOC, Cycle

The gathering of relevant big data plays a significant role when working with data-driven models. A small dataset will increase the chance of error, so a big relevant dataset will lead to proper training of the model and reduce the chance of error. Acquiring huge amounts of data is a time-consuming process. This paper is based on a variety of battery chemistry and drive cycle online open datasets that have been used in other papers.

1.2. Battery Modeling

Designing, controlling, and optimizing battery models will help analyze proper functioning and accuracy under different conditions. There are broadly three categories of battery models, namely electrical models, thermal models, and hybrids, i.e., electro-thermal coupled models, as shown in Figure 3. The electrical model is further divided into electrochemical, equivalent circuit, reduced-order electrical, and data-driven models [16]. The electrochemical model (EM) [22,23] is known for its highly accurate prediction model and also accurately describes the internal electrochemistry of the battery. The disadvantage of the electrochemical model is that it requires high computation effort, complex equations, and is complicated to solve. It is also not suitable for real-time applications. In [23], it is stated that EM has several dependent variables like electric potential, lithium-ion concentration, and molar flux of lithium at the surface of spherical active materials, which are partially differentiated by independent variables like spatial macro-scale x along with micro-scale r and temporal t. Then, the model is reduced or reformed into a differential algebraic equation. Due to numerous unknown parameters related to battery electrochemistry, such as chemical composition, it requires high computation time to solve. By making a suitable assumption, full-order EM can be converted into the reduced-order model. In reduced-order electrical models, there are fewer parameters (voltage and current signals); hence, less computation time is required, which is why it is used for real-time battery applications. In the equivalent circuit model (ECM), the electrical behavior of the battery is represented by circuit components such as voltage source, resistance, and capacitance. ECM has a simple structure and fewer parameters; therefore, it is widely used for real-time applications. The resistance–capacitor (RC) network in ECM represents the charge transfer or diffusion process of battery electrical behavior, and this RC network is less complicated. RQ and Warburg network in ECM characterize the electrochemical performance of the battery, and their Laplace Transform is difficult for real-time applications [24]. RQ and Warburg networks are used for time-domain analysis, and the RC network is used for frequency-domain analysis. The data-driven model shows the relationship between the input and output signals of the battery. Conventional ECM has to identify model parameters via individual tests such as the Hybrid Pulse Power Characterization (HPPC) test, which is time-consuming and impractical for EV applications. The accuracy and performance of data-driven models [25–28] are dependent on the nature of the test data and training methods involved.

Various data-driven models are support vector machines (SVMs), random forest (RF), artificial neural networks (ANNs), ensemble learning [29], and decision tree-based, which do not require prior knowledge of the internal characteristics of the battery. In [25], it is mentioned that the SVM algorithm is used for state of health (SOH) estimation by reducing the data size requirements to train the model to achieve good accuracy results.

Thermal characteristics like the temperature of the battery play a vital role in battery performance and lifetime. Four categories of thermal models include heat transfer, heat generated, data-driven, and reduced-order thermal models. Activation, concentration, and ohmic loss are the three methods that determine the heat generation of a battery. There are many reasons for heat generation, such as high-current passes through battery and internal resistance, over-voltage across RC networks, and entropy change or Joule heating. Three modes of heat transfer between the inside and surface of the battery include conduction, convection, and radiation. The three-dimensional heat transfer electrical and thermal model is capable of determining the distribution of temperature and electric potential and detecting hotspots inside of the battery [30]. Reduced-order thermal models can control battery thermal management [31,32].

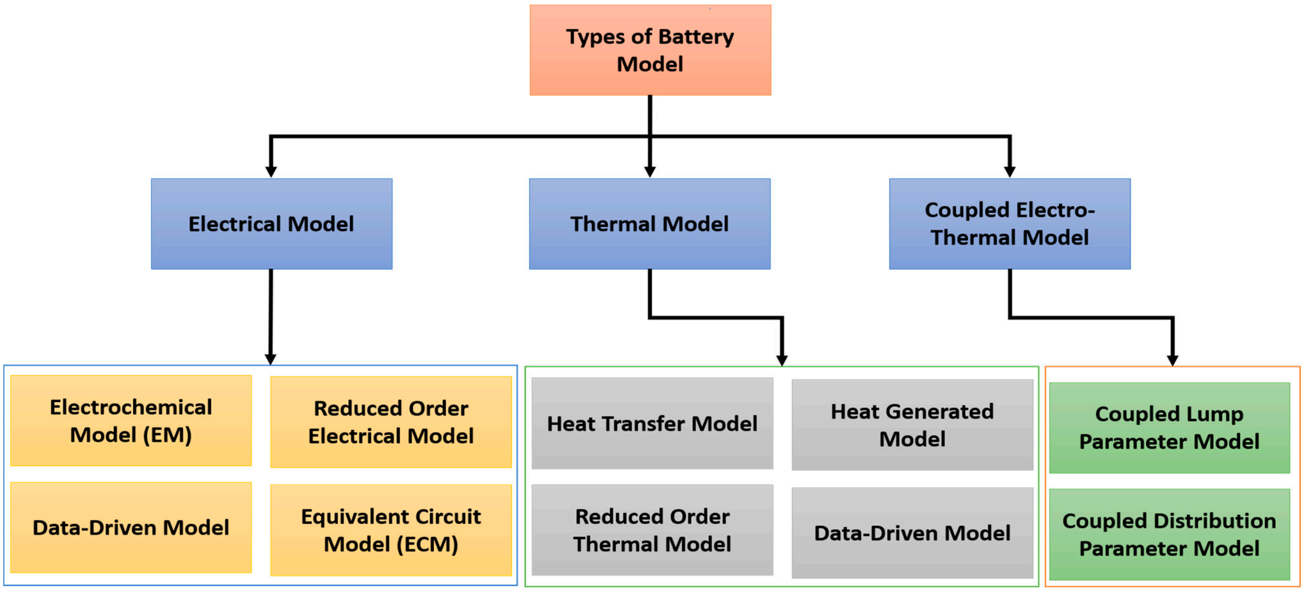

Figure 3. Categories of battery models.

To capture electrical parameters (voltage, current, and SOC) and thermal parameters (internal and surface temperature) simultaneously, the electro-thermal coupled model [24] is considered. The lumped and distributed parameters are used to develop the electro-thermal coupled model. In [33], the three-dimensional coupled electrochemical, thermal model is used to predict the temperature effect on series connection, parallel connection, contact resistance, coolant flow rate, and the discharge current of the battery pack and individual cells. [34] developed a 3-D electro-thermal coupled model that determines the SOC and heat generation of a lithium-ion pouch cell battery pack.

In [35], there are three methods used to estimate the state of health (SOH): experimental, model-based, and machine learning. In [36], a review of different SOH estimation methods is discussed in which model-based approaches like ECM, EM, Electrochemical Impedance Spectroscopy (EIS), and data-driven approaches like neural networks (NNs), SVMs, fuzzy logic, fusion model and data-driven are used for estimation. In [37], different methods to estimate SOC are discussed such as conventional methods like the Open-Circuit Voltage (OCV) method, Electromotive Force (EMF) method, Coulomb Counting (CC) method, internal resistance method, EIS, model method and ECM- and EM-adaptive filter methods like Kalman Filter (KF), Extended Kalman Filter (EKF), Unscented KF (UKF), Sigma Point KF (SPKF), Particle Filter (PF), H∞ Filter, Recursive Least Square (RLS), machine learning methods like NN, fuzzy logic, SVM, Genetic Algorithm (GA), non-linear observer methods like Sliding Mode Observer (SMO), Proportional Integral Observer (PIO), Non-Linear Observer (NLO) and other methods like Multivibrate Adaptive Regression Splines (MARS), Bi-linear Interpolation (BI), Impulse Response (IR), hybrid approach. In [38], thermal models, like heat generation models, associated thermal issues, and different cooling methods are discussed. Other ECM models used in vehicles are discussed in [39], like the Rint model, Thevenin model, dual polarization model, N-RC Thevenin model, RC model, and the PNGV model.

The RUL prediction method is divided into three categories: model-based, data-driven-based and hybrid-based; model-based and physics-based modeling composed of mathematical algebraic equations or derivative equations or empirical equations. This approach is designed for a specific purpose (intended for batteries and cannot be used for bearings). In data-driven-based modeling, feature selection, theoretical statistics and

ML-based modeling is performed [40]. This algorithm approach can only be used for different applications by changing the value of the parameters [41].

Section 2 focuses on the terms related to battery management system. Section 3 reviews different methodologies used for SOC estimation. Section 4 reviews various techniques for SOH estimation. Section 5 provides the concluding remarks.

2. Battery Management System Terminologies

Lithium-ion batteries show non-linear characteristics; cells will degrade based on cycling or usage pattern. Lithium-ion batteries catch fire or explodes due to malfunctions of the battery management system or when crossing the limit of the safe operating region. Lithium-ion batteries are used in EV automotive applications, so end-customer safety is essential. A battery management system (BMS) acts as the brain of an EV battery, which is required to monitor, control, and communicate and allows operating in a safe region. BMS is an electronic device, mechanical system, or any possible technology that can manage the individual cells, modules, and packs. BMS has hardware and software parts that manage the whole battery system. A BMS in an EV is composed of different kinds of sensors, actuators, and controllers with inbuilt algorithms and communication signal wires. The function of a BMS is cell balancing, battery parameter identification, state estimation, fault diagnosis, battery safety, control, thermal management, communication, and storage of data. Figure 4 shows different functions of BMS and how it is achieved.

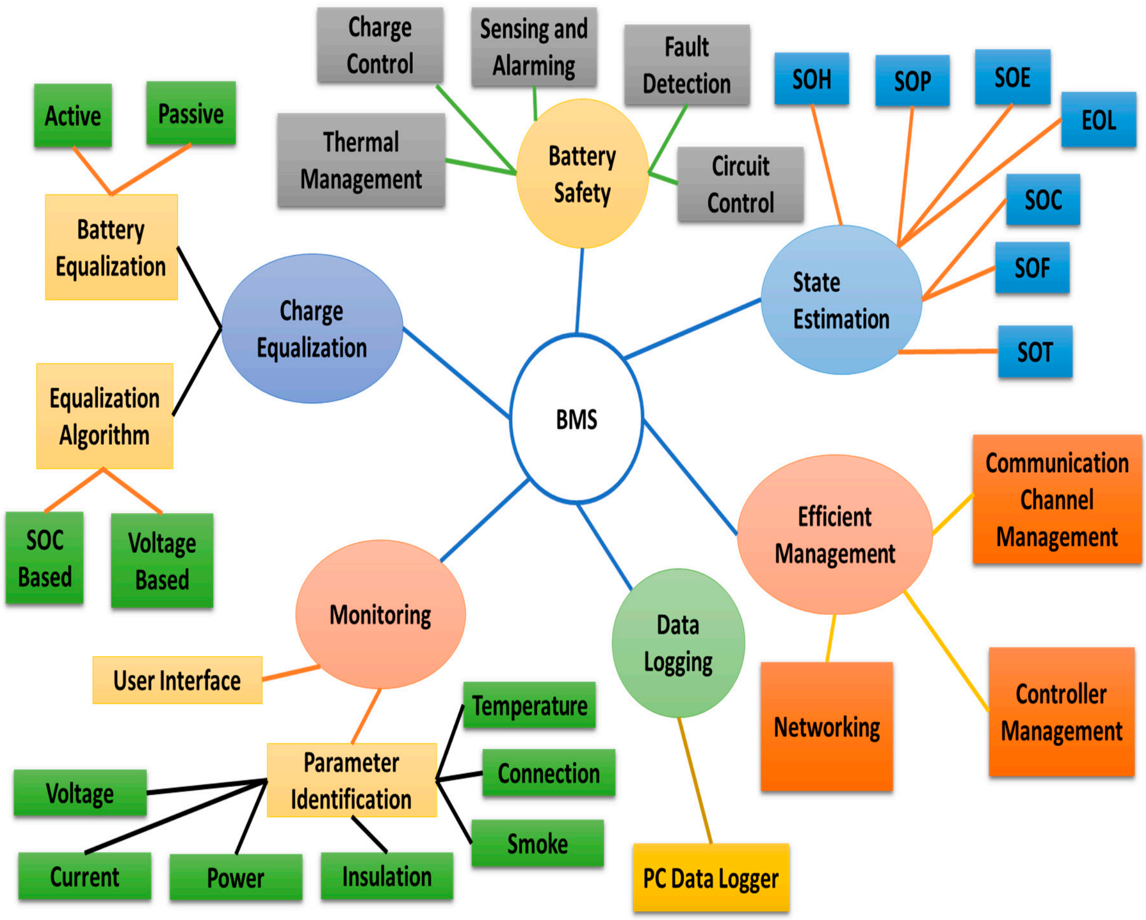

Figure 4. Various functions of BMS.

Figure 5 shows the number of publications in battery state estimation terminologies produced in the last ten years. From Figure 5, SOC is the central research area focused on by authors and achieves the highest number in terms of annual publications. State of the art (SOA) is the second highest on the list, then End of Life (EOL), then Remaining Useful

Life (RUL), then State of Health (SOH), and then other states. Different state estimation topics serve various purposes other than battery-related topics. Few documents on state estimation are focused on lead–acid batteries, apart from lithium-ion batteries. Some of the documents on EOL testing have been produced for products in the electronics industry and in relation to tires, vehicles, aircraft, engines, transformers, transformers for the oil industry and other areas. The same terminology is used in different industry areas for different research purposes. These data were collected from the Web of Science (WoS) on 22 January 2022 by refining the research terms as Energy Fuels or Electrochemistry or Chemistry or Engineering and the English language. Battery states play a significant role in proper functioning, maintaining and providing information about present or future conditions of use. Battery states can be monitored by using proper estimation techniques.

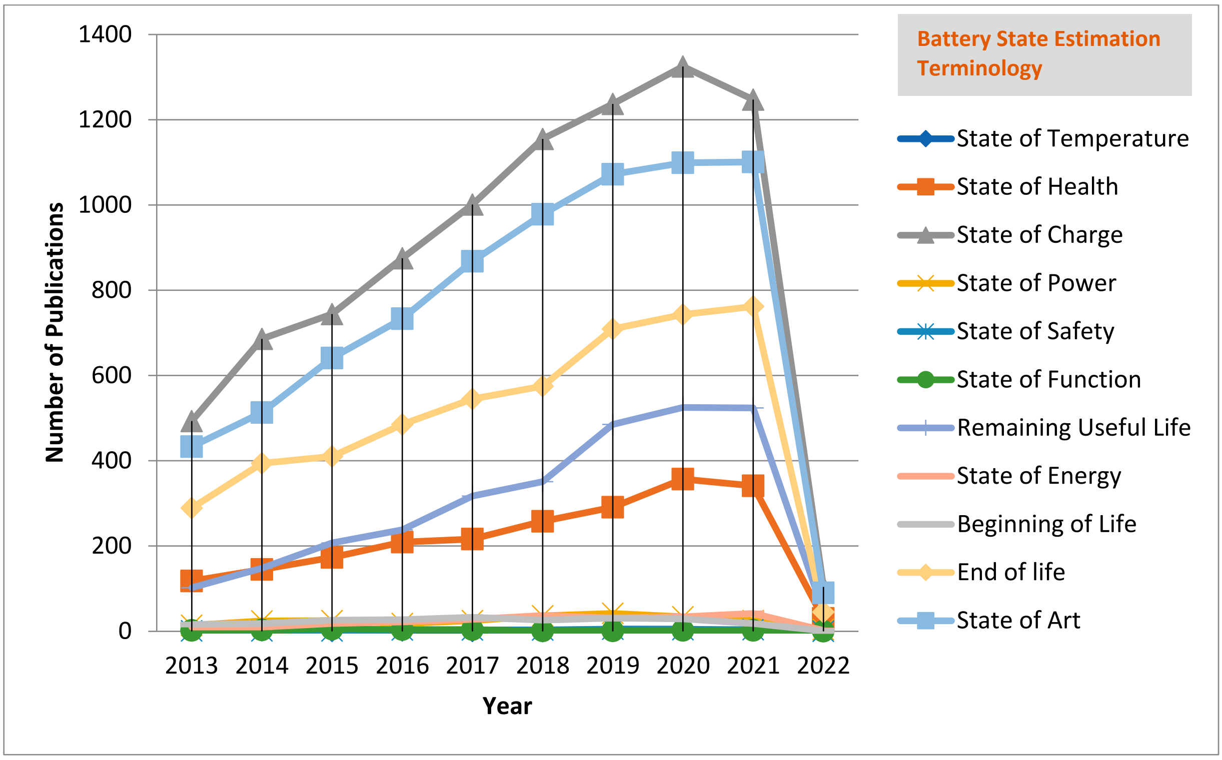

Figure 5. Last ten years publications in different battery state estimation terminology.

Some common terminologies related to BMS state estimation must be addressed and are discussed below.

2.1. State of Health (SOH)

Lithium-ion batteries experience gradual degradation of service life due to cycling and calendar aging. The health of the battery degrades inevitably and leads to a loss of lithium inventory. Electrochemical changes occur in batteries, like side reactions, lithium plating and cracks. For EV applications, degradation of the battery results in capacity reduction and an increase in internal resistance [42]. When the capacity is reduced by 20−30% or the internal resistance of the battery is doubled, then the battery is declared fully degraded (0% SOH). A fresh battery has 100% SOH. The SOH limit is set based on the lithium-ion battery chemistry composition and OEM operating range settings. From BMS, voltage, current, and temperature can be measured directly, whereas the direct measuring of different states is not possible. Equation (1) shows a general formula to calculate SOH in two ways [16].

$$\left\{ \begin{array}{l} SOH = \frac{C_{aged}}{C_{in}} \times 100\% \\ \\ SOH = \frac{R_{increase}}{R_{in}} \times 100\% \end{array} \right\} \quad (1)$$

where C_{aged} = reduced capacity after a certain interval;

$R_{increase}$ = increase in resistance after a certain interval;

C_{in}, R_{in} = initial or nominal capacity, initial or nominal resistance, respectively.

Accurate SOH estimation and prediction are necessary to understanding how the battery is degrading based on different driving profiles, road conditions, weather conditions, and traffic congestion.

2.2. State of Charge (SOC)

The remaining capacity or charge in the battery by total capacity is known as SOC. It indicates how long a vehicle can run, similar to a fuel gauge. For example, 100% SOC means the battery is fully charged, whereas 0% SOC indicates that the battery is empty or discharged. Direct and indirect methods estimate SOC. In the direct or conventional method, the Ampere-hour (Ah), Coulomb Counting (CC), or Open-Circuit Voltage (OCV) method is used [16]. This method's estimation results are not satisfactory as compared to data-driven or filter model-based methods. SOC at time t is expressed as shown in Equation (2) [16,19]. Other battery states are dependent on SOC, like State of Function (SOF) and State of Safety (SOS). High SOC accuracy is required for other battery states to protect against the inevitable failure of BMS.

$$SOC(t) = SOC_{in} \pm \frac{1}{C_{rated}} \int_0^t \eta i(t) dt \quad (2)$$

where SOC_{in} = initial or total SOC of the battery;

C_{rated} = rated capacity of battery;

η = charge–discharge efficiency of battery;

i(t) = battery current at time interval t.

An accurate estimation of SOC and remaining driving range is necessary; otherwise, drivers may face the problem of an empty battery. SOC also determines how long xEV can run, and a better route plan can be considered.

2.3. State of Temperature (SOT)

Lithium-ion batteries show dynamic and non-linear characteristics. The battery is sensitive to temperature variation. Due to the high energy density of lithium-ion batteries and their small size, they are used for many static and movable applications. High energy density batteries face issues related to thermal management during charging–discharging. A rise in the temperature of the battery causes capacity degradation or resistance increment. Thermal runaway occurs in batteries due to thermal, mechanical, and electrical stress. The study of characteristic changes during thermal management, like heat generation, transfer, and dissipation inside the battery, is important. The minimization of stress factors is carried out by introducing safety techniques in the battery. Studies related to heat flow and distribution inside the battery denote the State of Temperature (SOT) [43]. An accurate thermal model and parameters are used to obtain precise thermal dynamic characteristics of the battery.

2.4. State of Energy (SOE)

SOE [44–47] determines the remaining energy in the battery so that EV BMS can predict the remaining driving mileage. During battery discharge, the voltage decreases, whereas charging voltage increases at different SOC levels. Correspondingly, the energy also varies [48]. During a high discharge rate, a significant amount of internal energy loss occurs, whereas a small change in capacity takes place. SOC represents the residual capacity (Ah) in the battery rather than the available energy (Wh) in the battery. In [49], the author discusses the difference between SOC and SOE. This difference is represented as a parameter for SOH estimation. When this difference increases, temperature decreases, whereas aging increases. Equation (3) expresses SOE in the mathematical form, which is very similar to Equation (2).

$$SOE\ (t) = SOE_{in} + \frac{1}{E_{rated}} \int_0^t P(\tau) d\tau \quad (3)$$

where SOE_{in} = initial SOE of the battery;
E_{rated} = rated energy of battery;
$P(\tau)$ = battery power at time interval τ.

2.5. State of Power (SOP)

SOP plays a vital role in EV dynamic driving conditions like ramp climbing, speeding acceleration, overtaking, cruise mode driving and braking suddenly. This dynamic driving condition information is given to the vehicle control unit in order to control the power flow from the battery. SOC and SOP [50–52] are the two deciding factors of energy management in the battery. SOP [53] is the available power that can be absorbed or delivered from the battery to the power train of the EV.

2.6. State of Function (SOF)

SOF denotes the battery peak power capability, and it is estimated with the help of SOC, voltage, current, and temperature parameters [54]. Battery manufacturers give upper and lower limits of voltage, current, and temperature in order to use batteries safely. Battery function deteriorates, which results in changes in the safe operating area (SOA) of the battery due to aging and environmental conditions. SOF indicates the battery's instantaneous maximum power capability during charging–discharging and denotes the battery operating within SOA. SOF is obtained from SOP. The SOF of the battery can be estimated via the co-estimation of SOC and SOH [55–57].

2.7. Remaining Useful Life (RUL)

The RUL [15] of a battery is also known as the residual service life of a battery before it degrades to a point after which it can no longer be used. The prediction of RUL is necessary because it prevents the battery from failing or fully shutting down in a controllable fashion, and its maintenance can be undertaken properly. RUL prediction plays a significant role in battery technology, but very little literature work has been produced in this area [58]. RUL prediction helps in enhancing battery life and also helps in finding the current health status of the battery from past collected data, hence helping in detecting the chance of failure. In [59], the diagnostic model is developed to identify the health indicator for online SOH estimation of supercapacitors. In [60], the author discusses several issues related to the safety and reliability of batteries. A battery malfunction leads to a fire explosion and increases the chance of system failure. In 1999, the US Space Research Laboratory failed due to the nonstandard internal impedance of the battery, and in the year 2013, the Boeing 787 caught fire due to abnormal behavior in the battery. NASA's MARS probe failed due to continuous overcharging of the battery. In [61], RUL is also used in electronic devices for predictive maintenance, and in this paper, the RUL model is developed using Unscented Kalman Filter and Baysein Progression neural network.

3. Issues and Challenges in Battery Management System

This paper discusses the BMS's various tasks or functions and also analyzes the issues or difficulties associated with it. There are various issues that need to be addressed in order to meet the demand for the safe and secure operation of lithium-ion batteries. Key issues related to BMS are battery management of cell voltage, greater accuracy in state estimation, battery equalization, and real-time fault diagnosis [62,63]. A BMS optimizes the performance of EVs and prevents overshooting, over-current, overvoltage, over-charge, high temperature, and anomalous behavior of the battery.

3.1. Cell Voltage Management

Thousands of cells are connected in series and parallel fashion in the battery pack. All the cell voltage needs to be measured by the BMS. The function of the BMS is to manage and make balance in each cell voltage. High precision to maintain the same cell voltage is necessary. There are two ways of cell balancing techniques, namely active balancing [64–66] and passive balancing [67–69]. A slight change in load or weather conditions leads to a change in cell voltages. A BMS needs to balance voltage among all the cells of the battery pack. If one of the cells is charged fully and another is partially, then it creates cell imbalance, leading to the sudden collapse of the battery pack or even heating up of the battery, degrading performance.

3.2. State Estimation

A BMS estimates and predicts the different states of batteries, such as SOC, SOH, SOP, SOF, End of Life (EOL), Beginning of Life (BOL), RUL, State of the art (SOA), and SOT. The inaccurate estimation and prediction of battery states leads to severe issues in BMS; therefore, precise estimation is necessary. Suppose there is no charge in the battery (0% SOC) and the SOC indicates 15%, then the driver will drive thinking that there is some charge left in the battery, and suddenly, when the vehicle stops in between running traffic or a highway, an accident may occur. Therefore, errors in SOC estimation will be dangerous. Different battery states play a major role in battery diagnosis; therefore, timely monitoring of states will secure the battery from any unknown hazard. For an efficient BMS, timely updating of data without noise is necessary.

3.3. Battery Equalization and Normality

There exists a certain difference between the characteristics of each freshly manufactured cell, such as voltage, SOC, capacity, internal resistance, and self-discharge rate [63]. If the production line is manual, not automatic, then the difference in characteristics is much more than automation. If the manufacturing environment is not as per standard and the production line is manual, not automatic, then it is inevitable that there will be differences between cell characteristics.

3.4. Fault Diagnosis

Intelligent fault diagnosis [40,70,71] of batteries is necessary for the safe and reliable operation of batteries. Much research and development are going on to improve fault detection techniques. A good BMS has to respond immediately, and the switch-on alarm or relay will cut off immediately from the main supply. There are mainly two kinds of faults in BMSs: hardware and software. Different types of faults may occur in BMS, like over or under current, over or under voltage, short circuit, thermal run away, contractor fault, internal short circuit (ISC) and external short circuit (ESC) fault, connection fault, sensor fault, over-charge and over-discharge fault [72]. If these faults are not solved in time, then passengers might experience endangering conditions, high battery temperatures, lithium plating, efficiency will decrease, battery aging, and electric power quality may decrease. A battery model is developed, which is compared with the real battery system and checked for different fault conditions [73]. This paper also discusses different voltage ranges for warnings under faulty conditions, and their relay action and BMS behavior is also discussed. Figure 6 shows battery fault diagnosis stages for under-voltage and over-voltage conditions. There are two limits for each input condition. The first limit is set for alarming and declaring a particular fault occurred, whereas when a particular fault reaches the second limit, then the BMS declares a particular fault reached the danger zone and immediately stops the system.

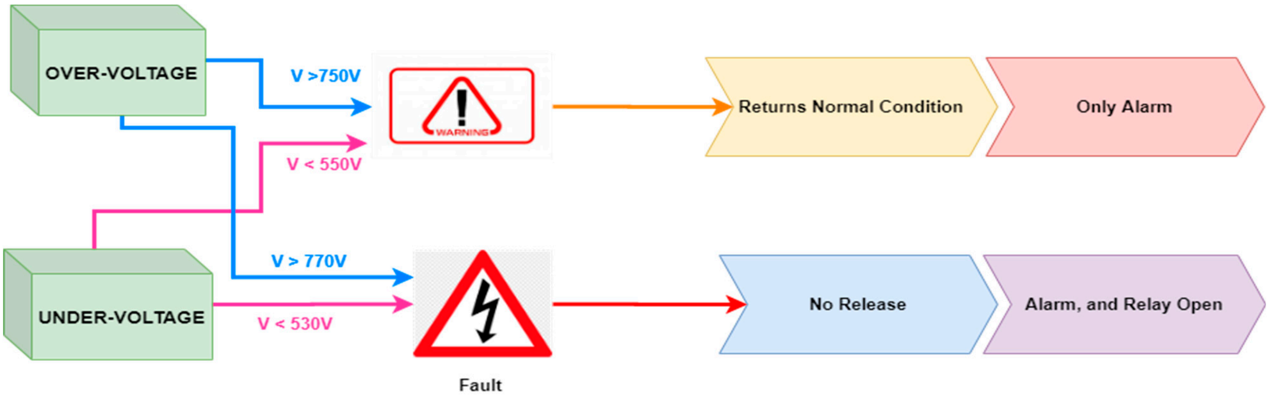

Figure 6. Battery fault diagnosis stages.

3.5. Diverse Application of BMS

There are various functions that a BMS has to perform at a time; therefore, the BMS has to be flexible, manageable, and rapid in operation. The BMS monitors all of the cell parameters and estimates and predicts different states. The concept of a wireless BMS [74] is an emerging technology leading to copper saving and reducing the congestion of wires. Very little literature has been published on wireless BMS and less research work has been performed in this area, which should be further focused on.

3.6. Handling of Unknown Hazard

An intelligent BMS has to respond quickly in unforeseeable hazardous situations. Lithium-ion batteries, when retired, need to be recycled, reduced and reused for the second life of battery applications. The separation of components from retired lithium-ion batteries is a difficult task. The separation of lithium, copper, aluminum, nickel, manganese, cobalt, and iron requires separate equipment to sort these elements. The manual separation is time-consuming, and automatic methods are more costly, so a lot of research work needs to be performed in this area. Lithium-ion undergoes an exothermic reaction when exposed to oxygen or water. Gases coming out when opening retired batteries are harmful to health and known to cause breathing problems.

3.7. Lack of Safe Operating Area (SOA) of Battery

Lithium-ion operates non-linearly; therefore, the operating area also changes. When cells are connected in series or parallel, there is a certain amount of difference in characteristics existing between each cell, like difference in capacity, internal resistance, or voltage. This difference causes inconsistency, is unreliable, and decreases efficiency. Therefore, BMS has to operate in safe operating regions for better performance of the battery.

3.8. Ensure the Power Converter Operates in a Safe Operating Region

Small changes in the design or working of the power converter [75–77] will change the direction of the current flow. Hence, the operation of the control signal generated by the controller will change and leads to an unprecedented issue with the BMS of the battery. Therefore, ensuring that the power converter operates in a safe region for the proper functioning of BMS is important. BMS with a power converter will extend the capacity in the second life of the battery [78]. BMS controls the individual cell's temperature level, voltage level, charge level, and current level and also estimates present and future SOC, SOH, SOF, and SOP.

4. Solutions to Tackle Problems in Battery Management Systems

BMS is the heart of EV, and in order to ensure its safe, reliable operation and proper communication, the BMS has to be handled carefully by monitoring the temperature of integrated circuits, wiring harness, controlled area network (CAN) communication protocol between BMS and connected device, checking power supply from PDU, and avoiding direct contact between the BMS and the battery pack. In between the battery pack and the BMS, an insulation layer has to be established to protect against the heat transfer between them. Checking communication protocols such as Serial Peripheral Interface (SPI), Inter-Integrated Circuit (I2C), and Universal Asynchronous Receiver Transmitter (UART) in the BMS board components in the case of BMS failure. Checking the power supply of the BMS board components in the case where the BMS LED is not glowing.

5. Bibliometric Analysis of Research Trend

SOH plays a significant role in the BMS in terms of a battery health diagnosis of the battery. If the battery is not safe and secure, then the EV is in a risky state. End-users always have uncertainty about when the battery will expire or catch fire due to some anomalous activity. Therefore, continuous monitoring of battery health is essential. SOC also plays an important role in order to know how much charge is left in the battery and how long the driver can drive. In EVs, SOC is a replacement for the fuel gauge, and SOH is a replacement for the odometer compared to conventional vehicles. Many of the algorithms are developed for SOC estimation and prediction. Figure 7 shows the research trend of both SCOPUS and the Web of Science (WoS) databases accessed on 21 October 2021.

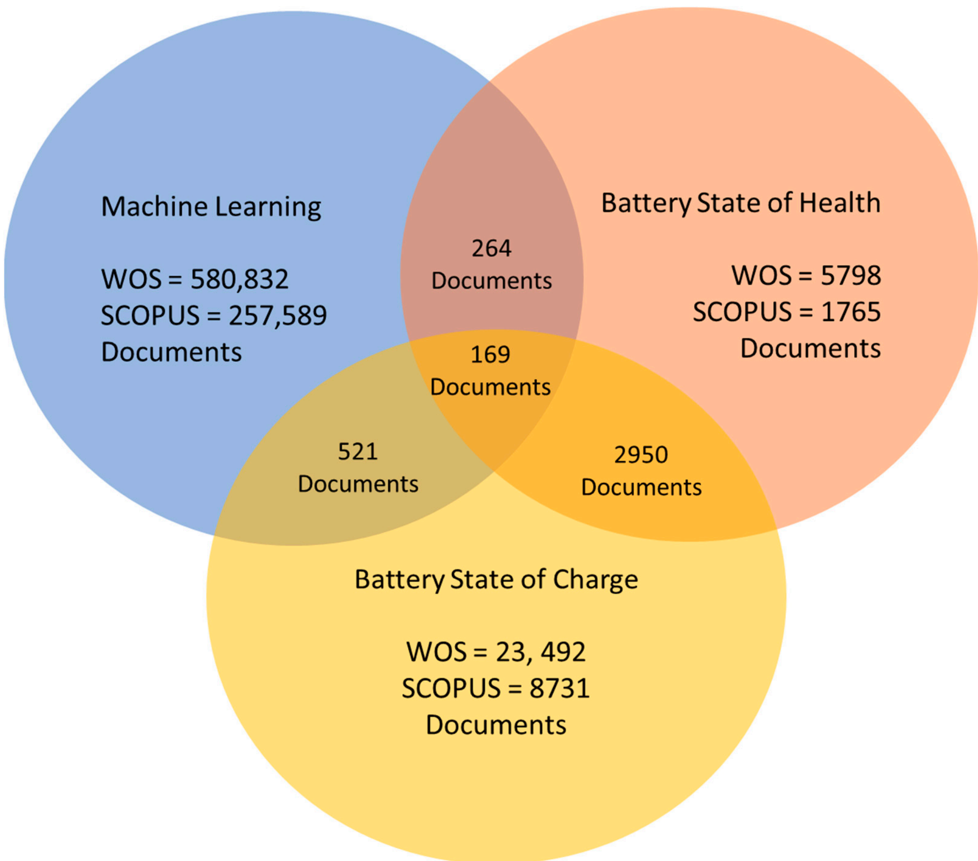

Figure 7. Research trends in SCOPUS and WoS databases (accessed on 21 October 2021).

Common documents in machine learning (ML) and SOC are 512, whereas common documents in ML and SOH are 264. This shows that many studies have been undertaken with a focus on SOC, but very little research work has been carried out for SOH. SOH plays a more significant role than SOC. Very few documents have been published concerning the combination of ML, SOC, and SOH, which is 169 documents.

There are some duplicate papers that exist in both SCOPUS and WoS databases, which need to be excluded. Table 3 shows the outcomes of SCOPUS and WoS databases.

Table 3. Outcome of Scopus and WOS databases.

S.No.	Keyword/(s)	NoD in SCOPUS	NoD in WoS	Duplicate Documents
1.	Machine Learning	257,589	580,832	
2.	State of Health	1765	5798	
3.	State of Charge	8731	23,492	
4.	Machine Learning AND State of Health	64	246	46
5.	Machine Learning AND Charge State of Charge	104	476	59
6.	State of Health AND State of Charge	659	2291	588

Table 4 summarizes the review papers related to EV, HEV, battery, BMS, and charging technology. Most of the review papers are concentrated on SOC or SOH only, not on both state estimation techniques. Many of the review papers have not explained state estimation methods and research trends in detail. When taking different operating conditions, like different driving conditions [79], temperature conditions, battery chemistries, and different vehicle loads, experiments are not performed. All of the experiments are performed in a controlled laboratory environment; therefore, the failure rate and accuracy rate are higher in real-time experience. Most of the documents are focused on cell behavior control at different conditions, not on the battery pack behavior control.

Table 4. Summary of review documents published on electric vehicles.

S.No.	Reference	Topic of Review Documentation	Discussion on Paper
1.	[16]	BMS	Battery types, modeling categories, state estimation techniques, and charging approaches are discussed.
2.	[19]	BEV and HEV components estimation techniques	Different estimation strategies for battery management, vehicle energy management, and vehicle control are discussed.
3.	[35]	HEV battery SOH estimation methods	Experimental-based, model-based, and Machine Learning based SOH estimation methods are discussed, along with the advantages and disadvantages.
4.	[36]	Battery SOH estimation	Different SOH estimation methods are discussed
5.	[37]	SOC estimation methods	Conventional, adaptive filters, learning algorithms and non-linear observer methods are discussed for SOC estimation. Challenges and issues in battery management are also discussed.
6.	[14]	SOH estimation methods	Different SOH estimation methods discussed in different papers comparison along with advantages and disadvantages
7.	[15]	SOC estimation methods, RUL prediction methods	Different SOC estimation methods, voltage and capacity estimation, and RUL prediction methods are discussed.

Table 4. *Cont.*

S.No.	Reference	Topic of Review Documentation	Discussion on Paper
8.	[77]	BMS issues	Detail discussion on BMS operation, function, and key issues faced in BMS
9.	[38]	Battery thermal issues and management techniques	Detail discussion on battery thermal behavior, problems, ways to manage thermal issues by cooling techniques in battery, challenges, and future scope
10.	[80]	ML-based SOH estimation methods	Different non-probabilistic ML-based SOH estimation methods are compared in terms of publication trend, advantages, disadvantages, challenges, and also according to different metrics. Non-probabilistic ML algorithms are Linear Regression, Ensemble Learning, Nearest Neighbor regression, Support Vector Machines, Artificial Neural Networks, and their variants.
11.	[39]	BMS	BMS functions, reconfiguration topology, and challenges like fault diagnosis are discussed
12.	[81]	Battery monitoring methods	SOC, impedance, capacity, power, SOH, and RUL estimation techniques are discussed in general
13.	[82]	SOC estimation methods	General discussion on types of battery models for SOC estimation and battery pack SOC estimation methods
14.	[83]	SOH estimation techniques	Differential analysis-based, ML-based SOH estimation methods are discussed, along with advantages and disadvantages. RUL prediction methods are also discussed.
15.	[84]	EV charging management	EV charging control strategies, charging management techniques and their pros-cons are discussed.
16.	[85]	Battery health prognostic	Challenges in battery health and different techniques for health issues are discussed
17.	[86]	Cell Balancing	Different cell balancing techniques and importance of cell balancing are discussed
18.	[56]	State Indicators	Familiarizing with the terms SOC, SOH, SOF, SOT and research trends on state indicators
19.	[63]	BMS	BMS performing stages, monitoring, protection, management strategy, key issues in BMS and opportunities-challenges in battery are discussed
20.	[48]	BMS	Defining battery state terminologies, methods for state estimation and related key issues and future direction are discussed
21.	[12]	SOC and SOH control methods	Aging and SOC control methods for super-capacitors are discussed in general.
22.	[87]	Charging methods	Different charging methods are discussed in general

6. Literature Review on SOC Estimation Methods

In Figure 8, a summary of SOC estimation techniques is shown. Different documents have different classification categories. Battery voltage, current, and temperature can only be measured directly. At a high-temperature charging rate, then Solid Electrolyte Interface (SEI) growth is increased, which causes cycle life degradation. At low temperatures, SEI growth is decreased, but lithium plating is initiated at the anode side of the battery [88]. Through SOC, the remaining battery power and capacity can be determined, and through SOH, the remaining useful life of the battery can be determined.

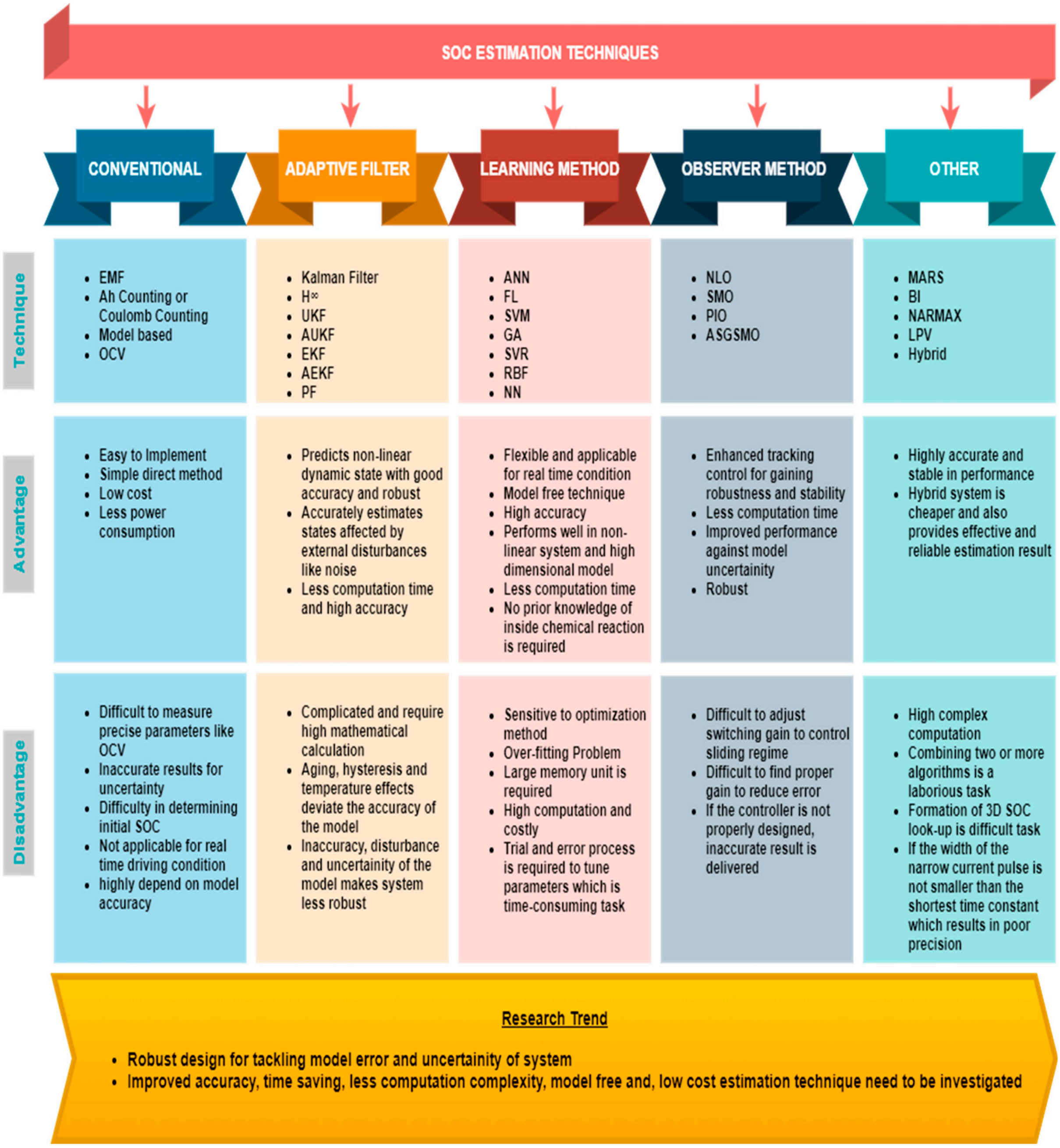

Figure 8. SOC estimation methods and their advantages, disadvantages, and research trends.

There are different methods through which SOC and SOH can be known. Different degradation factors influence the real SOC value; among them, the temperature is one of the reasons leading to the fluctuating results. Other degradation factors include the hysteresis curve and self-discharging. The main reasons for the aging of the battery are due to capacity and resistance. The battery also ages due to calendar life and cycling activity. Due to structural changes, and also the use of different anode/cathode materials, aging occurs [37]. Plenty of data under different conditions need to be collected to better monitor battery health. A BMS can be integrated with IoT, cloud servers, ML, and big data in order to improve performance in a realistic pattern. It is critical to achieve an accurate SOC for safety, behavioral changes, range determination, designing cost, and passenger comfort experience. Battery SOH determines the degradation of battery capacity with respect to the new battery. Lithium-ion battery diagnosis is necessary for energy management in order to control and keep the battery performance within desired limits and safety.

Different authors and researchers have different thought processes and different ways of selecting particular niche algorithms. Every method has its own benefits and drawbacks; based on the use case, data, input-output requirement and condition scenario, a particular method is selected. Conventional or traditional methods are categorized into different techniques, such as Electro Motive Force (EMF), Coulomb Counting (CC), Open-Circuit Voltage (OCV) and model-based methods [89]. These techniques are simple and easy to implement. Therefore, it is also called the direct method. This method requires low power and, therefore, costs less. There are some drawbacks of using this method, such as difficulty in measuring precise parameters, such as OCV. For different environmental uncertain conditions or for real-time operations, this technique is not suitable. In this method, the initial SOC value is unknown, and the accuracy of this technique is highly dependent on model accuracy. Another technique is adaptive filter, which is used for non-linear, uncertain, and real-time systems. This technique accurately estimates SOC in less time. There are various types of filter techniques, such as Kalman Filter (KF), Extended KF (EKF), Unscented KF (UKF), Adaptive EKF (AEKF), Particle Filter (PF) and H∞. This technique requires high mathematical calculation, and computation complexity makes it complicated. The accuracy of the model is reduced by external disturbance, aging, temperature, uncertainty, and hysteresis, making the overall system less robust. There are different learning algorithms or data-driven methods used for SOC estimation, and these methods are model-free. Some of the learning methods are Artificial Neural Networks (ANNs), Fuzzy Logic (FL), Support Vector Machines (SVMs), Genetic Algorithm (GA). This technique is used for online parameter estimation and the identification of new parameters for accurate state estimation. The main problem with this technique is over-fitting. Deep knowledge of the domain to handle data is required in this technique. Next, the SOC estimation technique is the Observer method, such as Non-Linear Observer (NLO), Sliding Mode Observer (SMO), and Proportional Integral Observer (PIO). This observer method controls the gain in the model and enhances the stability, accuracy, and robustness of the model. Designing and adjusting proper controller gain is a laborious task. There are some other SOC estimation techniques, such as the hybrid method or fusion method, Multivariate Adaptive Regression Splines (MARS) and Non-linear AutoRegressive Moving Average with eXogenous input (NARMAX). These methods are highly robust, accurate, and stable for SOC estimation. The drawback of these methods is high computational complexity, and combining two or more algorithms for estimation is laborious. SOC estimation by using the LSTM-RNN model with average voltage as an input feature. This average voltage is calculated by using the sliding window technique in order to reduce the fluctuations in the data [90].

SOC is one of the important parameters in battery management. Accurate SOC estimation is necessary to improve energy management in the system and allows for the efficient utilization of the battery by optimizing the performance, extends the lifetime, and prevents permanent damage of batteries in vehicle systems. Reduction in SOC leads to less power supply by the battery to drive the motor, and the magnitude of the charge–discharge cycle is increased.

The capacity of the battery changes with changes in ambient temperature and changes in cycle time. The most common technique used for SOC estimation is the Ah counting method. This method is simple, easy to implement and direct. The drawback of this method is that it is costly for accurate current estimation.

KF is a highly accurate method for dynamic systems, but it requires high computation. Non-linear autoregressive moving average with exogenous variables (NARMAX) is also used for non-linear system prediction, high convergence rate, and high approximation precision. SOC helps in preventing the battery from over-charge and over-discharge. It also helps in recognizing how far a vehicle can go [91]. The Kalman Filter (KF) is stated as being an intelligent and robust method for SOC estimation [92]. KF is good for estimating time-varying states in dynamic environments and handles noise gently. In Equation (2), SOC_{in} varies with the change in current, but KF does not bother changing in the initial

SOC. SOC_{in} has errors in measurement or due to external factors. According to [93], Battery Available Capacity (BAC) is defined as the amount of electrical power delivered by a fully charged battery at a certain discharge current profile and temperature until a certain cut-off voltage is reached; in this paper, the cut-off voltage is 10.8 V. According to [94], KF and NN achieve high performance, but computational complexity and high cost of implementation limits their usage. SVM is used to solve classification and regression problems. NN solves local minimization problems, whereas SVM solves quadratic problems and is used as a global minimization solution. Multilayer feed-forward networks, such as MLP, compete with SVM, therefore, the total replacement of ANN is not possible. ANN has a fixed size and has single or multiple outputs, whereas SVM model size varies, increasing in nature and has a single output. Table 5 shows a comparison of different SOC estimation methods. Battery performance depends on various factors like DoD, SOC, charging strategy, temperature, environmental condition, and driving pattern. These factors are necessary to predict battery life. The electrochemical and equivalent model-based approach is applied for charge/discharge cycle and battery lifetime prediction and gives better performance in simulation or offline mode. In contrast, data-driven methods do not require prior electrochemical or in-depth composition knowledge to do the analysis. Data-driven approaches require a large amount of data for analysis. A machine learning-based data-driven approach is used for online real-time estimation and the prediction of model and has been known to yield more accurate results [19]. Battery capacity is predicted via the fusion of empirical and data-driven methods [95]. Two cases are taken for study, in case 1, discretized Arrhenius aging model (DAAM) is used along with two EKF, and in case 2, the linear aging model is used along with the PID controller and Luenberger observer. The error in both cases is under 1%.

Table 5. Comparison of various Soc estimation methods.

Ref.	Year of Publication	Battery Type	Parameter Condition	Model/Method	Description	Average Error	Future Scope
[96]	2012	Li-NMC, 4.2 V and, 100 Ah	Charge/discharge pulses at different current levels	Recursive least squared algorithm (RLS)	Ah counting method along with ECE 15 European drive cycle	Max. error @ 0.8% and the mean relative error @ 0.07%	
[97]	2002	NiMH	Charging/discharging cycle	Model-based	State-space model-based estimation	unspecified	Comparison of estimator by considering uncertainty in battery parameter
[98]	2008	NiMH 80 Ah, 96 V	Current, voltage	NARMAX	Estimate residual capacity by using FUDS drive cycle	Max. avg. error @ 0.02%	Investigation of robustness of the model to overcome external disturbance
[99]	2005	NiMH 45 Ah, 24 V, 25 °C	3 Discharging current profile, terminal voltage	3-layer NN	32 testing dataset, discharging and regenerative current distribution and, temperature. Low-cost microcontroller is used	Avg. Relative error @ 2.67%	Performing on different battery modules and influence of aging effect, perform on dynamic models of NiMH battery and on HEV for determining fully charged state
[91]	2002	NiMH	Constant current discharge, random discharge and standard discharge	ANFIS	Low-cost microcontroller is used.	Avg. Relative error @ 2%	Can be performed on other battery types.
[100]	2010	NiMH 100 Ah, 1.2 V	Charging discharging	OCV	Takacs model is used which is based on hysteresis phenomenon of OCV	10%	
[101]	2011	6 series NiMH, 8 Ah, 1.2 V	Charging discharging at constant current	radial basis function network (RBF)	MATLAB and ADVISOR software are used, data collected between 15–85% SOC	MSE@ 1.618%	
[102]	2004	3 cells series NiMH, 2.7 Ah	EIS over 100 cycles	Fuzzy Logic	Charged @ C/3 rate at 4 h, discharged C/2 rate for 28 cycles	±5%	
[103]	2009	NiMH	Current, voltage and past SOC	ANN	4 networks	5%	
[104]	2009	NiMH	Current, voltage and past SOC	BPNN	Short term (ST), long term (LT). BPNN has good self adaptability	1.94%@ ST, 0.93% @ LT	To improve local minimum, training speed and accuracy GA should be added to BPNN
[105]	2010	NiMH 27 Ah	Different temperature, charge and discharge current rate	Ah method	0 °C, −18 °C, −12 °C, 25 °C @ temperature, 1/3 C, 1 C, 3 C @charge rate, 1/3 C @ discharge rate	3.6%	Coulomb efficiency and SOC analysis in high temperature can be performed with this model in future
[106]	2009	NiMH, HEV on dynamic model	Hysteresis effect, polarization effect, internal resistance	EKF	Capacity balance test and capacity consume test	Mean error @ 3%, maximum error @ 7%	
[107]	2005	Lead–acid, HEV on dynamic model	Real-time drive cycle	Hybrid (KF + EKF)		2%	This work can be extended for different models and cell chemistries
[108]	2008	HEV, NiMH	Voltage, current, SOC	Hybrid or Adaptive (EKF + Coulomb accumulation + OCV)	• OCV method is good for steady state condition SOC estimation. For, e.g., When vehicle is parked. • KF method is good for SOC estimation with dynamic current. • Coulomb accumulation method is good for HEV dynamic and time-varying system, but unsuitable for dynamic current and incorrect initial SOC.	• Starting estimating SOC with wrong SOC after 500 cycles match with true SOC. • For random noise: estimating SOC without EKF variance @ 0.0122 and estimating SOC with EKF variance @ 0.0059 • Estimated SOC by coulomb accumulated method @ 57.1%, OCV method @ 46.3%, combined method @ 51.3%	

Table 5. *Cont.*

Ref.	Year of Publication	Battery Type	Parameter Condition	Model/Method	Description	Average Error	Future Scope
[109]	2010	10NiMH batteries in series @1.2 V, 8 Ah, HEV	Different charging rates @ 4 C, 3 C, 2 C, 1 C, 0.5 C	Hybrid (GA + BPNN)	Fast convergence speed and strong learning ability	MSE BP @ 0.9408%, 8 steps MSE GA-BP @ 0.7577%, 3 steps	
[110]	2009	NiMH	C/3 rate discharge test, current and voltage record during FUDS drive cycle	Hybrid (AEKFAh)	Max. Discharge current @ 129.2 A, max. Charge current @ 63.8 A, temperature ranges @ 25.91–27.52 °C	AEKFAh error @ 2.4%, Ah error @ 11.4%	
[111]	2007	NiMH battery	C/3 rate discharge test, current and voltage record during FUDS drive cycle	Hybrid (KalmanAh)	Max. Discharge current @ 129.2 A, max. Charge current @ 63.8 A, temperature ranges @ 25.91–27.52 °C	KalmanAh error @ 2.5%, Ah error @ 11.4%	
[93]	2007	12 V lead–acid battery, EV	Discharge and regenerative capacity distribution, which represents different discharge current profiles @ theoretical and practical data, different temperature	NN	7 Input neurons @ different discharge current, regenerative current, temperature. 1 Output neuron @ State Of Available Capacity (SOAC). 11 hidden neurons	Avg. Relative percentage error (ARPE) of NN@ 2%	This work can be extended for other types of EV battery
[112]	2008	6 Ah, 2 V lead–acid battery, HEV,	Discharging current, OCV test for initial parameters	Dynamic ECM model with EKF	Comparison of static (R_{int}-based SOC estimation) and dynamic (EKF-based SOC estimation)	3%	
[113]	1998	Sealed-type lead–acid battery	Temperature, terminal voltage, discharge current, internal impedance	NN	4 Input neurons @ discharge current, temperature, terminal voltage, internal impedance. 10 Output neurons @ 0–100% in 10% step size SOC. 50 hidden neurons	Max. Error @ 10%, avg. Error @ 3%	Finding new ways for improvement is the next research plan
[114]	2005	Lead–acid battery, HEV	Dynamic ECM model	KF	Charging discharging of cells through observer technique	1%	
[115]	2007	24 V lead–acid battery	Charging, internal resistance	Fuzzy Logic	Proposed method avoids over-charging and under-charging	5%	
[116]	2011	Li-polymer battery	Full discharge test (4.15–2.5 V) @ 1 C, 2 C, 5 C	Reduced-order EM	Different ECM, reduce order EM, full order EM, experimental model is analyzed	1%	Perform analysis with high discharge current rate up to 10 C along with different ambient temperature
[117]	2014	Li-polymer battery, V_{oc}-SOC relationship, charging–discharging	RC ECM	Adaptive method	EKF and state-observer is used for over-potential dynamic of battery	Max. Error: SOC co-estimation @ 0.063, EKF @ 0.077, Sliding Observer @0.12	
[118]	2008	Li-polymer battery, HEV	Charge–discharge test at different temp.	Sliding mode observer	RC model is developed by OCV test and then SMO is applied for SOC estimation	3%	
[119]	2006	3.8 V, 7.5 Ah, Li-polymer battery, HEV	16USSD cycles, separated by 40 A discharge pulse and 5 min. rest time, 90–10% SOC range	Sigma Point KF(SPKF)	Enhanced Self Correction Model (ESCM) which is a discrete-time state-space model. ESCM is used for cell modeling because it includes effect due to OCV, internal resistance, voltage time constant and hysteresis. Comparing error in SPKF with EKF for SOC estimation	• By correctly initializing SOC @ 100%: RMS error: EKF@ 0.64, SPKF @ 0.49 • By incorrectly initializing SOC @ 80%: RMS error: EKF@ 0.75, SPKF @ 0.69	This work can be extended for accurately estimating SOC if cell parameters are taken real time in order to overcome manufacturing difference between cells and also tracking aging effect in cell parameters

Table 5. *Cont.*

Ref.	Year of Publication	Battery Type	Parameter Condition	Model/Method	Description	Average Error	Future Scope
[120]	2006	GEN3 (old cell) 20 C capable, 7.5 Ah and GEN4 (new cell) 30 C capable, 5 Ah, both Li-polymer battery, HEV	18USSD cycles, separated by 15 A discharge pulse and 5 min. rest time, 90–10% SOC range	Square Root-Sigma Point KF(SR-SPKF)	One cell data is used to fine-tune cell model parameter and another cell data is used to test in dynamic condition for filter analysis	• By correctly initializing SOC @ 100%: RMS error: SPKF, SR-SPKF @ 0.3, joint SPKF @ 0.29, dual SPKF @ 0.32, dual SR-SPKF @ 0.27, • By incorrectly initializing SOC @ 80%: RMS error: SPKF, SR-SPKF @ 1.44, joint SPKF @ 1.13, dual SPKF @ 1.35, dual SR-SPKF @ 1.26	
[121]	2013	3.7 V, 32 Ah Li-polymer battery, EV	Voltage, current, DST test	Adaptive Extended KF (AEKF), lumped battery model	Multi-state joint estimator is used along with 3 different degraded cells capacity. SOC estimator is verified via DST test	1%	
[122]	2014	3.7 V, 32 Ah Li-polymer battery, EV	Voltage, current	lumped battery model, AEKF	RLS-based online parameter updating, SOC estimator is verified at 5 different loading profiles (DST and FUDS) and different degradation capacity	Max. Error @1.5%	In future, data-driven approach based on joint SOC and peak power estimation
[123]	2014	50 Ah, 51.2 V Lithium-ion battery, HEV	Charging–discharging @ 285A max. rate, current and voltage measured @ 1s. interval, temperature (20 °C)	RC model, H_∞ filter	0.3 C discharging from 100% SOC to 90% SOC. Then, OCV, HPPC test @ I_d = 1 C, I_c = 0.75 C, performance of filter is verified via 6 USSD cycle test.	Without time-varying parameter @ 4% (Max. error), 1.4813% (Mean error). Time-varying parameter @ 2.49% (Max. error), 0.8436% (Mean error)	
[94]	2013	60 Ah Lithium-ion battery, LFP chemistry	3 times discharge test at particular C-rate in controlled environment, Dynamic Stress Test, current, voltage, temperature	SVM- SVR, RBF kernel	Charging @ 0.3 C up to 3.6 V (18 A), discharging @ 0.33 C (20 A), CCCV charging method, cut-off voltage @ 2.8 V	Max. error @ 6%, RMSE @ 0.71%	This model can be further applied and tested for different similar battery chemistry
[124]	2014	Lithium-ion battery, LFP chemistry, EV	Temperature, current @ input variable and terminal voltage @ output variable	Dual particle filter (DPF) based battery model	Temperature and current taken as input to model parameters to find the relationship between voltage, internal resistance and temperature of battery	MAE: DPF @ 0.67%, UKF @ 1.37%, EKF @ 2.05%	Study of energy loss in internal resistance and efficiency of charging–discharging will improve the energy range of the battery
[125]	2013	60 V, max. charge–discharge current @300 A, Lithium-ion battery, LMO chemistry, PHEV	Current, voltage, temperature	AEKF, Dynamic electrochemical polarization battery model, joint estimation approach	Available capacity test, HPPC test, OCV test, UDDS driving test, dynamic cycle test	Max. error @ 0.02 or 2%	In future, dynamic battery model has to focus on online parameter identification method and systematic validation test for available peak power capacity estimation
[126]	2013	NMC, 40 Ah Lithium-ion battery, EV	Voltage, current	EMF	By using EMF-OCV, SOC is estimated	2%	
[127]	2014	Lithium-ion battery	Voltage, current	PIO	RC battery model, USSD drive cycle	2%	
[128]	2013	LFP, 3.2 V, 12 Ah Lithium-ion battery	Battery terminal voltage, current, temperature @ input, SOC @ output	LS-SVM	Select sample data, prepare and process it, build training and prediction sample dataset, select k-function and parameter, set objective function, find Lagrange Multiplier a and b, build prediction model and predict future SOC	LS-SVM @ 2%, BPNN @ 3%	

Table 5. *Cont.*

Ref.	Year of Publication	Battery Type	Parameter Condition	Model/Method	Description	Average Error	Future Scope
[129]	2013	LFP, 3.2 V, 100 Ah Lithium-ion battery, 0.3 C rate charging	Battery current, voltage, temperature	MARS	SOC (25–90%), CCCV @ charge method, CC @ discharge method	1%	Using this model for testing of dynamic data profile
[96]	2012	Lithium-ion battery, EV	Battery current, voltage, temperature, SOC	RLS	ECE 15 drive cycle, real data and RNN-based SOC predictor used for battery modeling and terminal voltage estimation	Max. error @ 1.032%, mean error @ 0.1744%	
[130]	2013	Lithium-ion battery	Voltage, temperature	AWNN	AWNN response of SOC estimation is comparable to BPNN and WNN	2%	
[131]	2013	Lithium-ion battery	Charge–discharge	EKF	SOC varies from 5–95%	1%	
[132]	2012	7.5 Ah Lithium-ion prismatic battery	Cell terminal voltage, current, SOC	Hybrid (EKF + coulomb counting)	ESC model, 15 UDDS test, 100–4% SOC	Dual EKF @ 6.573%, Multi-scale framework @3.93%	To investigate the effect of time-scale on accuracy and State of Life (SOL) prediction of proposed work with lifetime cell aging test

The Coulomb counting (CC) method is also known as the Ampere hour (Ah) counting method and is easy to implement but time-consuming and also yields inaccurate results in uncertain conditions. The CC method is the most commonly used method because of its simplicity and because it does not significantly affect parameters like DoD, temperature, and C-rate, which the battery performance is dependent upon [18,133,134] in this paper, the authors have compared different SOC estimation methods.

Support Vector Machine (SVM) and fuzzy logic are complex algorithms, and they are used for non-linear and high-dimensional vectors. The fuzzy logic method has a high computational cost, and battery parameters frequently change with the battery lifecycle [135]. The least-square SVM (LS-SVM) has higher accuracy than SVM; in [136] paper, SOC is determined quickly with more accuracy by LS-SVM as compared to conventional SVM and also has the ability to tolerate noise. Similarly, weighted LS-SVM (WLS-SVM) also quickly determines SOC with less computation. SVM-based feature identification can operate at different capacities, resistances, and temperatures for SOH estimation. This new feature shows a good correlation with capacity and is, hence, useful in SOH estimation. Proper knowledge of hyperparameters for tuning in Support Vector Regression (SVR) is necessary; otherwise, the training model is inappropriate. SVR is used as a regression algorithm for non-linear problems and is best suited for SOH estimation.

Kalman Filter (KF) is a fast as well as accurate method for linear applications and does not require any SOC/SOH parameters for measurements. KF is also helpful in filtering noise errors from sensors [14]. Extended KF (EKF) is an advanced method for non-linear applications. In this EKF method, non-linearity is converted to linear with the help of a linear time-varying system. Initial SOC is required to estimate SOC after a certain period of time, and in the case of the Ah counting method, it is difficult to extract, so Adaptive Extended KF (AEKF) is used to extract the initial SOC, and then the improved Ah counting method is used for better SOC estimation. A hybrid method, AEKF, along with the Ah counting approach (AEKFAh)-based SOC estimation for an Ni-MH battery for FUDS drive cycle yields a 2.4% error [110].

A deep Neural Network (DNN) is used to extract non-linear, complex SOH values and other parameters. These can also be fitted in a model to find the correlation between these parameters. Results show that diverse SOH parameters will enhance system performance. The Artificial Neural Network (ANN) technique is simple and used for non-linear data. ANFIS and group method data handling (GMDH) are employed for the analysis of SOH and selected features.

Extreme Learning Machine (ELM) and Random Vector Functional Link (RVFL) are two of the latest emerging learning algorithms whose training speed is thousands of times faster than conventional learning, and are discussed in much detail in another widely cited paper [137]. ELM and Ensemble Learning are used as single-step and multi-step ahead prediction techniques. Random learning-based ELM is proposed to find HI, a small voltage range is used to find HI in 1 ms, and this method is robust for different load profiles and temperature conditions. Probabilistic approaches, like Gaussian process regression (GPR) and Relevance Vector Machine (RVM), are used for predictions under uncertain conditions, like environmental uncertainty, measurement error, or model error. GPR is based on low data precision and changeable parameters and is good for uncertain conditions. GPR is a non-parametric approach based on Bayesian learning. State transition and equivalent circuit model were combined to find the SOC, SOH, and SOL of a lithium-ion battery [92]. Different battery models are compared and discussed in [138]. Different ECM and EM model features and corresponding equations are compared in this battery model paper. Among seven models, the DP model shows better performance than the other models.

7. Literature Review on SOH Estimation Methods

In Figure 9, a summary of SOH estimation techniques is shown. Different techniques for SOH estimation are discussed in different documents. Some documents have been classified according to whether they are experiment-based, model-based, or machine-learning-based methods [35,56]. Some have categorized SOH estimation techniques into direct, indirect, adaptive and data-driven methods [139]. Some have categorized SOH estimation techniques into physically based, empirically based, Incremental Capacity Analysis (ICA)-Differential Voltage Analysis (DVA) and data driven approaches [48]. Adaptive filter and data-driven techniques for both SOC and SOH estimation are similar. Model-based approaches are highly accurate when combined with other algorithms. This technique is sensitive to small changes in a system and is not suitable for real-time dynamic conditions. The accuracy of this model highly depends on the model parameters. Direct and indirect methods are categorized under experimental methods. Direct methods require high-quality test equipment and a controlled environment to achieve highly accurate results. The direct method measures internal resistance or charging capacity in the offline mode. Electrochemical Impedance Spectroscopy (EIS) and current pulse tests are conducted to find the internal resistance and impedance of a battery. Charging–discharging cycles are conducted to identify charging capacity depending on voltage or different temperature conditions. The Hybrid Pulse Power Characterization (HPPC) test is conducted to determine the power capability and measures cell voltage in a short high-current charge–discharge pulse [140]. In the indirect method, ICA-DVA incremental curves of capacity and voltage, respectively, are generated throughout the experiment. Based on the curves, peak analysis is performed. This technique is not suitable for real-time operating conditions and results in temperature changes. This method requires constant current charging to conduct this method of experiment. High-precision current and voltage is required to gain good accuracy.

A battery has non-linear characteristics and degrades due to many reasons. Battery aging is categorized into two parts: cyclic aging and calendar aging. Cycling aging is when a battery is in a use case and mainly occurs due to the frequent charging/discharging of the battery. Inside the battery, there is a chemical reaction taking place, which causes aging. Some of the stress factors are high SOC, low temperature, high temperature, high cycling rate, over-charge and over-discharge. Their corresponding degradation mechanisms are loss in lithium-ion, lithium plating, SEI decomposition, metallic loss of the active material, loss in active material and corrosion in the current collector, respectively. Calendar aging occurs when the battery is in an idle state or not in use. Calendar aging is caused due to high SOC and high temperatures. Calendar aging occurs throughout the life of the battery and does not depend on whether the battery is cycling or not [83].

A comparison of different SOH estimation methods is discussed in Table 6. Cell capacity is recovered during rest periods after long cycling [140]. Measuring battery capacity after cycling without a rest period and with a rest period is different. This is one of the critical issues when discussing battery accelerated aging tests and degradation patterns. One piece of literature [141] suggests that a 2-day rest period between every 50th cycle will double the battery's cycle life. In another piece of literature [142], the minimum duration required for a rest period is 2 h in order to noticeably recover capacity. Capacity recovery depends on rest periods at different SOC. A 0% SOC has better capacity recovery than a 10% or 20% SOC. In [143], this phenomenon of capacity recovery is known as self-recovery or regeneration. Regenerative capacity can be detected by using the particle filter method and isolating the influence of regeneration in the life cycle model to improve the initial conditions in long-term prediction. Prognostics or predicting the health condition is a summation of knowledge gathered from past usage data, present usage data, and future usage data. Past usage data are obtained from historical operational data; current state knowledge is obtained from sensor feedback or a feature obtained from it. Future usage depends on operational and environmental conditions [144].

Table 6. Comparison of various SoH estimation methods.

Ref.	Year of Publication	Battery Type	Parameter Condition	Model/Method	Description	Average Error	Future Scope
[96]	2012	Li-NMC, 4.2 V and, 100 Ah	Charge/discharge pulses at different current levels	Recursive least squared algorithm (RLS)	Ah counting method along with ECE 15 European drive cycle, battery internal resistance is identified	Max. error @ 0.92% and the mean relative error @ 0.14%	
[145]	2014	5 different Lithium-ion batteries (NMC/LTO, 20 Ah), (LFP/C, 60 Ah, 11 Ah), (LMO/C, 35 Ah, 10 Ah), pure EV	Different temperature (45 °C, 5 °C) at different seasons	Genetic Algorithm, Semi-empirical capacity loss model for online and offline SOH estimation	Reference Performance Test (RPT) (combination of HPPC test and capacity test), cycle life test	1%	
[146]	2013	Pouch cell, 32 Ah, 4.05 V full voltage, Lithium-ion battery, EV, HEV	Diffusion capacitance, current, terminal voltage, different charge/discharge rate	Genetic Algorithm, 2-order RC model	RC model diffusion capacitance is compared with experimental result capacity obtained. Diffusion capacitance is reciprocal of capacity or SOH.	5.11%	Further improving convergence speed
[147]	2012	4 V, 30 Ah Lithium-ion battery	Temperature (−30 °C to 90 °C), current (0 to 400 A)	Fuzzy Logic (FL)	FL-based SOH estimator is developed by varying temperature and current	Unspecified	
[148]	2014	Lithium-ion battery (LMO chemistry)	Different charging/discharging rate, interval time, voltage, temperature	ECM	6 different cells are tested under different charging/discharging current rates, voltages, temperatures, end of charge/discharge current–voltage and times. Model parameters are identified via the Least Square method	2%	
[149]	2014	Lithium-ion battery, PHEV	Current, temperature, SOC @ input parameters, voltage @ output parameter	SVM	Dynamic conditions, such as temperature-dependent/independent resistance/capacity and different SOC range taken for virtual and experimental analysis	unspecified	
[150]	2013	Lithium-ion battery, HEV	Temperature, cell aging, current, voltage	Linear Parameter Varying (LPV) Model	Central Difference KF (CDKF) based LPV model	unspecified	
[151]	2011	6.5 Ah Lithium-ion battery, HEV	Measured terminal voltage, current, temperature	ECM	Temperature, SOC, current affects internal resistance of battery incorporating ohmic and polarization resistance	unspecified	Further research will be performed on considering inner cell temperature and dynamic load condition
[152]	2014	2150 mAh Samsung Lithium-ion battery (NCA chemistry)	Change in voltage and current during charging/discharging process	Dynamic Impedance Technique	Calculating a, b, SOC values through mathematical equation then SOH is calculated and this method is independent of temperature variation, data recorded @ 1 s	SOC estimated and actual SOC error @5%	
[153]	2014	3.7 V, 6000 mAh Li-Mn battery	Terminal voltage of battery recorded during constant charge process	Dynamic Bayesian Network (DBN)	Capacity test, lifecycle test, SOC @hidden nodes, terminal voltage @ observed nodes, data recorded @ 10 s, categorizing aging states into 5 @ >95%—brand new, 95–90%—new, 90–85%—ok, 85–80%—old, <80%—very old	5%	
[154]	2018	Four 3.2 V, 2.5 Ah Lithium-ion battery (LFP chemistry)	Voltage and current during charging process at CV mode	1st order RC ECM	Current time constant is correlated to nominal battery capacity @ −0.988 to indicate SOH, sampling freq. 1 Hz. In original BMS sampling freq. is 100 Hz	2.5%	In future, higher-order RC model tested under different battery chemistry, charging protocol and temp.

Table 6. *Cont.*

Ref.	Year of Publication	Battery Type	Parameter Condition	Model/Method	Description	Average Error	Future Scope
[155]	2015	Lithium-ion battery (NMC chemistry), EV		1st order RC ECM, 2 EKF	Sampling freq. 10 Hz, HPPC test, RLS algorithm is used for polarization resistance and capacitance extraction, FUDS and DST drive test	unspecified	
[156]	2016	Battery, EV	10 driving profiles, current, voltage, temperature, charging/discharging rate	NN	Combination of different temperature, charging/discharging rate and driving profile 80 dataset is prepared. Classification and regression both take place on offline and online dataset	2.18%	Charging/discharging experiment data can be taken along with rest period for more realistic condition
[157]	2009	Lithium-ion battery	Charging–discharging voltage and current of battery	CC method	SOC determination by three modes: charging, discharging, open-circuit mode. Hence, SOC(t) = SOH(t)—DOD(t)	1.08%	
[158]	2011	Li-polymer battery	OCV, internal resistance	ECM, Internal resistance method	Lookup table and simulation of adaptive control method for controlling parameters	1%	
[159]	2017	10 Lithium-ion battery (LPF chemistry), 10 Ah, 25 °C		1st order ECM, 3-layer BPNN	HPCC test is conducted for model parameter identification and verification		
[160]	2014	32 Ah Lithium-ion battery	Change in level time scale of RC parameter	Lumped battery model, Data-driven method multi-scale EKF	Different tests have been performed for characterization and aging. Then, macro and micro-level evaluation other cases are performed for capacity estimation, inaccurate initial SOC and current integral	Peak estimation error @ 2%	
[161]	2014	8 Lithium-ion battery, NMC chemistry	Discharge curve voltage sequence, different temperatures	Sample entropy	HPPC test is conducted to obtain voltage sequence. By non-linear LS optimization, capacity at different temperature is estimated. Finally, prediction of other 7 batteries capacity at different temperatures is calibrated.	Avg. relative error @ 2%	
[143]	2013	Lithium-ion battery, NASA dataset	Charging–discharging cycles	GPFR	Battery 5,6,7 is taken for analysis. Regeneration is taken into account for SOH estimation.	For battery 7, MAPE @ 0.017, RMSE @ 1.73	Self-recharge phenomenon is taken into account for SOH estimation.
[144]	2009	18650 Lithium-ion battery	Electrochemical model parameters	Bayesian Framework (RVM-PF)	RBPF model is used for finding correlation between capacity and EM parameters (R_E and R_{CT}) and RUL prediction.		This model-based approach can handle uncertainty like NN and GPR.
[162]	2018	38 Ah, 3.7 V Lithium-ion battery, NMC chemistry	Electrochemical model and ECM	PSO-GA	PF is employed in SOC and OCV for noise reduction occurring in battery terminal voltage and current drift. RSLM is used to update cell capacity		In future, SOH estimation can be evaluated by using different temperature condition
[163]	2017	2.8 Ah Panasonic Lithium-ion battery, NCA chemistry, EV	Different driving load profiles at constant current discharge @ different temperature, cycle depth and SOC	Real-time driving profile	Effect of regenerative braking, calendar aging and cyclic aging @ different temperature.	Calendar aging decreases with low temp., whereas cyclic aging increases. Cycling at high SOC will lead to capacity recovery, due to regenerative braking cycle depth decrease.	

Table 6. *Cont.*

Ref.	Year of Publication	Battery Type	Parameter Condition	Model/Method	Description	Average Error	Future Scope
[164]	2021	Lithium-ion battery	NASA dataset (charge, discharge, impedance)	NPSO-SVR, ORPF model	SVR and NPSO are used for SOH estimation and ORPF is used for RUL prediction.		
[165]	2021	50 Ah Lithium-ion battery	Voltage data from 11,000 charging processes (charged capacity and incremental capacity)	Ridge regression, PSO	IC and charged capacity curves are extracted from raw data. 250 features are extracted from angles are optimized by using the feature wrapper method. Then, ridge regression method is used for SOH estimation. PSO is used for multi-objective optimization of features.		In future, battery pack characteristics will be considered for SOH estimation.
[166]	2020	Lithium-ion battery, NASA dataset	CC-CV charging curve	LS-SVR with polynomial kernel function	Grey relational analysis is used for feature selection. In SVR model, K-fold cross-validation is performed for hyper-parameter tuning.	RMSE @ 0.95–1.36%	
[167]	2016	Lithium-ion battery	Vehicle dynamics (speed, acc., slope), energy usage (data obtained from battery terminals)	Indirect method	Real-time vehicle data is captured for calibrating energy usage.		
[168]	2021	Lithium-ion battery, BEV	Km driven, charge through-put, SOC, C-rate, temp., age of vehicle	NN	By using Pearson correlation, it is found that C-rate and SOC are less correlated to SOH.	RMSE @ 3%	In future, different algorithms will be tested for these 704 real-time vehicle datasets.
[169]	2021	Lithium-ion battery	Different parameters extracted from field and physical modeling-based.	Data-driven, physical model	By conducting RPT tests SOH can be easily determined.		

Figure 9. SOH estimation methods and their advantages, disadvantages, and research trends.

The state transition model is helpful in identifying and eliminating noise. Short-term current pulse tests have been applied to estimate SOH. The publicly available datasets, data pre-processing, and ML are applied for better understand and compare feature extraction and selection [40]. Different features from current in the CV charging phase were used to find battery SOH [92].

ML-based SOH estimation for three differently grouped sets of data is analyzed for Bayesian Ridge Regression (BRR), GPR, Random Forest (RF), and DNN; for fast charging protocol, DNN yields the better response. BRR and GPR were unable to measure the level of uncertainty naturally. GPR and BRR are suited for random samples drawn from uniform distributed work, whereas RF and DNN are suitable for random initialization and provide better results. RF is based on a decision tree and sequentially conducts a homogenous split of data. In the RF technique, the number of decision trees in the forest is controlled by the user.

When the driver turns off the vehicle, voltage reduces to Open-Circuit Voltage (OCV), and then the recovery voltage is identified as a new parameter of SOH estimation. Recovery voltage is a parameter of temperature and aging. Selecting more no. or redundant features for SOH estimation will lead to reducing the performance. An indirect technique to convert available vehicle data into power and tested was conducted in their experiment and errors were found between global energy consumption and experimental analysis between 1.4% and 4.5%. used ICA-Bi-LSTM in a NASA dataset to estimate SOH [167,170]. Physics-based internal chemical changes while cycling a lithium-ion battery were observed and analyzed for SOH estimation in [171].

The reverse of the unit time voltage drop (1/V) is taken as a new parameter for SOC, and this new parameter is directly proportional to SOH. Clustering the driving behavior patterns is then used to model SVM for state estimation. The fusion of CC- and Differential Voltage (DV)-based SOH estimation will reduce the computational time but is only applied to CC charging profiles. Frequency and time domain indicators are treated as internal condition indicators, which are based on onboard data like the voltage and current profiles will give less than 1% error in GPR. The advantages and disadvantages of semi-empirical, empirical, and ML-based techniques are discussed. EVS with EMF works well for different C-rates. The NMC532 battery system under other operating conditions is analyzed on a model-based approach. Multi-vibrate Adaptive Regression Splines (MARSs) are used to build a non-linear model automatically from a linear model and interact with a non-parametric regression algorithm. The MARS tool is used for SOC capacity estimation, and battery model parameters are extracted from direct current, voltage, temperature, and the charge–discharge cycle. The experiment is conducted using the model, and 1% accuracy is achieved from a 25% to 90% SOC range data profile. This accuracy result was achieved in the experimental results. The MARS tool is used to generate non-linear model from a linear model. Random SOC ranges are selected for analysis, the highest accuracy is completed in the 25–90% SOC region, i.e., 1%. Accuracy is calculated from the closeness of the correct prediction of the test data. The hybrid method consists of a combination of two-three algorithms in order to enhance efficiency, accuracy and overcoming short comes of the independent algorithm in order to perform well. The hybrid method also decreases the cost of BMS. Hybrid approaches are formed by applying two or more different techniques in the same dataset. These hybrid algorithms are helpful when a single algorithm cannot give good results or faster results. Using filter techniques along with ANN or LSTM will improve the performance. The filter technique is used to cancel noise in the dataset, whereas ANN is used for complex data and LSTM is used for time-series data. Each method has its own unique quality; therefore, the combination or hybridization of methods will improve the performance of system and yield precise results. Where SOC is determined by OCV and CC with reduced error, and then KF is applied to increase accuracy. RBF is used to adjust the parameter of the model, and AUKF is applied to estimate SOC. Cell imbalances, aging, and degradation factors such as hysteresis curve, temperature variation, self-discharge, rate of charge–discharge affects the battery state. Charge imbalance of cells is caused due to frequent charge–discharge cycles, which results in reduced capacity and the lifetime of the battery. The over-charge of a lithium-ion battery may cause distortion, rise in pressure, and leakages, which result in the explosion of cells, whereas over-discharge of a lithium-ion battery is due to high current flow out of the battery, which results in reduced battery life cycle.

8. Critical Analysis of Literature Survey

The status, techniques and performance of SOC and SOH estimation are described in Sections 5 and 6, respectively. Through this comparative table, it is clear that there are numerous methods used for state estimation, with the primary goal of obtaining high accuracy. To achieve high accuracy and improvement in state estimation, most research focuses on hybrid algorithms. The combination of two or more than two algorithms to improve accuracy is a good choice, but complexity, model size and the time required to run the model will increase. The environment and operating conditions can easily affect the results of state estimation. Different chemistry of lithium-ion batteries, capacity grading and form factor also affect the aging characteristics. Therefore, the previously mentioned factors need to be kept in mind when choosing algorithms. ECM, selected in the current literature, are traditional methods, which are based on Thevenin theorem, first-order RC models, or second-order RC models. The primary battery models do not consider physical and electro-chemical changes. Internal reaction changes non-linearly and unpredictably in a rapid manner, and describing these changes in a model is complex. There are various SOC and SOH estimation methods that operate in simulated conditions and laboratory environments but are not practically applicable due to low performance in terms of uncertainty. The lack of publications focusing on both SOC and SOH estimation seems to be one of the gaps to be filled by this work. The focus of future research should be to make state estimation more realistic and accurate. The hybrid battery model consists of both ECM and EM characteristics that better serve online real-time performance measures. Data-driven modeling can be performed in two ways: first, by considering hybrid ECM-EM along with ML/DL algorithms, and second, without the ECM-EM model, by selecting relevant features from raw data and then pre-processing and applying ML/DL algorithms. A review of machine learning (ML)/data-driven approaches and publicly available datasets seems to be another gap to be filled by this work. Data-driven modeling uses external features like uncertainty for online real-time monitoring of battery state. Self-recharge capacity plays a significant role in capacity estimation. Very little literature has been published in relation to the field of self-recharge capacity and the polarization effect for SOH estimation. After the development of a model algorithm, validation with a similar experimental kit scenario will give a better picture and ideas for improvement of the model in terms of design and accuracy. Different SOC, SOH, and RUL estimation methods have been discussed in different pieces of literature due to the fact that different authors have used different datasets, different filtering techniques, different test scenarios, and different applications.

Some literature focuses on evaluating the performance of the different chemistries used in lithium-ion batteries, whereas some focus on different filtering techniques, reducing noise from data. Some literature covers different test scenarios to test their model accuracy for non-linear behavior, whereas others focus on applications, like EVs, aircraft, solar panels, and military equipment. In some places, real-time monitoring is necessary so that model is fast and should take less time to provide estimation or prediction results. In some applications, microcontroller storage space is less so that the model can be light (takes less storage space) and fast to operate.

9. Limitation and Future Perspective

The common limitation of existing conventional SOC estimation methods [152] are: (a) error in finding the correct initial value of SOC will cause error in estimated or predicted SOC values; (b) existing methods are unsuitable for real-time estimation; (c) there is difficulty in battery modeling due to changes in temperature, charge/discharge rate, SOC and diffusion current, and ECM parameters value changes. From the battery, we can record voltage, current, and temperature data, whereas internal resistance and capacity can be known via characterization tests. Some instruments show internal resistance and capacity, but it depends on instrument accuracy. More accurate instruments are more costly compared to low accuracy instruments. EV's maximum capital cost is shared by the battery if more instruments with high accuracy are fitted into the BMS, which will further increase the cost and weight of the battery with the BMS. Keeping a minimum number of sensors with high accuracy and an algorithmic model for different state estimations will balance overall battery cost and weight. Existing SOH estimation methods are limited by the fact (a) conventional methods are not suitable for real-time application health estimation; (b) require additional testing equipment's or circuits; (c) and existing methods are time-consuming due to testing for full cycle charging/discharging. For better accuracy and performance, the optimization of state parameters is necessary. Data collected from sensors must be noise-free and be high-quality, and it is observed that hybrid algorithms perform far better than conventional algorithms. There are different publicly available datasets present, and many authors are performing SOH estimation verification on the basis of that. The judgement of the accuracy of an EV battery system on the basis of publicly available datasets may be insufficient. Still, it is clear that the estimation and prediction model accuracy are based on diverse datasets, and very few research works have been undertaken on data-driven approaches for real-time analysis. The data-driven models require many datasets and an optimal feature extraction selection method. This process is time-consuming, and if the data set is large, then the required modeling, training, and testing time is greater. For online real-time data analysis, a properly trained and tested model is required; however, very little data are available for analysis. Datasets based on different temperature conditions, driving profiles, charging–discharging profiles, charging modes, different chemistry, and arrangement of cells are required for analysis. In many pieces of literature, only one dynamic condition is considered, but working with one scenario is not sufficient for real-time analysis. With this, one needs to work on an available, focused dataset to effectively analyze the outcomes of the model. ECM and EM battery models vary with temperature variation; therefore, designing a real battery using simulations is difficult. The main challenges in health estimation are, firstly, the fact that online estimation of capacity requires a complete charge/discharge cycle process, which is a time-consuming and difficult task in many applications. Secondly, the prediction of direct health indicators (DHI) from the early cycle with negligible capacity fade is low [41]. Refined health indicator (RHI) performs better in predicting HI than DHI. Some RHI is mean voltage drop and time interval of equal discharging voltage series. Some DHI is minimum, mean, and variance of change in discharge voltage curve, sample entropy of measured voltage sequence. Many literature survey documents considered in this paper are reviewed and are based on operations/testing undertaken under different laboratory conditions; they differ in techniques used and battery types and are compared only on the basis of errors or accuracy level. However, different models are applied to different datasets, and comparing these makes it difficult to verify the accuracy claim mentioned in the documents and judge the model. In order to claim accuracy and compare models, comparative analyses of different methods have to be performed on the same dataset. By considering these conditions when analysis is performed, the results will be more appropriate, authentic, and easier to accept globally. Other application areas of batteries include E-boats, golf carts, space technology, missile systems, telematics, and hybrid EVs. The size of a battery is decided based on the application type, capacity requirement, voltage and current requirement, and battery type. Battery health not only depends on cycling but also on the pattern of usage and environmental conditions. The scope is to achieve online-controlled BMS to monitor battery parameters and enable better visibility of battery state during driving under different environmental conditions; OEMs would be able to showcase their warranty claims and scale up their EV sales, saving the battery from any dangerous situation by achieving the correct prognosis of the battery's health condition. From the initial few cycles of battery usage, the consumers will receive information concerning their battery's health condition and take the proper step at the right time to maintain, replace or exchange the battery. After completion of the first life use–case, then, the battery is used for the second life use–case. Estimating the present battery health and predicting the later stage in advance based on dynamic use–case patterns will help the OEMs to develop a good BMS for better control. Different factors affect battery capacity, and the selection of highly correlated factors is difficult. Artificial Intelligence, IoT. and cloud computing came into play to make an unbiased and quick decision in selecting the features and algorithm development.

10. Conclusions

The objective of this paper was to summarize the history of EVs, study different battery characteristics available on the market, discuss publicly available datasets, functions, challenges, solutions and basic terminologies related to battery management system, and lastly, provide an in-depth discussion of different approaches used in other documents to estimate SOC and SOH. Critical analysis, challenges and future directions are also discussed in this paper. This paper aims to provide guidance to select the correct option among the listed methods or improve the model to achieve reasonable accuracy. After reviewing different estimation methods, hybrid ECM and data-driven technique will give better results in terms of accuracy and the non-linearity of batteries. This article focuses on dragging researchers' interest away from SOC estimation and towards battery health estimation, RUL, and the importance of these states in battery lifetime assessment. Nowadays, news about EVs catching fire is spreading, and in order to prevent dangerous incidents, battery health status has to be observed carefully and driving–charging behavior must be properly managed. Combining IoT, Amazon Web Service (AWS), and data analytics will help improve real-time BMS performance and enhance battery life. There are some real challenges in modeling the battery's state estimation, such as data quality, model processing time, model storage space, and the fact that the model must be accurate for non-linear scenarios and that the model should operate under different working environments.

The benefits of this paper are:

- Enable OEMs to visualize their battery performance and bring attention to whether their batteries working up to warranty or not.
- Allow OEMs to upscale sale by demonstrating their battery performance.
- To spread awareness that the replacement of batteries in proper time can and must be undertaken.
- Predictive maintenance of the battery will enhance battery life.
- By tracking SOC and SOH parameters: parking, charging strategy, and driving patterns can be improved.
- Based on the battery capacity, battery retirement, reuse, recycling, and disposal can be planned accordingly.
- Based on the available capacity and aging patterns, pricing of the retired batteries can be determined.
- To spread awareness about the usefulness of disposed batteries and how they can be reused, or that purchasing retired batteries is also helpful.
- Encourage the accumulation of old battery packs, and then identify and cluster the good cells with life and then assemble them to make a new battery.

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