Review

A Review on State-of-Charge Estimation Methods, Energy Storage Technologies and State-of-the-Art Simulators: Recent Developments and Challenges

Tawanda Kunatsa *[ID], Herman C. Myburgh [ID] and Allan De Freitas [ID]

Department of Electrical, Electronic and Computer Engineering, University of Pretoria,
Pretoria 0028, South Africa; herman.myburgh@up.ac.za (H.C.M.); allan.defreitas@up.ac.za (A.D.F.)
* Correspondence: tawanda.kunatsa@tuks.co.za

Abstract: Exact state-of-charge estimation is necessary for every application related to energy storage systems to protect the battery from deep discharging and overcharging. This leads to an improvement in discharge efficiency and extends the battery lifecycle. Batteries are a main source of energy and are usually monitored by management systems to achieve optimal use and protection. Coming up with effective methods for battery management systems that can adequately estimate the state-of-charge of batteries has become a great challenge that has been studied in the literature for some time. Hence, this paper analyses the different energy storage technologies, highlighting their merits and demerits. The various estimation methods for state-of-charge are discussed, and their merits and demerits are compared, while possible applications are pointed out. Furthermore, factors affecting the battery state-of-charge and approaches to managing the same are discussed and analysed. The different modelling tools used to carry out simulations for energy storage experiments are analysed and discussed. Additionally, a quantitative comparison of different technical and economic modelling simulators for energy storage applications is presented. Previous research works have been found to lack accuracy under varying conditions and ageing effects; as such, integrating hybrid approaches for enhanced accuracy in state-of-charge estimations is advised. With regards to energy storage technologies, exploring alternative materials for improved energy density, safety and sustainability exists as a huge research gap. The development of effective battery management systems for optimisation and control is yet to be fully exploited. When it comes to state-of-the-art simulators, integrating multiscale models for comprehensive understanding is of utmost importance. Enhancing adaptability across diverse battery chemistries and rigorous validation with real-world data is essential. To sum up the paper, future research directions and a conclusion are given.

Keywords: state-of-charge; battery management system; battery energy storage technologies; modelling and simulation tools; state-of-charge estimation methods

1. Introduction

Researchers in academia and industry are placing a high priority on designing energy storage systems as a result of the recent global movement to replace fossil fuels with renewable energy sources for power generation [1]. Battery management systems (BMSs) have drawn more attention in this area over other energy storage technologies owing to their lower self-discharging and excellent power densities. A BMS provides accurate information on the battery's condition and ensures that the energy within the battery is used safely and effectively [2]. The block diagram of a BMS, as shown in Figure 1, consists of various sensors, controllers, actuators and signal lines.

The BMS has the capacity to signal if the battery is operated in an abnormal situation. This is attained by controlling and monitoring the working process of the battery [3]. The control circuit evaluates the battery's state-of-charge (SoC), state-of-health (SoH), state-of-available-power-capability (SoP) and state-of-life (SoL) by employing methods that involve

measuring battery current, temperature and voltage through analogue signals [2]. The information derived from this is further utilised to give important decision factors for the effective performance of the energy management system [4].
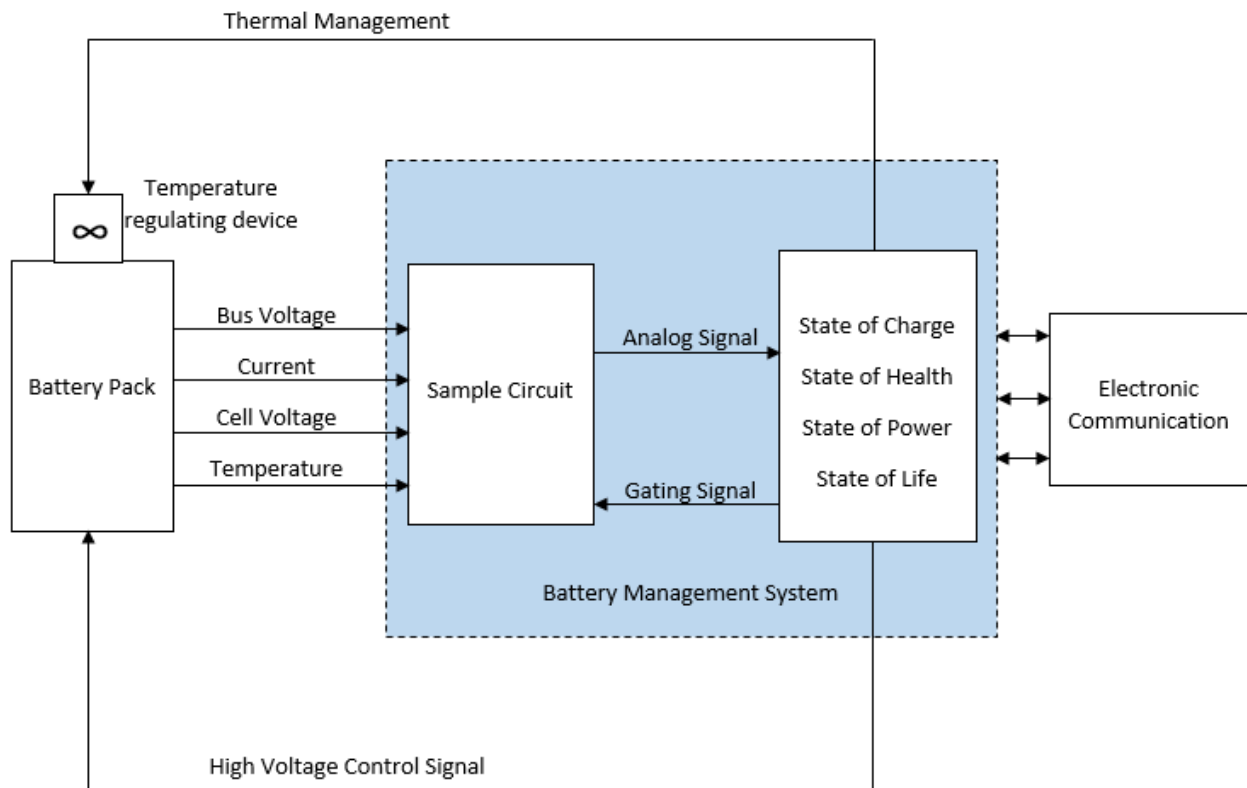

Figure 1. Block diagram of a battery management system.

This study mainly focuses on the SoC since it is an important parameter for most systems that require batteries and also a lingering issue that is yet to be fully explored in research and development [5]. The SoC is seen as a crucial index utilised in accessing photovoltaic (PV) battery storage systems for home energy management systems (HEMSs) [6]. In this case, the effective battery SoC information should be availed to the user to either switch off or reduce the number of electrical appliances within the home to save more energy. A battery's SoC is the proportion of its total capacity that remains untapped at any given moment [7]. It can also be described as the battery's charge level compared to its full capacity, where 0% represents empty and 100% represents a full charge [8]. Furthermore, the SoC is seen as a crucial state that needs to be observed in order to enhance performance and increase system longevity [4]. Generally, the SoC is defined by the ratio of the system's current capacity (Q_t) to its nominal capacity (Q_n) as follows:

$$SoC_t = \frac{Q_t}{Q_n} \tag{1}$$

Knowing the exact SoC not only gives details about the real-time energy status of batteries but also provides assurance of smooth operation [9]. The accuracy of SoC estimation is a challenge since batteries are electrochemical devices that are complex, with unique characteristics that depend on their different internal and external conditions [10]. Furthermore, factors that affect battery performance, for instance, temperature, current rate, ageing of the battery and measurement noise, make accurate estimation of the SoC difficult. Hence, researchers have endeavoured to come up with effective SoC estimation approaches for batteries [11]. In the work by Hannan et al. [6], they suggested employing machine learning methods—specifically, recurrent nonlinear auto-regressive models with exogenous

inputs and the lightning search algorithm (LSA)—to improve the accuracy, efficiency and speed of SoC estimation. They confirmed the effectiveness of their method by conducting experiments on lithium–ion batteries, accounting for temperature, ageing effects and noise, demonstrating its superiority over alternative approaches. The authors asserted that their method is ideal for online battery management systems due to its rapid real-time SoC estimation, which is facilitated by minimal computational complexities during testing.

The authors in [12] devised a battery monitoring system using supervised machine learning to gauge both the battery's health and its SoC. This model was crafted to forecast the battery's behaviour in real-time, furnishing users with insights into its performance. Hemavathi [13] introduced and compared the use of feedforward neural networks and layer recurrent neural networks employing scaled conjugate gradient (SCG) and Levenberg–Marquardt (LM) training methods for estimating the battery SoC. Conducted with an 18,650 single-cell Li-ion battery in real-time using MATLAB, the experiment revealed that the LM method surpassed others for accurately estimating the Li-ion battery SoC while also demonstrating faster convergence. To develop a system for estimating battery parameters such as the SoC, Narayanan et al. [14] suggested a machine-learning-based approach that links the battery static SoC and open-circuit voltage (OCV) utilising real-time data from lithium–ion batteries at various temperatures. Their experiments showcased the neural network approach's superior performance, displaying high R-square and low root mean square error (RMSE) indices compared to other techniques.

Lithium–ion batteries are essentially widely used because of their great energy density, extended lifespan and environmentally friendly characteristics. However, irrespective of these factors, their capacity begins to drop gradually (70–80%) after a number of years when used in EVs. This affects the energy and power capacity requirements, and as time goes on, such batteries must be retired or withdrawn from use to maintain safe operations and the provision of adequate power supply [15,16]. Research has shown that such batteries that are retired from EV applications can still serve a useful life in applications such as energy storage plants, electric bicycles and smart grids [17,18]. Hence, delving into the efficiency and dependability of repurposed retired lithium–ion power batteries is essential. This research will further support and foster the widespread adoption and sustainable growth of electric vehicles (EVs).

In the existing literature [19], retired lithium–ion batteries face inconsistencies stemming from their initial manufacturing, making their utilisation in secondary lifecycles challenging. These batteries undergo diverse usage scenarios leading to performance degradation, susceptibility to overcharging or over-discharging and potential risks such as ageing, thermal runaway and hazards like explosions [20,21]. In [22,23], the authors stress the significance of assessing and screening retired lithium–ion batteries before integrating them into battery packs, aiming to preserve their remaining capacity and ensure ongoing safe operation of the battery system. It is essential to acknowledge that despite these conditions, retired lithium–ion batteries cannot match the precision of newly manufactured ones. Their distinct parameters: terminal voltage, open-circuit voltage, internal resistance, charge/discharge current and SoC exhibit notable inconsistencies [23]. Therefore, achieving accurate estimates of the remaining capacity of retired batteries is vital for sustaining the power needs, durability and safety of the battery pack.

In Loukil et al.'s study [4], a comprehensive review was proposed to determine battery parameters, particularly focusing on the SoC. The methods used in this evaluation combined several strategies, making it difficult to determine a direct correlation between method robustness and accuracy. However, these techniques kept their execution complexity modest [24]. Dao et al. [25] introduced a lithium–ion battery SoC estimation design using a combination of a Kalman filter and artificial neural network. This approach, trained with Google TensorFlow's open-source library, exhibited superior performance, displaying an error rate of less than 1% compared to other methodologies. Additionally, Dewalkar et al. [26] demonstrated the effectiveness of artificial intelligence methodologies over traditional approaches, leveraging realistic battery testing for training purposes. Table 1 consolidates

the diverse approaches utilised by researchers for developing SoC estimation methods for batteries. Despite extensive research in this domain, accurate estimation of battery SoC remains a persistent challenge. Hence, this article presents a survey focused on SoC estimation methods tailored for energy storage systems, particularly in the context of photovoltaic system applications. The contributions of this work are as follows:

- SoC estimation methods for batteries are discussed, and much focus is given to the different methods applicable. Specific application approaches in the literature are presented based on different SoC methods.
- A battery energy storage system is a major requirement for a reliable and sustainable power supply. From this perspective, commonly used battery technologies for solar PV configurations and their unique characteristics are presented.
- An overview and a quantitative comparison of the technical and economic modelling simulators for energy storage applications are presented in order to assist researchers in decision-making on the choice of potential simulators. Summaries of the potential modelling simulators for designing, testing and analysing battery energy storage are given.
- The intermittent nature of renewable energy sources is highlighted, and recommendations for novel approaches for battery SoC estimations in solar PV applications for sustainable and reliable power supplies in austere and remote communities are given.

The subsequent sections of this article are outlined as follows: Section 2 presents a discussion of energy storage technologies with an emphasis on battery energy storage systems and their characteristics, and this is followed by parameters for deep-cycle batteries for PV applications. Section 3 discusses the different SoC estimation methods, including direct-measurement-based methods, bookkeeping-based methods and adaptive-based methods. Additionally, the advantages and disadvantages of the various estimation techniques are discussed. Section 4 provides an outline and quantitative comparison of both the technical and economic modelling instruments designed for applications in energy storage. Ultimately, Section 5 gives the paper's conclusion and points out some recommendations and possible future research directions.

Table 1. Summary of research works on SoC estimation for battery storage systems.

Authors	Year	Remarks
Hannan et al. [6]	2020	Recurrent nonlinear auto-regressive techniques paired with the lightning search algorithm (LSA) were employed to improve SoC estimation, aiming for higher accuracy and performance and faster convergence. Validation of their approach was conducted through experiments involving lithium–ion batteries, considering factors like temperature variations, ageing effects and noise interference.
Varshney et al. [12]	2021	A monitoring system for batteries was created utilising supervised machine learning to evaluate both the battery's health and its SoC. This model can forecast the real-time behaviour of the battery.
Hemavathi et al. [13]	2010	Evaluated the estimation of batteries' SoC by contrasting the performance of feedforward neural networks and layered recurrent neural networks, employing scaled conjugate gradient (SCG) and Levenberg–Marquardt (LM) training methods.
Narayanan et al. [14]	2022	Suggested a machine-learning-driven approach for determining battery static SoC through open-circuit voltage (OCV) analysis. The method's effectiveness was assessed and compared using real-time lithium–ion battery data collected at various temperatures.
Loukil et al. [4]	2021	Proposed a comprehensive analysis aiming to identify battery parameters, particularly focusing on SoC. The techniques employed encompassed a blend of diverse approaches.
Dao et al. [25]	2021	Introduced a design for estimating the SoC of lithium–ion batteries. Their method integrated a Kalman filter and artificial neural network approach, constructed specifically for SoC estimation and trained using the open-source Google TensorFlow library.
Dewalkar et al. [26]	2022	Showed how artificial intelligence approaches are more effective compared to conventional methods since they are trained to utilise realistic tests of batteries.

2. Energy Storage Technologies

Energy storage technologies can be grouped into various types depending on their utilisation, such as thermal, flywheel, thermochemical, pumped, compressed air, magnetic, electrochemical/battery and chemical. For the interest of this work, discussions in this section are based on the different and available battery energy storage that can be utilised for general applications, buildings and communities, transportation, energy utilities and renewable energy utilisation. For evaluation, the main components and related characteristics are presented to indicate the difference between the various battery energy storage strategies.

Battery energy storage technology has undergone substantial advancements, becoming a pivotal solution in the quest for efficient and sustainable energy systems. The evolution of battery chemistries, especially lithium–ion batteries, has significantly improved energy density and cycle life, enabling their widespread deployment in various applications, from portable electronics to electric vehicles and grid-scale storage. However, despite these strides, critical research gaps persist. One notable gap lies in the quest for alternative materials beyond lithium–ion, aiming to enhance energy density, safety and sustainability. Exploring and developing novel chemistries such as solid-state batteries, metal-air batteries, or next-generation lithium-based chemistries remains a focal point. Challenges abound, including the need for scalable production methods, the understanding of complex electrolyte interactions, and ensuring cost-effectiveness without compromising performance or safety [27,28].

Moreover, the development of effective management systems to optimise battery performance, enhance safety and extend the lifespan presents another significant research gap. Intelligent battery management systems (BMSs) are crucial for real-time monitoring, accurate state estimation and implementing appropriate control strategies to maximise efficiency and durability. Addressing these gaps in BMSs involves integrating advanced algorithms for state-of-charge and state-of-health estimation, mitigating issues related to cell imbalances and thermal management, and devising smarter control strategies for diverse applications. Additionally, ensuring the cybersecurity of these systems is becoming increasingly imperative, demanding robust measures to protect against potential cyber threats [29–31]. Closing these research gaps is crucial for advancing battery technology towards safer, more efficient and more sustainable energy storage solutions for the future.

2.1. Electrochemical and Battery Energy Storage

Photovoltaic (PV) solar systems serve as an energy generation source, allowing storage through a battery storage system (BSS). This ensures a relatively steady energy supply for later use, addressing the fluctuating power output of PV systems caused by the intermittent nature of renewable energy sources. Batteries are one of the available energy storage technologies that are commonly used in recent times. A battery energy storage system (BESS) represents cutting-edge technology designed to store electrical energy for various applications within power systems. A BESS solution is based on the combination of different low-voltage power battery cells that are connected either in series or parallel to produce the required electrical capacity. It has been shown that a BESS is a combination of a control and power-conditioning system (C-PCS), batteries and other related plant accessories for reliability and sustainability of the entire system [32]. Electricity can be stored electrochemically in batteries and capacitors. These batteries are effective energy storage systems that are known for their high voltages and energy densities. Examples of such batteries encompass lithium–ion (Li-ion), nickel–cadmium (NiCd), lead–acid (PbA), sodium-sulfur (NaS), lead-carbon and flow batteries [33–35]. Capacitors such as electrochemical capacitors, electrostatic capacitors and electrolytic capacitors can also be used for the storage and delivery of energy electrochemically.

2.1.1. Lead–Acid (PbA) Battery

Lead-acid batteries are preferable for use in PV configurations considering their availability in terms of the base cost-per-watt, reliability and good energy storage density. Lead battery cells consist of two lead plates submerged in a diluted sulfuric acid solution, which

generates approximately 2 V between the plates. To produce 12 V batteries, these cells are connected in series [36]. The grid structure within a typical lead-acid battery is composed of a lead alloy. As pure lead lacks structural strength, additional metals like calcium, antimony, tin and selenium are commonly added as fortifying agents to the alloy. Based on these additives, they are commonly called "lead-calcium" and "lead-antimony" batteries [37]. The charging process of lead–acid is not fast, and for most types, it takes up to 14–16 h for a full charge. Additionally, it is crucial to emphasise that the battery should be stored at its maximum SoC. Allowing the charge to drop too low can lead to sulfation, a condition that significantly impacts the battery's performance [38]. Lead–acid has the best charge retention among rechargeable batteries, has a moderate lifecycle and is not subject to memory as compared to nickel-based systems [37].

Various configurations of lead–acid batteries are accessible, including flooded or vent-based lead–acid and sealed or maintenance-free lead–acid. Flooded lead–acid batteries are equipped with vents to allow hydrogen gas, produced during electrolysis, to escape. Consequently, close attention is needed to monitor the electrolyte level and replenish it using distilled water. The initial sealed lead–acid batteries emerged in the mid-1970s [39], sparking debate among engineers regarding the term "sealed lead–acid" as misleading due to the inability to completely seal lead–acid batteries. To manage venting during high-stress charging or rapid discharging, mechanisms to alleviate pressure buildup have been integrated. These batteries contain less electrolyte (known as "acid-starved") compared to flooded lead–acid types [37]. The prevalent varieties of sealed lead–acid batteries are gel, also referred to as valve-regulated lead–acid (VRLA), and absorbent glass mat (AGM). It is also worth noting that smaller packs having capacities of up to 30 Ah are referred to as SLA (sealed lead–acid) [37].

Lead–acid batteries are known for their affordability and reliability but have a limited depth of discharge (DoD). To maximise their lifespan, it is recommended to limit the DoD to around 50% [40]. Discharging beyond this threshold can drastically reduce the number of charge cycles, often leading to a lifespan reduction by up to 50% if regularly discharged to 80% DoD [41]. Optimal charging rates for lead–acid batteries range between C/10 to C/20, with a nominal voltage of about 2.23–2.25 V per cell for float charging [42,43]. Overcharging or maintaining a high SoC beyond the recommended voltage can lead to sulfation, decreasing both capacity and efficiency. Properly managing these parameters, such as avoiding deep discharging and overcharging, is crucial to enhancing the battery's efficiency and extending its service life.

In summary, these batteries are generally cost-effective and easy to manufacture, have adequate performance in low and high temperatures and have high specific power that can result in high discharge currents. However, irrespective of the above merits, some of their limitations are that they take a longer time to be charged and their lifecycle is limited. The battery lifespan reduces due to repeated deep-cycling, they cannot be stored in undercharged conditions due to sulfation, and finally, the flooded type requires watering. Table 2 presents some of the applications of lead–acid batteries.

Table 2. Applications of lead–acid batteries.

Lead–Acid Battery	Applications
Sealed lead–acid (SLA)	These batteries are suitable for wheelchairs, lighting emergencies and small UPS systems [37]. SLAs are the best option for healthcare usage in hospitals and retirement communities because of their low cost, dependable service and low maintenance requirements.
Absorbent glass mat (AGM)	These batteries can be used in marine and recreational vehicles (RVs) as well as for starter batteries for motorbikes and micro-hybrid cars.
Valve-regulated lead–acid (VRLA)	These batteries are used as a backup power source for numerous locations, including banks, hospitals, Internet hubs and cellular booster towers.

2.1.2. Nickel–Cadmium Battery (NiCd)

Because of its many advantages over existing lead–acid batteries such as long lifespan, resilience to excessive discharges, low maintenance requirements, low-temperature capacity retention and non-critical voltage regulation, a NiCd battery is better suited for use in stand-alone photovoltaic systems. The cell is submerged in an alkaline potassium hydroxide (KOH) electrolyte solution and comprises positive electrodes made of nickel hydroxide (NiOH2) and negative electrodes composed of cadmium (Cd). These batteries are very costly but are more convenient for use when dealing with harsh weather conditions. The airline industry widely accepts the standard nickel–cadmium battery, which is regarded as one of the most resilient batteries [44]. However, its longevity requires careful consideration [44]. Nickel–cadmium and its classes, including nickel-metal-hydride (NiMH), possess a memory effect that, if ignored for an entire periodic discharge cycle, causes capacity loss.

NiCd batteries are resilient to deep discharges and can be fully discharged to 100% DoD without significant degradation, making them suitable for applications requiring high discharge rates [45]. However, they suffer from the memory effect, which necessitates periodic full discharge cycles to maintain optimal capacity. The ideal charging rate for NiCd batteries is typically between C/10 and C/2, with a nominal charging voltage of about 1.4 V per cell [46]. Consistent overcharging or improper charging can lead to increased internal resistance and capacity loss, significantly reducing the battery's longevity. Optimizing the charge–discharge cycles by adhering to the recommended rates can improve both the efficiency and the lifecycle of NiCd batteries, especially in high-demand applications.

In summary, NiCd batteries can easily be fast-charged with little stress, they have a long shelf life and can be stored in a discharged state, which requires priming before use. They have a good load and low-temperature performance and are rugged batteries with high cycle counts and adequate maintenance. Some of their limitations include but are not limited to the fact that they have a memory effect, they are are subjected to high self-discharge, cadmium is toxic, they are not ideal for disposal in landfills, and they have a low cell voltage of 1.20 V (which requires more cells to produce high voltage).

2.1.3. Sodium–Sulfur Battery (NaS)

The NaS battery is one of the emerging alternatives for high-power energy storage systems. NaS is a molten metal battery that is manufactured based on sodium as the anode and sulfur as the cathode. This technology uses ceramic Beta-Al_2O_3 as a form of electrolyte and separator at the same time [47]. The chemistry of the reaction between ions transfers the sodium ions to the cathode, which react with sulfur anions to produce sodium polysulphide NaSx. NaS batteries are well-known for their extremely high energy density, excellent charge and discharge efficiency (89–92%), extended lifespan and easily accessible materials [48]. These cells are mostly utilised for large-scale non-mobile applications due to their high temperature of operation, which ranges from 300 °C to 350 °C [49] and the high reactivity of the electrodes [35,48].

Sodium–sulfur batteries operate at high temperatures (300–350 °C), making them suitable for large-scale energy storage systems [50]. They typically function efficiently at a DoD of 80–90%, with an optimal charge rate around C/10 [51]. Discharging beyond this range can lead to rapid capacity degradation due to the high reactivity of sodium and sulfur at elevated temperatures. The charge voltage for NaS batteries generally ranges between 1.78–2.0 V per cell [52]. Precise control of the charge–discharge cycle and maintaining the operating temperature within the ideal range are critical to ensuring the battery's longevity and performance. Studies indicate that maintaining these parameters can significantly extend the battery's lifecycle and improve its energy efficiency.

The pros and cons of sodium–sulfur batteries are as presented in Table 3.

Table 3. Summary of the advantages and limitations of sodium–sulfur batteries, adapted from [48].

Pros	Cons
• Raw materials are readily available and there is no maintenance configuration • Possesses high cell voltage and excellent energy and power density • Energy efficiency is high • High cycle life; liquid electrodes • Lack of responsiveness to surrounding environments; enclosed systems operating at elevated temperatures • SoC voltage rise; top-of-charge and end-of-discharge determination	• Highly corrosive nature of the electrodes, which has high combustion with water • Its temperature range of operation is within 300–350 °C • It requires strict operation and maintenance • It requires additional cost for the enclosed structure to avoid leakage

2.1.4. Lithium–Ion Battery (Li-Ion)

Lithium–ion (Li-ion) batteries commonly find application in electronic devices, including laptops, cameras, mobile phones and electric vehicles, among others. Li-ion battery cells consist of anolytic and catholytic plates and are immersed in a liquid electrolyte solution [53]. The catholyticplate is made of lithium cobaltate ($LiCoO_2$), and the anolytic plate is based on porous carbon. The electrolyte is a non-aqueous organic solution dissolved in lithium salts [35]. The flow of ions takes place from the anode to the cathode via the electrolyte and separator during the discharge process, and charging is the reverse process. This battery type has the highest energy density, is known to be safe and has no memory or cycling requirements to prolong the lifespan [54]. Li-ion batteries are of different varieties but all have a unique feature: the "lithium–ion". Their performance varies, with unique characteristics based on the choice of the active materials used. Examples of such batteries include lithium cobalt oxide (LCO), lithium manganese oxide (LMO), lithium nickel manganese cobalt oxide (NMC), lithium iron phosphate (LFP), lithium nickel cobalt aluminum oxide (NCA) and lithium titanate (LTO).

Recent advancements in lithium battery technology have introduced groundbreaking methodologies and designs that significantly enhance battery performance and safety. One of the most notable innovations is the development of solid-state batteries, which replace the conventional liquid electrolyte with a solid electrolyte [55]. This design minimises the risk of leakage and combustion, thereby enhancing safety. Moreover, solid-state batteries offer higher energy densities, which translate to longer battery life and improved performance [56]. The research by Manthiram et al. highlights that solid-state electrolytes can effectively mitigate dendrite formation: a common issue in lithium–ion batteries that can lead to short circuits and potential battery failure [57].

Another significant advancement is the implementation of nanotechnology in lithium battery design. Nanomaterials such as nanostructured silicon anodes have shown remarkable potential for increasing the capacity and efficiency of batteries [58]. Silicon anodes can store significantly more lithium ions compared to traditional graphite anodes, leading to higher energy densities [59]. However, silicon expands and contracts significantly during charge–discharge cycles, which can cause mechanical degradation. Researchers have addressed this challenge by designing silicon nanowires and nanoparticles that can accommodate these volume changes without compromising structural integrity, thus improving battery lifespan and performance [58,60]. Additionally, the use of advanced coating techniques and novel electrode architectures has contributed to enhanced thermal stability and reduced degradation rates, further improving the safety and longevity of lithium batteries [61].

The integration of machine learning and artificial intelligence in battery management systems is also a groundbreaking development [62]. These technologies enable real-time monitoring and predictive maintenance, which enhance the overall performance and safety of lithium batteries [63]. By analysing large datasets of battery usage, machine learning algorithms can predict potential failures and optimise charging cycles to extend battery life [64]. This proactive approach to battery management significantly reduces the risk of overheating and other safety hazards [65].

Lithium–ion batteries are widely used due to their high energy density and efficiency. The optimal depth of discharge for Li-ion batteries is about 80%, balancing between capacity and lifespan [66]. Discharging beyond this point, especially below 20% SoC, can significantly reduce cycle life, potentially dropping to as low as 300–500 cycles at 100% DoD compared to over 2000 cycles at 80% DoD [41,67]. The optimal charge rate is typically 0.5C to 1C, with a nominal voltage of around 3.6–3.7 V per cell, although fast charging at higher rates can increase the risk of thermal runaway if not properly managed [68]. Maintaining the charge–discharge cycles within these parameters, particularly avoiding deep discharges and high charge rates, can greatly enhance both the efficiency and longevity of Li-ion batteries, making them ideal for high-performance applications such as electric vehicles and portable electronics.

In summary, lithium–ion batteries have high specific energy and load capacities due to their power cells. They have low self-discharge, have a simple charging system with short charge times and have high capacity. They have low internal resistance and good coulumbic efficiency. A few drawbacks involve requiring a protective circuit to avert overheating under stress and facing considerable difficulty in achieving fast charging in low temperatures. Recent innovations in lithium battery technology, including solid-state designs, nanotechnology applications and advanced battery management systems, have led to substantial improvements in performance and safety. These advancements address critical issues such as energy density, thermal stability and mechanical degradation, paving the way for safer and more efficient energy storage solutions. The incorporation of solid-state electrolytes, nanostructured materials and intelligent monitoring systems represents a significant leap forward in the evolution of lithium battery technology, ensuring their continued relevance and reliability in various applications, including electric vehicles.

2.2. Parameter Identification for Deep-Cycle Batteries

Deep-cycle batteries are designed to meet the charging and discharging cycles that are required specifically in solar PV systems. These batteries have unique characteristics such as a high discharge rate, high power density, flat discharge curves and better performance in terms of low temperatures. For solar PV system configurations, maintenance-free lead–acid batteries are common since they are the most cost-effective. This subsection briefly outlines specific parameters linked to deep-cycle lead–acid batteries that are necessary for effectively monitoring and optimising the battery storage system, as outlined in [36].

Battery Current

This indicates the flow of electrons, and its rate per unit time is known as ampere. Batteries can store energy in the form of direct current (DC) to light up or power an inverter, which converts it into alternating current (AC). Usually, deep-cycle batteries are linked together in parallel to boost the total output current.

2.3. Battery Voltage

Voltage is known as the electrical pressure. For instance, the standard voltage for a car battery is 12 V as a result of the series connection of six (6) smaller lead–acid cells of 2 V each. Battery banks are primarily linked in series to generate DC voltages such as 12, 24, 36, or 48 V, making them suitable for various energy systems.

2.3.1. Rated Battery Capacity

This defines the energy capacity within a battery and is often quantified in ampere-hours (Ah) at a specific voltage. For example, a 100 ampere-hour rated battery can supply 10 amperes for 10 h, 1 ampere for 100 h and so on. Gauging this rated capacity repeatedly is challenging when these batteries are actively employed in PV systems.

2.3.2. Depth of Discharge

The depth of discharge signifies the proportion (%) of the battery's designated capacity that has been utilised. The construction of the battery is key for determining its capacity to withstand discharge. Battery construction can be categorised into shallow-cycle batteries (like most sealed, maintenance-free batteries) and deep-cycle batteries (which can endure repetitive charging and discharging to very high and low levels, respectively, without harming the cells).

2.3.3. Temperature Charts

Batteries are generally designed to be temperature sensitive and, as such, will not provide substantial power in a cold state compared to a warm condition. Manufacturers offer temperature correction charts to distributors and customers to address temperature-related impacts. For instance, a battery stored at 25 °C will exhibit 100% capacity when discharged at a rate equivalent to C/20, with the discharge rate typically calculated relative to the battery's rated capacity, C. It is advisable to maintain batteries at or near room temperature: around 25 °C.

2.3.4. Charging Cycle

Consideration of the optimal charging process for a battery involves several factors: firstly, charging with a consistent current until reaching a set voltage; secondly, maintaining a constant voltage while the charging current decreases; finally, reducing the charging voltage at an appropriate point to prevent excessive gassing and electrolyte loss. Achieving this ideal charging cycle is challenging in a PV system due to the continuous charging from available power. In standalone systems, the battery cycle typically spans 24 h: charging throughout the day and discharging during the night.

2.3.5. Battery Cycles

Predicting a battery's lifespan is highly challenging due to its reliance on various factors such as charging and discharging speeds, depth of discharges, cycle count and operational temperatures. The lifecycles of batteries in a PV configuration depend on the make and the conditions of operation.

2.3.6. Days of Autonomy

This indicates the duration during which the battery system can sustain the connected load without requiring a recharge from the photovoltaic array. This determination relies on factors such as the system itself, seasonal variations, the geographical location, the total connected load and the characteristics of the load within the system. The condition of the weather is also a major factor in determining the number of no-sun days.

2.3.7. State of Charge

The state-of-charge indicates the remaining capacity available in a battery at a specific moment.

$$SoC = 1 - DoD. \tag{2}$$

3. Overview of SoC Estimation Methods

The realm of SoC estimation methods for batteries has undergone significant evolution, ranging from simplistic voltage-based approximations to complex model-based algorithms. While each approach has its merits, there persist substantial research gaps necessitating attention. Current methodologies often struggle with accurate SoC determination under varying operational conditions, such as high charge/discharge rates or extreme temperatures, demanding improved robustness and adaptability. Additionally, the impact of ageing on battery performance remains a critical area requiring comprehensive exploration. Existing methods often falter in accurately estimating the SoC as batteries degrade over

time, highlighting a need for innovative strategies to account for ageing effects to extend the accuracy and reliability of these estimations throughout a battery's lifecycle [69,70].

Furthermore, the integration of diverse estimation techniques or hybrid approaches emerges as a promising avenue for enhancing accuracy and reliability across different battery chemistries and applications. Combining the strengths of, for instance, model-based algorithms with machine learning or data-driven approaches might yield more robust SoC estimations that are capable of handling nonlinearities and can mitigate the limitations observed in individual methods. However, this interdisciplinary approach also presents challenges, primarily in ensuring seamless integration and avoiding computational complexities that could hinder real-time application [71,72]. Addressing these gaps in research demands a concerted effort toward not only refining existing methodologies but also innovating new, comprehensive approaches capable of accurately estimating the SoC across diverse operating conditions and ageing scenarios.

As discussed in the previous section, knowing the battery's exact SoC is an important part of the BMS as it allows for the necessary assessment factor for battery management in photovoltaic systems. Therefore, techniques have been introduced to estimate the SoC of batteries. In this section, the different methods in the literature have been grouped and classified as shown in Figure 2. Additionally, the works of researchers who have utilised these methods for developing the SoC for batteries are highlighted in the subsequent subsections.
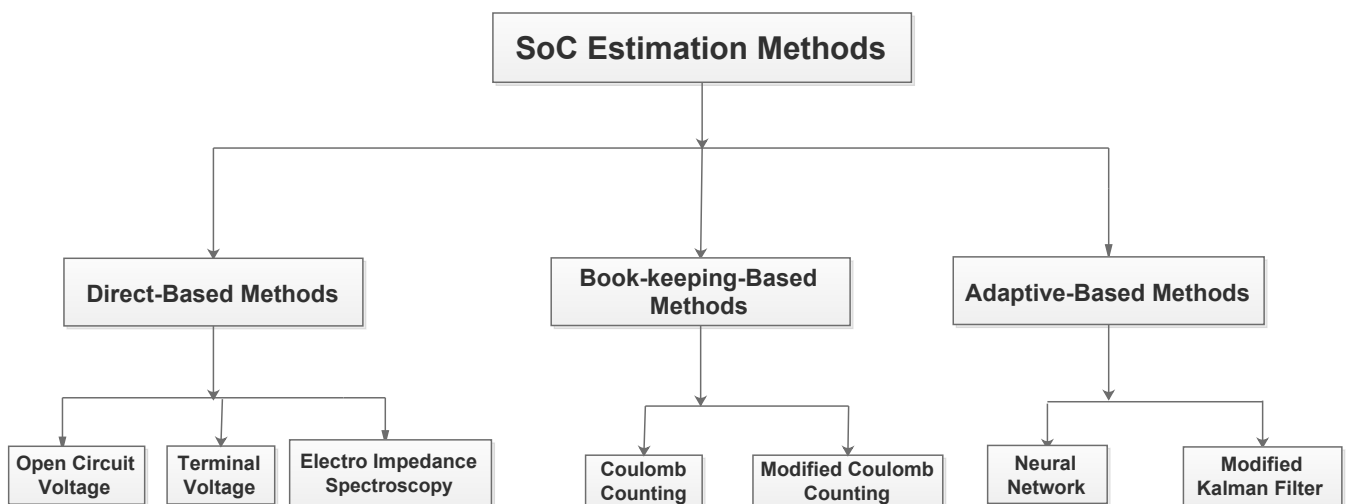

Figure 2. SoC estimation methods.

3.1. Direct-Measurement-Based Methods

These methods use the physical properties of batteries, like the impedance, terminal voltage and current, to measure the SoC [73]. They encompass techniques like the open-circuit voltage method, terminal voltage method, impedance method and impedance spectroscopy method.

3.1.1. Open-Circuit Voltage Method

As defined by [74], the open-circuit voltage (OCV) is the maximum voltage that a device can produce when it is illuminated. It is also described as the maximum voltage available that is drawn out from a solar cell and occurs at zero current while operating linearly to the SoC. In scenarios where the OCV is available, estimating the battery's SoC involves a direct measurement between the SoC and OCV. This relationship is examined to enhance battery management technologies and refine SoC estimations [75]. However, real-time measurement of OCV is challenging as it requires shutting off the power and allowing the battery to cool down for a specific duration [76]. Additionally, the OCV is

influenced by the cell ambient temperatures, and each cell in batteries possesses distinct chemical characteristics, leading to varied voltage profiles among cells [77]. Moreover, the OCV decreases in low temperatures compared to higher ones, impacting battery voltage measurements. This temperature dependency often introduces errors in SoC estimation during battery operation [78]. Therefore, achieving accurate SoC estimations requires allowing the battery sufficient rest to reach a cell equilibrium state before evaluating its OCV [78]. Employing this approach frequently during rest periods can be combined with other techniques to further validate the SoC indication [79].

Furthermore, when integrating various techniques, OCV measurement can fine-tune other approaches [80]. Ideally, when estimating a battery management system's SoC via the OCV approach, the battery should be in a floating state without a load for accurate assessment [81]. The OCV method incorporates the Randles battery model, encompassing parameters like internal resistance (R_s), double-layer capacitance (C_d) and polarisation resistance (R_{ct}), as depicted in Figure 3 [77].
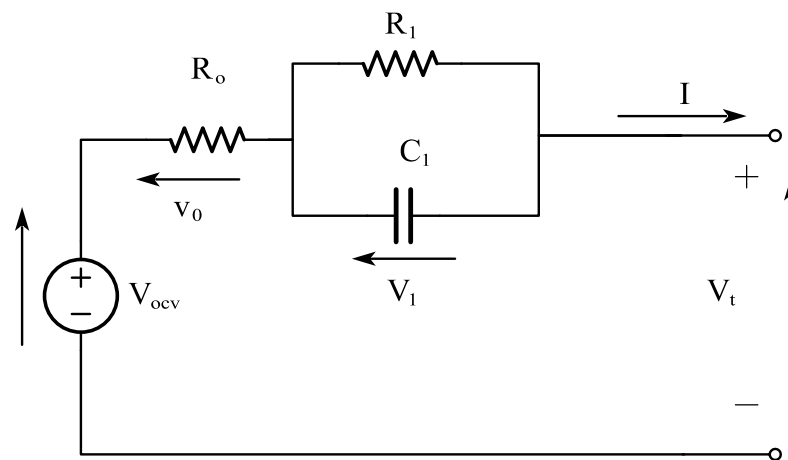

Figure 3. Randles equivalent model of a standard battery, adapted with permission from Ref. [77].

The figure represents a battery terminal at the condition of no load. Based on the Randles equivalent circuit, the battery's terminal voltage $V_{terminal}$ can be presented as:

$$V_{terminal} = OCV(SoC) - i(R_s + R_{ct}(I - \exp^{-t/\tau}))$$ (3)

where the parameters can be calculated using τ.

$$R_s = \frac{V_1}{i}; R_{ct} = \frac{V_2}{i}; C_d = \frac{\tau}{R_{ct}}$$

where V_1, V_2 and τ can be derived by the time-varying battery terminal voltage, as shown in Figure 4. The figure also exhibits the time constant within the RC parallel circuit ($\tau = R_{ct} = C_d$), denoting the duration for the battery terminal voltage to decline to 63.2% of its typical value [77]. As such, one can represent the charge of a battery as a function of its SoC. Consequently, the OCV method uses Equation (3) data along with OCV measurement to estimate the battery's SoC.

Through this method, Gismero et al. [82] successfully reset the SoC estimation process, preventing the accumulation of errors. Additionally, the SoH is determined by assessing the charge accumulated between two distinct SoC levels using the least squares method. Tian et al. [83] employed the OCV test to detect ageing in lithium–ion batteries, forming a foundation for SoC estimation. Their method estimated what they called electrode ageing parameters (EAPs), which are offline OCV-based ageing diagnosis results that include electrode capacities and initial SoCs. In order to assess EAPs without feature extraction, this method required daily charging profiles to be run through a convolutional neural network. Experiments conducted on eight cells demonstrated the method's efficacy at

swiftly detecting lithium–ion battery ageing. Dang et al. [84] introduced an OCV-based method for SoC estimation that utilised a dual-neural-network-fusion battery model. The model was trained using dynamic stress test data, establishing an offline relationship between the OCV and SoC. Results of the experiments showed that the first/second-order electrochemical model served as the basis for the SoC estimation in the dual-neural-network-fusion battery model.
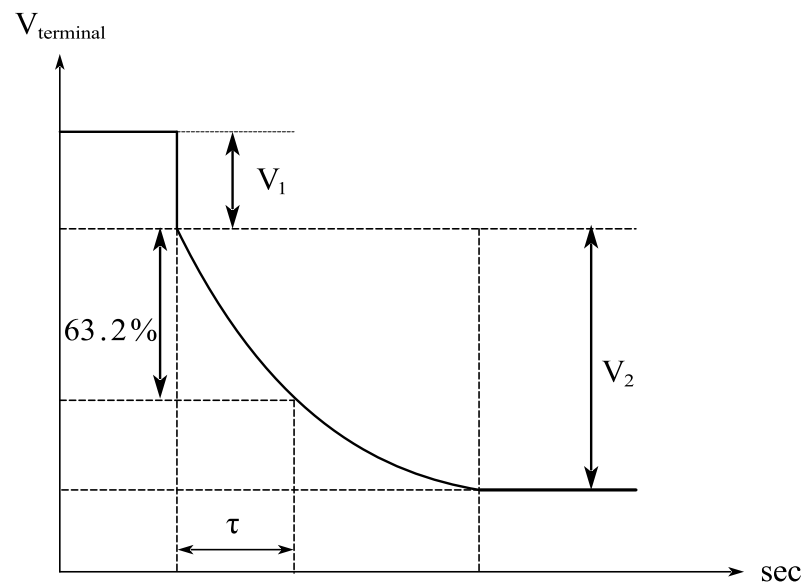

Figure 4. Time-varying battery terminal voltage, adapted with permission from Ref. [77].

3.1.2. Terminal Voltage Estimation Method

This method relies on the decrease in terminal voltage caused by internal impedances during battery discharge. The battery's electromotive force (EMF) is directly correlated to the terminal voltage [85]. Moreover, a linear relationship between the EMF and the battery's SoC can be established [86]. During discharge, the battery's terminal voltage is contingent on the internal impedance voltage [68]. Thus, the battery's terminal voltage exhibits a linear correlation with the SoC. In this method, the SoC can be expressed mathematically as:

$$\frac{d_s}{d_t} = \frac{i}{36Q_a}; Q_a = Q_{a0} - Q_f \tag{4}$$

where S represents the cell's SoC, Q_a stands for the real-time capacity of the battery, Q_{a0} denotes the actual capacity of the battery, and Q_f refers to the capacity decline due to ageing effects [77]. Several researchers have employed this approach to determine the SoC in batteries. For instance, in the work by Ren et al. [87], the authors developed a battery management system aimed at detecting the SoC and enhancing battery performance. The terminal voltage of each cell is measured, and the balancing system is notified when the SoC falls below or exceeds the defined threshold, reducing the output voltage ripple. Sato et al. [85] proposed an equation based on the terminal voltage. Experiments on discharging of lead–acid batteries were conducted, and the results demonstrated acceptable performance in contrast to alternative approaches.

3.1.3. Electrochemical-Impedance-Based Method

The electrochemical-impedance-based method uses the battery's voltage and current to gauge its internal resistance. Voltage measurement involves tracking the current changes over a brief period [88]. The ratio between the voltage and current fluctuations yields the direct current resistance, which represents the battery's capacity in DC [88]. To capture the ohmic effect and lessen the influence of transfer reactions and acid diffusion, a brief

interval is usually required. Extended durations cause the estimated resistance value to be inaccurate [89]. Moreover, this method showcases adaptability and demonstrates higher accuracy in estimating the SoC during the latter stages of discharging [90]. However, due to its low value, obtaining precise internal resistance becomes challenging. The internal resistance varies significantly with a wide range of SoCs and is scarcely detectable, thereby complicating the estimation of the SoC using the DC internal resistance [91].

3.1.4. Electrochemical-Impedance-Spectroscopy-Based Method

The electrochemical impedance spectroscopy (EIS) method gauges battery impedances across a broad spectrum of AC frequencies under varying currents [92]. Widely utilised to explore electrochemical processes, it has been extensively studied for diverse battery systems, including for assessing the SoC [93]. Model impedance values are derived by fitting measured impedance values using the least squares methodology. EIS is non-destructive and measures parameters effectively. The battery management system (BMS) produces a distinct frequency sine wave current response when a sine wave voltage signal is applied to it. The system's electrochemical impedance spectrum is formed by the ratio between the excitation voltage and the response current [94].

Current battery impedances can be analysed and used to indirectly determine the SoC relative to known impedances across different SoC ranges [95]. Additionally, the EIS method yields more accurate state-of-health (SoH) estimations for lead–acid batteries compared to SoC estimations. For Li-ion batteries, EIS is initially used and proves practical for SoC estimation [96]. The ambient temperature notably affects battery impedance, particularly at low frequencies during electrochemical processes, thus requiring SoC and SoH estimation through EIS at higher frequencies.

In Xu et al.'s work [97], the authors introduced a way to estimate a lithium–ion battery SoC. They analysed impedance spectra from electrochemical impedance spectroscopy to represent the battery impedance using a constant-phase element. A fractional-order calculus technique was used to design this element in the impedance model. Subsequently, a Kalman filter was employed to evaluate the battery's SoC and showed satisfactory performance. Zhang et al. [98] suggested an EIS-based method for estimating the state-of-health (SoH) of batteries that takes temperature and SoC variations into account. Originally, to connect the SoH at various SoCs, an analogous circuit model employed the charge transfer resistance and solid electrolyte interface resistance. For Li-ion battery SoH estimation, they developed a probabilistic model integrating the temperature and SoC as input variables. Experiments revealed this approach's superiority over existing EIS-based techniques. In a different study [99], the authors measured and identified dependency levels by performing correlational analysis of equivalent circuit parts and impedance ranges of several commercial Li-ion batteries across different SoCs and internal temperatures. They used a curve-fitting approach to match the measured impedance spectra onto an equivalent circuit model. Impedance variables were revealed to be highly reliant on the SoC and internal temperature.

3.2. Bookkeeping-Based Methods

The bookkeeping estimation technique relies on the discharging current data from the battery as its input [91]. This method enables the incorporation of specific internal battery aspects like self-discharge, capacity degradation and discharge efficiency [100]. Techniques within this category encompass the coulomb counting method and the modified coulomb counting method, which are detailed in the subsequent subsections.

3.2.1. Coulomb Counting Method

The coulomb counting (CC) technique evaluates the discharge current of a battery and uses a time integration of this current to calculate the SoC [101]. It is also known as the ampere-hour method and operates on the premise of knowing a battery's maximum available capacity and evaluating its current. Through the ampere-hour integral method,

it is possible to precisely calculate the SoC variation. Additionally, an exact SoC value can be obtained if the starting SoC is known. Mathematically, the SoC can be derived from Equation (5) [77]:

$$SoC_t = SoC_{t_0} + \frac{1}{C_n} \int_{t_0}^{t_0+t} I_{bat} \, d\rho, \tag{5}$$

where SoC_{t_0} represents the initial SoC of the battery, C_n denotes the battery's nominal capacity, and I_{bat} defines the charging and discharging current of the battery. The coulomb counting (CC) method's preciseness is impacted by various factors such as discharging current, temperature, battery lifespan and ageing, prompting the introduction of an improved CC method to refine the conventional approach [102]. This method proves effective for batteries without causing side effects during regular operation. However, employing this method for SoC estimation comes with three drawbacks [103]. Firstly, it necessitates consideration of the initial SoC. Secondly, inevitable measurement errors arise in the battery current due to disturbances. Lastly, recalibration of the available capacity of the battery becomes necessary due to variations in operating conditions and battery usage levels [104].

In the study by Movassagh et al. [101], the issue of the SoC of rechargeable batteries was addressed. They outlined issues such as errors in current measurement, uncertainty regarding battery capacity, timing oscillator errors and approximations in current integration. They further recommended enhancement of the CC approach in order to solve these issues. Hence, due to these disadvantages of the CC method, researchers have envisaged to enhance the CC approach as discussed in the following subsection.

3.2.2. Modified Coulomb Counting Method

As stated in the previous subsection, the coulomb counting method calculates the SoC of a battery by integrating the current flowing into and out of the battery over time [105]. Although widely used due to its straightforward application, the precision of coulomb counting can be influenced by various factors, potentially leading to inaccuracies in SoC estimation. Key factors affecting the precision of coulomb counting include measurement errors and the initial SoC uncertainty [106]. Measurement errors primarily arise from inaccuracies in current sensing, where calibration, drift or offset errors in current sensors can significantly impact the results [107]. Even minor inaccuracies when integrated over time can lead to substantial errors in SoC estimation. Additionally, the sampling frequency can affect the method's precision, as infrequent sampling might fail to capture short-term fluctuations in current, especially in applications with variable load profiles [63]. The method also relies heavily on an accurate initial SoC estimate to begin calculations; any error in this initial value can propagate throughout subsequent calculations, leading to greater inaccuracies.

Moreover, the method does not inherently account for battery efficiency and ageing effects, which are crucial for accurate SoC estimations [106]. Charge efficiency varies and may not always be constant, as it depends on the battery's state and operational conditions. As batteries age, their capacity decreases, and internal resistance changes, further complicating precise SoC estimations. Coulomb counting typically does not include temperature effects directly, which significantly influences battery performance, including the charge efficiency and self-discharge rate [108].

To enhance the precision of coulomb counting, several improvements can be implemented. High-precision, low-drift current sensors can minimise measurement errors, and sensors with self-calibrating features may help maintain accuracy over time. Regular calibration of the system to account for sensor drift and other measurement system changes can also preserve the accuracy of SoC estimations. Additionally, integrating coulomb counting with other SoC estimation methods, such as voltage-based methods or impedance spectroscopy, can help offset some of its limitations [109]. For example, voltage measurements can periodically recalibrate the SoC estimation to correct any drifts arising from the coulomb counting method alone [110].

Incorporating temperature compensation algorithms can adjust SoC calculations based on temperature measurements, helping to account for temperature-dependent changes in battery efficiency and self-discharge rates [111]. Furthermore, employing machine learning algorithms can enhance the method's accuracy by predicting and adjusting for deviations caused by factors like ageing, temperature variations and load variability [112]. These models can utilise historical data to continually improve the precision of SoC estimations, making coulomb counting more reliable for modern battery management systems.

To refine the CC method, a modified version called the modified coulomb counting method was introduced. This approach utilises adjusted current values to enhance estimation accuracy, which are derived from the discharging current [113]. Moreover, there is a quadratic connection between the adjusted current and the battery's discharging current. Thus, through practical experimentation, the adjusted current is computed using Equation (6):

$$I_c(t) = K_2(t)2 + K_1 I(t) + K_0, \tag{6}$$

where the constants K_0, K_1 and K_2 are derived from empirical data obtained through practical experiments. In the modified coulomb counting method, the SoC is calculated using Equation (7).

$$SoC_t = SoC(t-1) + I_c(t)Q_n\delta_t \tag{7}$$

It has been confirmed in the literature that the modified coulomb counting method is more precise than the traditional coulomb counting approach [104]. Researchers have extensively employed the modified coulomb counting technique. In [114], the authors introduced a data-driven coulomb counting method for estimating the SoC of lithium–ion batteries. They adjusted the flawed initial SoC by transforming battery-voltage-based incremental capacity curves into SoC-based incremental capacity curves. Their approach was tested under conditions of rapid capacity degradation, demonstrating its ability to rectify inaccurate parameters and provide satisfactory SoC accuracy. Ko et al. [102] suggested a lithium–ion battery capacity estimation method centred around an enhanced coulomb counting methodology. However, their approach yields a wide error range in battery capacity estimation due to issues in SoC estimation, necessitating further methods to attain precise battery capacity values. Consequently, they introduced a Kalman filter and applied it to the capacity values estimated by their approach. Lithium–ion battery experiments demonstrated better performance compared to alternative approaches. In [115], the authors introduced a linear second-order extended state observer to solve the issues of the conventional coulomb counting method for estimating the SoC. Experimental results indicated that the suggested approach outperformed established conventional methods in performance evaluation.

3.3. Adaptive-Based Methods

A number of adaptive systems for SoC estimation have been developed as a result of developments in artificial intelligence (AI) and machine learning (ML). These methods encompass neural networks (NNs) and Kalman filters [116]. These systems possess self-designing capabilities, enabling them to intelligently adapt to changing environments or systems [117]. Considering batteries' susceptibility to diverse chemical influences and their nonlinear SoC behaviour, adaptive-based approaches offer solutions to SoC estimation challenges [77]. The different adaptive-based methods are discussed in the following subsections.

3.3.1. Machine Learning Modelling/Simulation

The application of machine learning algorithms for improving the accuracy and reliability of SoC estimation for batteries has seen significant advancements [118–120]. Supervised learning algorithms, for instance, involve training models on labelled datasets wherein the input features are paired with known outputs [121]. In the context of SoC

estimation, this typically means using historical battery data to predict the current SoC. A notable case study is the work by Zhang et al., which utilised support vector machines (SVMs) to estimate the SoC of lithium–ion batteries [122]. Their approach trained the SVM model using features such as voltage, current and temperature data. The results indicated that the SVM model demonstrated high accuracy and robustness, outperforming traditional methods like coulomb counting and model-based estimations. One of the main advantages highlighted was the SVM's ability to provide better generalisation to unseen data and to effectively handle nonlinear relationships [122].

Reinforcement learning (RL) presents another promising avenue for SoC estimation. RL involves an agent learning to make decisions by interacting with the environment to maximise cumulative rewards [123,124]. For SoC estimation, RL algorithms can optimise the estimation process by continuously learning and adapting to battery behaviour. Liu et al., demonstrated this through the application of deep Q-learning, a type of RL, to estimate the SoC dynamically [65]. Their method involved training the RL agent to predict the SoC by receiving rewards for accurate predictions and penalties for errors, using data such as charge/discharge cycles and temperature. The RL-based model showed significant improvements in adaptability and accuracy compared to static estimation methods. The primary advantage of RL models lies in their ability to adapt to changing conditions in real-time, providing more accurate and reliable SoC estimates under varying operational conditions [65].

Deep learning, particularly using neural networks, has also shown great promise in SoC estimation due to its ability to model complex and nonlinear relationships in data [125]. Chen et al. implemented long short-term memory (LSTM) networks to estimate the SoC of lithium–ion batteries [126]. The LSTM model was trained on sequential data such as voltage, current and temperature and captured temporal dependencies effectively. The results were impressive, with the LSTM model achieving superior performance in terms of accuracy and reliability, significantly reducing the root mean square error (RMSE) compared to traditional methods. Deep learning models, particularly LSTM networks, excel at handling time-series data and can capture long-term dependencies, leading to more precise SoC estimations [126].

Traditional methods of SoC estimation, such as coulomb counting and model-based methods, have several limitations. Coulomb counting tracks the charge/discharge current over time but suffers from cumulative error, while model-based methods use equivalent circuit models or electrochemical models but require precise parameter identification and are sensitive to model inaccuracies [105,127]. In contrast, machine learning approaches offer several advantages. They improve accuracy by learning complex patterns and relationships in data that traditional methods might miss [128]. They also provide adaptability, as machine learning models can continuously learn and adapt to new data, improving estimation under varying conditions [129]. Additionally, machine learning models reduce complexity as, once trained, they can provide real-time SoC estimation without the need for complex calculations or parameter identification [130].

In conclusion, machine learning algorithms, including supervised learning, reinforcement learning and deep learning, have significantly enhanced the accuracy and reliability of SoC estimation. Their ability to model nonlinear relationships, adapt to new data and provide real-time estimations offers substantial advantages over traditional methods. Recent research and case studies underscore the potential of these advanced algorithms for optimising battery management systems and enhancing the performance and lifespan of battery-powered devices.

3.3.2. Neural Network

A neural network (NN) applies a mathematical algorithmic model to handle tasks involving simultaneous processes [131]. It excels at processing data and resolving relationships among various initially complex factors [132]. Among NNs, a backpropagation neural network, a type designed to solve nonlinear problems, offers a simpler structure

compared to standard neural network methods [133]. A three-layered backpropagation neural network (input, hidden and output) is capable of estimating the SoC of batteries. Various factors, including battery voltage, current, resistance and ambient temperature are incorporated into the input layer. The output layer provides an estimated range value for the SoC, and the number of hidden layers is dependent on the precision of the system [134]. The primary objective of this SoC estimation approach is to minimise the margin of error. However, this error hinges on the volume of training data utilised during experiments [77]. Training data used for SoC estimation is derived from charging and discharging battery experiments. These errors escalate when the backpropagation neural network lacks sufficient training data encompassing SoC values [135]. Hence, achieving an accurate SoC value necessitates employing a large dataset from various batteries, as battery discharge characteristics can vary based on electrolyte volumes.

Figure 5 gives a general neural network structure for SoC estimation, and Table 4 gives a comparison of varied neural network structures used for SoC estimation. The application of neural networks in SoC estimation for batteries involves configuring input, hidden and output layers to enhance the accuracy and reliability [136]. The input layer receives features like voltage, current and temperature, while hidden layers with multiple neurons capture nonlinear relationships using activation functions such as ReLU, sigmoid and tanh [137]. The output layer, typically with one neuron, provides the continuous SoC value.
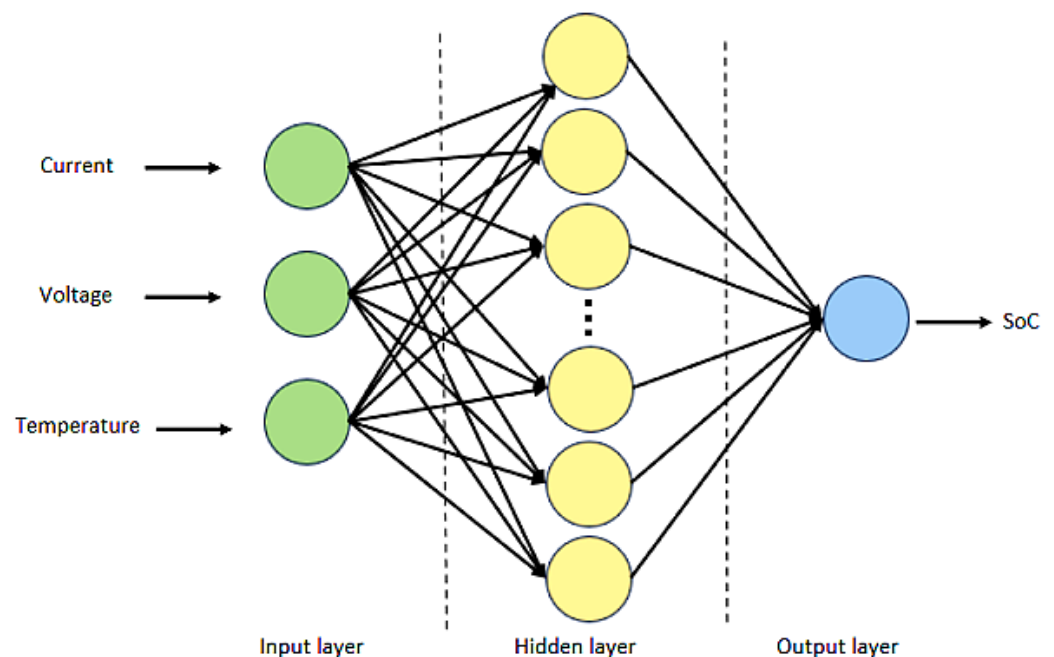

Figure 5. Neural network structure, adapted with permission from [138].

In [139], the authors proposed a comprehensive equivalent circuit model integrating neural networks to address battery model issues in real-time. Additionally, a radial basis function neural network was employed for estimating battery SoC. An experimental evaluation pitted this approach against an extended Kalman filter, where the former showcased faster convergence speed and higher precision. Yang et al. [140] developed a recurrent neural network with gated recurrent units to estimate battery SoC centred on the assessed current, voltage and temperature. Their approach demonstrated improved estimation accuracy compared to conventional neural network methods. Huang et al. [141] proposed a convolutional gated recurrent unit (CNN-GRU) network for estimating lithium–ion battery SoC. The training for this method was done using data from battery discharge processes. Experimental results revealed that their proposed technique outperformed other deep learning methods for lithium–ion battery SoC estimation.

Table 4. Comparison of neural network structures for SoC estimation.

Neural Network Structure	Number of Hidden Layers	Type of Machine Learning/AI	Inputs	Training Algorithm	Performance Metrics	Reference
Feedforward Neural Network (FNN)	2–4	Supervised Learning	Voltage, Current, Temperature	Backpropagation	Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Coefficient of Determination (R^2)	[142,143]
Recurrent Neural Network (RNN)	3–5	Supervised Learning	Voltage, Current, SoC History	Adam Optimizer	Root Mean Square Error (RMSE), Accuracy	[125,144]
Convolutional Neural Network (CNN)	4–6	Deep Learning	Battery Images (Thermal), Voltage	Stochastic Gradient Descent	Accuracy, F1 Score	[145]
Hybrid Neural Network (CNN-LSTM)	3–5	Deep Learning	Voltage, Current, Temperature, SoC History	Adam Optimizer	Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Coefficient of Determination (R^2)	[146]
Autoencoder Neural Network	3–4	Unsupervised Learning	Voltage, Current, Temperature	Adam Optimizer	Root Mean Square Error (RMSE), Mean Absolute Error (MAE)	[147]
Radial Basis Function Neural Network (RBFNN)	1–3	Supervised Learning	Voltage, Current, State of Charge	K-means Clustering + Gradient Descent	Mean Square Error (MSE), Root Mean Square Error (RMSE)	[148]
Extreme Learning Machine (ELM)	2–4	Supervised Learning	Voltage, Current, Temperature	Analytical Solution	Mean Absolute Error (MAE), Coefficient of Determination (R^2)	[149]

3.3.3. Kalman Filter

The Kalman filter used for SoC estimation relies on an algorithm that utilises precisely measured state variables to account for time-varying noise [150]. This filter estimates the SoC by creating a model of the battery system and other necessary parameters required for SoC measurement. Essentially, it functions as an algorithm that is employed to estimate the internal states of dynamic systems [151]. In the context of battery management systems (BMSs), the battery represents the dynamic system, and the SoC represents the internal state [152]. The Kalman filter intelligently offers estimated values within dynamic states, making it suitable for applications involving dynamic models [153]. However, owing to batteries' nonlinear traits, an extended Kalman filter (EKF) approach becomes necessary. This method necessitates a battery model that is capable of representing the dynamic state [79]. Despite its ability to estimate battery SoC during operational phases, the EKF method encounters a drawback wherein the SoC estimation duration increases as the number of state variables rises [154]. Additionally, since the EKF method relies on linearising the approximation of nonlinear functions using first- or second-order terms from complex formulas, it often fails to deliver precise performance [77]. To solve this, an unscented KF has been presented and was shown to have higher accuracy compared to the EKF [155]. Regardless of the KF method adopted, it is advised that the statistical information of battery noise is accurate to have an effective SoC estimation.

In the work presented in [150], the authors introduced a fractional-order adaptive extended Kalman filter (FO-AEKF) designed for SoC estimation. They proposed a fractional-order model to characterise battery behaviour, asserting its superiority over integral-order models due to its decentralised and diffuse characteristics for battery internal parameters. Using a genetic algorithm, they identified the parameters of this fractional-order model, ensuring adequate parameter identification. The authors claim that their method swiftly detects unknown and time-invariant factors, thereby enhancing SoC estimation accuracy. A different strategy presented in [156] conveys an adaptive square-root sigma-point Kalman filter (ASR-SPKF)-based SoC estimation technique built around a reduced-order electrochemical model. Their approach refines the estimation of anode and cathode SoCs by integrating constraints based on the principle of charge conservation. Evaluations across three filters considering estimation accuracy, error margins and computational time revealed satisfactory performance of their proposed approach.

Table 5 offers additional information for an in-depth analysis of the benefits and drawbacks of the various SoC techniques covered in this study.

Table 5. Summary of the advantages and disadvantages of various SoC methods discussed.

Method	Applicability	Advantages	Disadvantages
Open-circuit voltage [83]	Lithium–ion battery; lead–acid	Easy to use; accessible online	Long rest time is required; sensitive to temperature.
Terminal voltage [157]	Most energy storage	Easy to use; accessible online	Error in estimation due to drop in terminal voltage at the end of discharge.
Electro-impedance spectroscopy [158]	Most energy storage	Easy to use; accessible online; can estimate most of the battery parameters	Sensitive to temperature; high frequency is required.
Coulomb counting [159]	Most energy storage	Easy to use; low computational cost	Current leakage during charging, thereby affecting the estimation of SoC.
Modified coulomb counting [114]	Most energy storage	Easy to use; low computational cost	Current leakage during charging, thereby affecting the estimation of SoC.
Neural network [160]	Most energy storage	Adapts to time-varying characteristics; fast computational cost for online phase	Requires a lot of training data for accuracy; network convergence is slow; difficult to achieve global optimum.
Modified Kalman filter [153]	Most energy storage	Accessible online; dynamic	Battery model is required; initial parameter issues.

3.4. Factors Affecting the Battery SoC

There exist factors that disrupt the lifespan and performance of photovoltaic batteries [66]. The effectiveness of batteries can be derived from the availability of energy and the lost energy or battery capacity. Batteries are considered to be less effective when the effective materials are changed into their inactive phases through the process of charging and its chemical reactions [161]. Knowing the factors that can affect the SoC of batteries is important for their lifespan. Hence, this section highlights different factors that can affect the SoC of batteries. These include battery age, temperature, charge current, internal resistance, battery temperature, charge/discharge depth and charge/discharge rate [73].

3.4.1. Battery Age

The older the battery is, the less effective it becomes in terms of performance [162]. When batteries become old, they experience irreversible capacity loss due to liquid electrolytes drying up and a lithium–ion layer building up on the electrodes [163]. Also, the ageing of the battery results in diminished capacity, increased resistance and elevated self-discharge. All these reduce the battery SoC, thereby affecting the performance of batteries [164].

3.4.2. Temperature

Batteries' lifespans and performance depend on the process of charging and discharging, where temperature plays an important role [165]. Overheating of the batteries results in thermal runway, where the temperature can reach more than 400 degrees Celsius. A single thermal runway leads to a reaction with other cells, causing life or property loss [166]. To enhance battery longevity and ensure safety measures, batteries are equipped with a battery management system overseeing the charging, discharging and overall temperature regulation process [167]. Moreover, for added protection during charging and discharging, a thermal management system can be employed [168]. This thermal control mechanism serves to regulate the temperature across the entire battery system and encompasses cooling mechanisms and heating sources to warm batteries in cold environments [169].

3.4.3. Charge Current

The process of charging batteries causes changes within its internal chemistry [151]. Most importantly, charging batteries at a high current worsens these effects [151]. The ideal battery charging process should be in a manner in which the current is managed at a level that increases the battery's efficiency and lifespan [6]. When batteries are constantly charged at a high current, electrolytes and atoms protecting the anode become thickened, which later affects ions' access to the anode. Similarly, on the cathode, there is a gathering of lithium ions that causes electrolyte oxidation, which can cause thermal runaway [170]. Furthermore, charging the battery at a low current can increase its lifespan. However, it can reduce the battery's time performance [171].

3.4.4. Internal Resistance

Variations in factors like age, current and size can impact a battery's internal resistance [172]. A decrease in the internal resistance enhances the battery's efficiency [173]. Photovoltaic batteries usually have one of the lowest internal resistances, and the electrolyte interface layer improves the internal resistance [75]. The layer assists with the battery process since it manages the system and improves its lifespan. However, this can result in more internal resistance over time [174].

3.4.5. Charge/Discharge Depth

When batteries are unable to charge beyond a certain percentage of their initial capacity, this signifies that they have reached the conclusion of their practical lifespan [137]. The depth of discharge plays a role in determining the quantity of charge cycles a battery can provide throughout its useful existence [175]. Additionally, the depth of discharge serves as an indicator of the battery's health, offering an alternative to the SoC for assessment

purposes [176]. To manage battery life, researchers have come up with applications that can be embedded within battery management systems to decrease the problem of allowing batteries to drain and charge above certain particular levels [177].

3.4.6. Charge/Discharge Rate

Experts from both industry and academia recommend maintaining a constant current and voltage during the battery charging process [178]. This involves sustaining a steady current throughout the charging phase, ensuring the system delivers consistent current until the battery reaches its maximum charging voltage, after which the current is reduced to prevent overcharging the cells [137]. The idea is to maintain a manageable temperature and to avoid lithium coating of the electrodes.

3.5. Comparative Analysis of SoC Estimation Approaches

Accuracy, complexity, real-time implementation and trade-offs are the main criteria used when comparing different SoC estimation methods due to their critical roles in battery management. Accuracy ensures precise SoC readings: vital for preventing overcharging or deep discharging, which can degrade battery life and performance [179]. Complexity reflects the computational resources required, impacting the feasibility of deploying the method in various systems [180]. Real-time implementation assesses how well the method can operate within the constraints of real-time systems, ensuring timely and efficient battery management [114]. Trade-offs measure the method's ability to handle varying battery conditions and environmental changes, ensuring reliable performance under different scenarios [181]. These criteria collectively ensure that the chosen SoC estimation method provides reliable, efficient and effective battery management across diverse applications.

SoC estimation is vital for effective battery management in various applications. Different methods have been developed, each with its unique advantages and trade-offs in terms of complexity and accuracy. Coulomb counting is a basic method that measures the battery current over time to calculate the SoC [114]. It is straightforward to implement in real-time systems but is prone to cumulative errors due to sensor inaccuracies and integration drift, which can lead to significant deviations over extended periods [114,182]. Open-circuit voltage (OCV) methods rely on the relationship between the battery's open-circuit voltage and its SoC, providing accurate results when the battery is at rest [183]. However, this method requires the battery to be in an equilibrium state for accurate measurements, limiting its real-time applicability in dynamic environments [184,185].

More advanced techniques such as the Kalman filter (KF) and extended Kalman filter (EKF) offer higher accuracy by modelling the battery's dynamic behaviour and filtering out noise [186]. The KF strikes a balance between accuracy and complexity, making it suitable for real-time applications with moderate computational demands [187]. The EKF handles nonlinearities better than the KF, enhancing accuracy further but at the cost of increased computational requirements [182,188]. Particle filters provide very high accuracy by representing the probability distribution of the SoC as a set of particles. This method, while highly accurate, is computationally intensive and challenging to implement in real-time systems without substantial processing power [189]. Neural networks leverage machine learning to adapt to various battery conditions, offering high accuracy. However, they require extensive training data and significant computational resources, posing challenges for real-time implementation [108,189]. Each method presents distinct trade-offs between complexity and accuracy, necessitating careful consideration based on the specific requirements and constraints of the application [190,191]. Table 6 gives a summary of the comparison of the SoC estimation approaches.

Table 6. Comparative analysis of SoC estimation approaches.

Method	Description	Complexity	Accuracy	Implementation	Trade-Offs	References
Coulomb Counting	Measures current over time to estimate SoC.	Low	Medium	Simple	Simple implementation but susceptible to cumulative errors.	[114,182]
Open-Circuit Voltage (OCV)	Uses battery's open-circuit voltage to determine SoC.	Low	Medium	Simple	Requires resting periods for accurate measurement.	[184,185]
Kalman Filter	Models dynamic behaviour and filters noise.	Medium	High	Moderate	Balances accuracy and complexity well.	[187,190]
Extended Kalman Filter	Extends KF to handle nonlinearities in the battery model.	Medium	High	Moderate	Improves the Kalman Filter but with increased complexity.	[182,188]
Particle Filter	Uses a set of particles to represent the probability distribution of the SoC.	High	Very high	Complex	Highly accurate but computationally intensive.	[189,191]
Neural Network	Leverages machine learning to adapt to various conditions.	High	Very high	Complex	High accuracy and adaptability but requires extensive training data.	[108,189]

The incorporation of specific hybrid models for SoC estimation can enhance accuracy and reliability under variable operating conditions. Preliminary data and/or theoretical analyses that demonstrate the potential benefits of some of these hybrid approaches are discussed in the subsections below and are summarised in Table 7.

3.5.1. Kalman Filter (KF) + Artificial Neural Network (ANN) Hybrid Model

A Kalman filter (KF) + artificial neural network (ANN) hybrid model leverages the robustness of the Kalman filter and the adaptive learning capabilities of an artificial neural network to enhance the accuracy of SoC estimation. The Kalman filter is instrumental in providing real-time SoC estimation by effectively filtering out noise and uncertainties from measurement data, making it highly reliable in dynamic environments [160]. On the other hand, the ANN is trained on historical battery data, allowing it to learn complex patterns and predict the SoC under various operating conditions, particularly during rapid load changes or temperature variations [192]. The KF provides precision in real-time applications by accounting for noise and system uncertainties, which is crucial for maintaining reliability. However, its performance can degrade under nonlinear conditions or when rapid changes occur. The ANN addresses these limitations by compensating for model inaccuracies and nonlinearities, thereby enhancing the overall accuracy and robustness. Preliminary simulations using this hybrid approach have shown a reduction in SoC estimation error by approximately 15% compared to using the Kalman filter alone [160]. This improvement is most significant in environments with high variability, such as during rapid charging or discharging cycles, or when the battery operates under fluctuating temperatures, where the ANN's ability to predict the SoC based on learned patterns plays a crucial role in maintaining estimation accuracy.

3.5.2. Extended Kalman Filter (EKF) + Particle Filter (PF) Hybrid Model

An extended Kalman filter (EKF) + particle filter (PF) hybrid model is designed to improve SoC estimation accuracy in environments characterised by nonlinearities and time-varying conditions. The EKF, an extension of the standard Kalman filter, is used to linearise around an estimate of the current's mean and covariance, making it efficient for real-time estimation in near-linear systems [193]. However, its performance can be compromised in highly nonlinear regions. To address this, the particle filter (PF) is integrated into the

model. The PF is a sequential Monte Carlo method that uses a set of particles to represent the posterior distribution of the system states, providing a probabilistic estimate of the SoC that is more accurate in nonlinear conditions [193]. This combination allows the EKF to efficiently estimate the SoC in near-linear regions, while the PF enhances accuracy in nonlinear areas by offering a flexible and robust approach to handle nonlinearities and non-Gaussian noise. Theoretical analyses and simulations suggest that this hybrid model can improve SoC estimation accuracy by up to 20%, particularly in scenarios involving rapid changes in load and temperature [194]. This improvement is particularly valuable in applications such as electric vehicles and grid storage systems, where operating conditions can vary significantly and maintaining high accuracy of SoC estimation is critical for system reliability.

3.5.3. Adaptive Observer + Fuzzy Logic Hybrid Model

The adaptive observer + fuzzy logic hybrid model is designed to enhance the accuracy and reliability of SoC estimation, particularly under conditions of uncertainty and variability. The adaptive observer is responsible for real-time SoC estimation and continuously adjusts its parameters based on feedback from the system to track the true SoC more accurately [195]. This adaptability is crucial in scenarios where the battery is subjected to fluctuating loads and temperatures, which can significantly affect its performance. Fuzzy logic is incorporated to manage the uncertainties and imprecise data that are often encountered in real-world applications [196]. Fuzzy logic allows the model to handle approximate reasoning, providing a more nuanced estimation of SoC when exact data are not available or when battery behaviour is unpredictable. This combination ensures that SoC estimation remains reliable even when the battery operates under harsh or unpredictable conditions, making the model particularly suitable for applications where precision is critical, such as aerospace or military systems. Preliminary simulations indicate that this hybrid approach can reduce the maximum estimation error by 10–15%, especially in environments with fluctuating temperatures and varying load demands [197]. The adaptive observer ensures that the model remains responsive to real-time changes, while fuzzy logic compensates for the uncertainties that could otherwise lead to inaccurate SoC estimates.

3.5.4. Model Predictive Control (MPC) + Machine Learning (ML) Hybrid Model

A model predictive control (MPC) + machine learning (ML) hybrid model integrates the strengths of model predictive control for real-time optimisation and machine learning for predictive capabilities based on historical data. MPC is used to optimise the SoC estimation process by considering future states and adjusting control inputs accordingly, ensuring that the system remains on an optimal path even as operating conditions change [198]. This is particularly important in real-time applications where the system dynamics are complex and require constant adjustment to maintain accuracy. Machine learning algorithms that have been trained on large datasets provide predictions based on long-term trends and patterns, which can be used to correct and refine the MPC's estimates [199]. The integration of ML allows the hybrid model to learn from past data, improving its ability to predict the SoC under varying conditions that MPC alone might not fully capture. Initial theoretical analyses and simulations suggest that this hybrid model can reduce SoC estimation errors by 15–20% compared to using MPC alone [200]. This is especially beneficial in applications involving complex and dynamic operating environments, such as in grid storage systems or electric vehicles, where both short-term and long-term accuracy are critical for maintaining system efficiency and reliability.

Table 7. Proposed hybrid models for SoC estimation.

Hybrid Model	Model Overview	Theoretical Benefits	Preliminary Data	References
Kalman Filter (KF) + Artificial Neural Network (ANN)	Combines KF for real-time SoC estimation with ANN for predicting SoC under varying conditions.	KF handles noise and uncertainties, while ANN predicts SoC during rapid load changes and temperature fluctuations.	Reduces estimation error by approximately 15% under dynamic conditions.	[160,192,201]
Extended Kalman Filter (EKF) + Particle Filter (PF)	Integrates EKF for linearised state estimation with PF for probabilistic estimates in nonlinear regions.	EKF estimates in near-linear regions; PF improves accuracy in highly nonlinear regions.	Improves SoC estimation accuracy by up to 20% during rapid load and temperature changes.	[193,194]
Adaptive Observer + Fuzzy Logic	Uses an adaptive observer to estimate SoC and fuzzy logic to handle uncertainties and imprecise data.	Adaptive observer adjusts in real-time, while fuzzy logic adds robustness in uncertain conditions.	Reduces maximum estimation error by 10–15%, especially under fluctuating temperature and load.	[195–197]
Model Predictive Control (MPC) + Machine Learning (ML)	Integrates MPC for dynamic optimisation with ML to predict SoC based on historical data and patterns.	MPC optimises in real-time; ML corrects based on long-term trends, improving accuracy.	Reduces SoC estimation errors by 15–20% in complex, dynamic environments.	[198–200]

3.6. Deeper Technical Analysis of the Most Promising Techniques

SoC estimation for lithium–ion batteries is crucial for ensuring their efficient and safe operation. Among the most promising techniques are Kalman filters, machine learning algorithms and hybrid methods, each offering unique advantages in terms of accuracy and implementation. Kalman filters, including the extended Kalman filter (EKF) and unscented Kalman filter (UKF), are widely used due to their robust performance in handling system noise and model uncertainties [179]. EKFs extend the basic Kalman filter to accommodate nonlinearities in the battery model, enhancing accuracy while maintaining computational efficiency [180]. Successful implementations include their use in electric vehicles (EVs) to provide real-time SoC estimation under varying operational conditions, significantly improving battery management systems (BMSs) [179,202,203].

Machine learning approaches, such as neural networks and support vector machines, leverage historical data to predict the SoC. These data-driven models can adapt to diverse battery conditions without requiring detailed physical models [114]. For instance, neural networks have been successfully employed in grid storage applications, demonstrating high accuracy in SoC prediction by learning from extensive datasets of charging and discharging cycles [114]. This adaptability makes machine learning approaches highly effective in dynamic environments where battery behaviour can vary significantly.

Hybrid methods combine the strengths of model-based and data-driven approaches. A notable example is the integration of the Kalman filter with machine learning techniques, which enhances the robustness and accuracy of SoC estimation [181]. These hybrid systems have been effectively implemented in renewable energy systems, where they manage the intermittent nature of power generation and storage, ensuring reliable energy supply and optimal battery usage [181,204]. The combination of the real-time correction capabilities of Kalman filters and the predictive power of machine learning provides a comprehensive solution for SoC estimation [83,205].

Overall, these advanced SoC estimation methods not only improve the precision of battery management systems but also extend the lifespan and efficiency of lithium–ion batteries, which is crucial for their widespread application in the automotive and energy sectors. Accurate SoC estimation is essential for preventing overcharging and deep discharging, which can significantly degrade battery performance and longevity [114,181].

As battery technologies continue to evolve, the integration of these advanced estimation techniques will play a vital role in ensuring their optimal performance and reliability.

4. State-of-the-Art Modelling and Simulation Tools

State-of-the-art modelling and simulation tools for battery systems have made significant strides, offering invaluable insights into the complex electrochemical processes within batteries. These tools range from physics-based models that account for the intricate chemical and physical phenomena to empirical and data-driven models that leverage large datasets for predictive analysis. While these tools have facilitated understanding and prediction to a considerable extent, there are notable research gaps that need attention. One significant gap lies in the integration of multiscale modelling approaches, which aim to bridge the gap between the atomic/molecular level processes and the macroscopic behaviour of batteries. Current models often focus on either microscale or macroscale aspects, lacking seamless integration between these scales, hindering a comprehensive understanding of battery behaviour under various operating conditions [206,207].

Additionally, the robustness and adaptability of these models across diverse battery chemistries and configurations remains a critical challenge. While certain models excel at predicting behaviour for specific battery types, their applicability and accuracy might diminish when applied to different chemistries or novel electrode designs. Enhancing the versatility of modelling tools to encompass various battery chemistries, electrode materials and architectures would greatly benefit the design and optimisation of next-generation batteries. Furthermore, the validation and calibration of these models with real-world data, especially under dynamic and non-standard operating conditions, pose ongoing challenges that require meticulous attention to ensure accurate predictions and reliable simulations [208,209]. Closing these gaps necessitates concerted efforts in developing versatile, multiscale models while rigorously validating and calibrating them across diverse battery systems and operating conditions.

Efforts in research are directed toward model-based analysis of stationary storage systems tailored for specific storage technologies and applications [210–212]. However, most of these endeavours are typically executed, tested and evaluated using simulation platforms due to the absence of available test environments and ongoing real-time projects for development and implementation. Moreover, there is a range of individually developed software aimed at techno–economic modelling of grid-based stationary storage systems, as different approaches have distinct objectives. Hence, it is crucial not to generalise all potential battery storage systems under a single commercial software platform. As a result, this section explores notable cutting-edge modelling and simulation tools applicable for modelling, testing and analysing battery storage systems. It is worth mentioning that this is by no means an all-encompassing and comprehensive compilation of all pertinent tools necessary in the context of this subject matter. Furthermore, alongside the forthcoming modelling tools, it is noteworthy that open modelling approaches and an extensive array of accessible open-source tools have surfaced within the energy sector. These resources are accessible without restriction for both industrial and academic research, fostering collaborative model toolkit development within a broader community [210–212].

4.1. MATLAB/Simulink

MATLAB is a programming and numerical computation platform used by researchers and scientists based on 4th-generation programming languages (C, C++, and Java) for analysing data, developing algorithms and creating user interfaces [213]. This tool is commonly used to solve problems related to energy management, scheduling issues for home appliances and operations, analyses, multi-objective energy management and microgrid modelling problems. Simulink represents a graphical data flow of the programming language. This package is based on a customised set of block libraries that can easily be integrated with the rest of the MATLAB environment. It is applicable for use in simulating, modelling, digital signal processing and control theories applied to multi-objective

dynamic systems [214]. In micro-girds, this package is applicable for solving problems related to modelling and simulation, optimal automation levels and long-term economical optimisation planning [215–217].

MATLAB/Simulink is renowned for its robust scalability and user-friendliness, making it a preferred tool for both small-scale and large-scale projects, including battery systems. It accommodates complex simulations involving extensive datasets and multiple variables, making it highly adaptable for various applications, such as the modelling and control of battery systems in electric vehicles and grid storage solutions [218]. The software offers an intuitive graphical interface that allows users to build models using block diagrams and provides extensive documentation, tutorials and user communities for support. This ease of use is particularly beneficial for designing battery management systems (BMSs), as it allows engineers to simulate different charging and discharging scenarios, thermal behaviours and state-of-health estimations [219]. Its drag-and-drop functionality enhances usability, and seamless integration with other MathWorks products facilitates its application in diverse engineering and scientific projects, such as integrating battery systems with renewable energy sources or electric grid applications [218]. MATLAB/Simulink supports various file formats and protocols, ensuring easy integration with existing systems, which is essential for comprehensive engineering analyses and developing sophisticated battery system models that can be tested and validated before deployment [218]. MATLAB/Simulink requires substantial computational resources for large-scale simulations due to its capability to handle complex models and extensive datasets, often necessitating high-performance hardware for optimal performance [218]. For typical applications, it may require a multi-core processor, 16–32 GB of RAM and a dedicated graphics card to efficiently handle simulations [220]. It integrates seamlessly with a wide array of existing systems and supports various file formats and protocols, facilitating its use across diverse technological environments.

4.2. StorageVET

The financial viability of utility-scale storage is evaluated using the Storage Value Estimation Tool (StorageVET), which was developed by the Electric Power Research Institute in the United States [221]. Users can easily compute estimates for battery energy storage systems (BESSs) using pre-established technical and financial input parameters by utilising this web-based tool. StorageVET allows for fair comparisons in terms of profitability for different storage projects and grid services. It cuts across various technologies and sizes and also caters to varied locations. Based on battery specification modelling, StorageVET is strictly based on formalised parameters such as SoC constraints, efficiency of the battery and cycle and calendar lifetime estimations and, as such, does not support lithium–ion battery model specifications [222].

StorageVET is designed to evaluate the economic value of energy storage systems and is capable of handling both small- and large-scale battery storage projects effectively [222]. Its web-based interface simplifies data input and analysis, making the tool user-friendly, especially for stakeholders looking to evaluate the financial viability of different battery storage configurations and operational strategies. While the interface is straightforward, new users might require some time to become familiar with its economic evaluation functionalities. StorageVET integrates well with other energy management systems, facilitating the analysis of energy storage in various contexts, such as evaluating the cost–benefit of installing battery systems in commercial buildings, utility grids or residential setups [222]. This integration capability ensures that users can assess the potential savings, return on investment and environmental impact of different battery technologies and deployment strategies, making it adaptable for different scales of implementation. StorageVET is designed to be computationally efficient, but the complexity of the simulations can increase computational demands, especially for large-scale energy storage evaluations [223]. It typically runs effectively on systems with at least a quad-core processor, 8–16 GB of RAM and stable internet access for its web-based operations. Its web-based nature allows for

easy integration with existing energy management systems and data sources, although initial setup and data entry might require some effort [224].

4.3. DER-VET

An open-source program called the Distributed Energy Resource Value Estimation Tool (DER-VET) is intended to help determine, comprehend and maximise the value of distributed energy resources (DERs) in accordance with their technical advantages and limitations. With DER-VET, the EPRI's StorageVET tool is expanded to include site-specific evaluations of energy storage as well as other distributed energy resources (DERs) like solar, wind, demand response, EV charging, internal combustion engines, combined heat and power systems as well as microgrids. It uses load data, location-based parameters and financial benefits that can be gathered from specific use cases to determine the optimal size, duration and other parameters for maximising benefits [225].

DER-VET is scalable and can be used for analysing the value of distributed energy resources (DERs) across different project sizes, from small community installations to large utility-scale projects [226]. It is particularly useful for assessing the role of battery systems in enhancing grid stability, providing backup power and supporting renewable energy integration. Designed with user-friendliness in mind, DER-VET offers a clear interface and comprehensive guides to help users conduct detailed evaluations of DERs, including various types of battery storage systems. The web-based interface is intuitive, allowing users to easily navigate through the evaluation process and understand how battery systems can optimise energy use, reduce costs and improve reliability [226]. DER-VET supports integration with various data sources and energy management systems, making it versatile for different applications and adaptable to varying project scales. This makes it an excellent tool for planners and engineers looking to integrate battery storage into broader energy systems and to ensure efficient operation and to maximize benefits [226]. DER-VET has moderate computational demands, is suitable for evaluating distributed energy resources across various scales and can be run on standard computing hardware [227]. A typical setup might include a multi-core processor, 8–16 GB of RAM and a standard graphics card. It is highly compatible with existing energy management systems and integrates well with multiple data sources, enhancing its utility in diverse applications [228].

4.4. HOMER

The Hybrid Optimisation Model for Multiple Energy Resources (HOMER) was initially created by the National Renewable Energy Laboratories (NREL) in the United States. HOMER is a modelling tool that supports the technical and economic optimisation of microgrid systems and distributed energy resources. This software enables end-users in the ever-growing microgrid and distributed energy market to efficiently maximise costs and revenues in line with the hybrid microgrid value chain. The focus is not on the battery itself but on the entire grid system. HOMER comprises three powerful tools in a single software suite, including HOMER Pro, HOMER Grid and HOMER Front [229,230].

HOMER is highly scalable and is capable of modelling and optimizing both small off-grid systems and large grid-tied installations, including those that incorporate battery storage solutions [229]. The software is considered user-friendly, with a graphical user interface that simplifies the process of system design and optimisation. This feature is particularly advantageous for designing and evaluating hybrid energy systems wherein battery storage plays a crucial role in balancing supply and demand, storing excess renewable energy and providing power during outages. Extensive tutorials and user support enhance its accessibility for users of all experience levels, making it easier for users to simulate different scenarios and determine the optimal sizes and configurations of battery systems for specific applications [229]. The graphical interface supports drag-and-drop functionality for system components, making it easy to use and allowing for quick adjustments to the system design as new data and technologies become available. HOMER integrates well with other tools and data sources, allowing users to import and export data easily,

which is essential for comprehensive energy analyses that include detailed modelling of battery storage systems and their interaction with other energy sources and loads [229]. HOMER's computational demands are relatively low-to-moderate, making it accessible on standard PCs while capable of handling complex hybrid energy system simulations [231]. It can typically run efficiently on systems with a dual-core processor, 8 GB of RAM and an integrated graphics card. Its compatibility with various data formats and integration with other tools make it versatile for different technological environments [232].

4.5. PerModAC

PerModAC, developed by a team at the University of Applied Sciences Berlin (HTW Berlin) in Germany, is a software designed for simulating the performance of PV-BESS systems. This tool integrates various components that are crucial for modelling PV-BESS efficiency, including inverters, batteries, standby functions and energy management system (EMS) control. As of its current version, PerModAC is limited to AC-coupling of BESSs and does not include support for modelling battery ageing [233].

PerModAC is designed to handle various scales of energy projects, from small installations to large industrial applications, including those involving battery energy storage systems [234]. The tool is user-friendly, focusing on ease of use and accessibility for users with different levels of expertise, which is crucial for widespread adoption in both academic and industrial settings. Its interface is intuitive, providing clear guidance for modelling and simulation tasks, making it approachable for new users who need to simulate the performance of battery systems under different operating conditions. This includes evaluating the lifecycles, efficiencies and cost-effectiveness of various battery technologies, such as lithium–ion, lead–acid and flow batteries [234]. PerModAC integrates effectively with other software and data sources, facilitating comprehensive energy analyses and ensuring it can be adapted to different project scales. This integration capability allows users to conduct detailed performance assessments and economic analyses of battery systems in diverse applications, from residential solar-plus-storage setups to large-scale grid stabilisation projects [234]. PerModAC requires moderate computational resources, which can vary depending on the complexity and scale of the energy projects being modelled [234]. Systems with a quad-core processor, 8–16 GB of RAM and a standard graphics card are generally sufficient. It integrates well with other simulation tools and data sources, though users might need to adapt some processes to fully leverage its capabilities [235].

4.6. GridLAB-D

GridLAB-D is used to simulate and analyse power distribution networks. It offers useful data to users who build and manage distribution systems as well as utilities looking to utilise the newest energy technology. The technology is an adaptable simulation environment that has the ability to integrate with various data management and analysis tools from third parties. It was created by Pacific Northwest National Laboratory (PNNL) researchers working with academic and business partners. Its central algorithm coordinates the statuses of multi-component power system networks concurrently, each of which is characterised by a number of differential equations. The following is a comprehensive list of tools that GridLAB-D uses to design, arrange and evaluate studies: agent-based tools, data-driven simulation tools, tools for establishing and authenticating pricing mechanisms, evaluations of customers' responses, verification of how programs communicate and rely on other technologies and retail markets, tools to interface with industry-standard power systems, and analysis mechanisms. These tools can all be used by clients to create comprehensive simulations of the relationships between and the development of new end-use methodologies and distributed energy resources [236]. While the tool is capable of modelling a large-scale micro-grid with a variety of grid constraints, it is devoid of detailed simulation algorithms for energy storage systems and application-specific parameterisation. This limitation renders it unsuitable for in-depth techno–economic analyses and optimisation of storage projects [237].

GridLAB-D is highly scalable and is capable of simulating complex power systems, including large-scale grid operations that incorporate significant amounts of battery storage [236]. Although it is powerful, GridLAB-D can have a steeper learning curve compared to other tools due to its detailed and technical nature, which might require users to have a strong background in power systems engineering and programming [236]. The software interface is less graphical and more command-line based, which may be challenging for some users but offers great flexibility and control over the simulation parameters. This detailed control is particularly beneficial for modelling the dynamic interactions between battery storage systems and other grid components such as generators, loads and renewable energy sources [236]. GridLAB-D integrates well with other power system simulation tools and databases, enhancing its utility in comprehensive grid analyses and adaptability to different project scales. This integration capability is essential for conducting detailed studies on how battery storage can support grid operations, enhance reliability, and facilitate the integration of intermittent renewable energy sources [236]. GridLAB-D is computationally intensive, particularly for large-scale grid simulations, often requiring high-performance computing resources to run efficiently. Optimal performance typically requires a multi-core processor, 16–32 GB of RAM and a dedicated graphics card, along with a robust data management system. It offers strong compatibility with other power system simulation tools and databases, but its command-line interface might present integration challenges for users accustomed to graphical interfaces [238].

4.7. BLAST

The Battery Lifetime Analysis and Simulation Tool (BLAST) suite is a product of the National Renewable Energy Laboratory (NREL) in the United States (US). Proper optimisation systems must be factored in for battery ageing degradation analyses in order to accurately predict the longevity of batteries. BLAST has several variants that are applicable for assessing battery lifespans for behind-the-meter applications (BLAST BTM-Lite), stationary applications (BLAST-S), which allows for the evaluation of battery lifespans and performance in stationary applications, and vehicle applications (BLAST-V), which enables the evaluation of the longevity and the performance of the batteries used for EVs as well for hybrid electric vehicles, plug-in hybrid electric vehicles and battery electric vehicles (BEVs) [239].

BLAST is designed for scalability and is capable of handling both small and large-scale energy projects, including those involving battery storage systems [239]. The tool is user-friendly, featuring a clear and intuitive interface that facilitates easy modelling and simulation, making it accessible to users with varying levels of expertise. This ease of use is particularly important for quickly assessing the feasibility and performance of different battery storage solutions in various applications, such as residential solar-plus-storage systems, commercial demand charge management and utility-scale frequency regulation [239]. The graphical interface supports easy interaction and data input, making it accessible for users of various expertise levels and ensuring that complex simulations can be conducted efficiently. BLAST integrates well with other simulation tools and data sources, making it versatile for different applications and adaptable to varying project scales. This integration capability allows users to perform comprehensive evaluations of battery storage systems and to consider factors such as cost, performance and environmental impact [239]. BLAST's computational demands are relatively low, making it suitable for use on standard computer systems while still capable of conducting comprehensive energy simulations. A system with a dual-core processor, 8 GB of RAM, and an integrated graphics card is typically adequate. Its clear and intuitive interface facilitates integration with other tools and data sources, enhancing its adaptability to various technological environments.

4.8. SAM

System Advisor Model (SAM) is a no-cost software package designed to aid decision-making among various stakeholders in the renewable energy sector, such as policymakers,

project managers, engineers, technology developers and researchers. It allows modelling of a wide array of renewable energy systems encompassing photovoltaic arrays—from small-scale residential setups to extensive utility-level installations—concentrating solar power systems for generating electricity, and wind power systems, ranging from individual turbines to large wind farms. SAM also facilitates battery storage modelling, accommodating various battery types like lithium–ion, lead–acid and flow batteries for different applications—both in front-of-meter and behind-the-meter settings. The software employs detailed capacity, voltage, thermal and lifetime sub-models that are customisable using battery datasheets. SAM's financial tools are flexible for techno–economic evaluations in addition to financial modelling. This includes residential and commercial projects in which a renewable energy system is connected to the electric utility meter on the client's end. This makes it possible to minimise customer billing by utilising the system's power [240,241].

SAM is a robust tool used for estimating the thermal behaviour of Li-ion battery systems, which is crucial for optimising their performance and longevity. SAM incorporates detailed thermal models that consider the impact of various operating conditions on the battery's temperature and degradation [240]. By simulating different thermal management strategies, such as active cooling or passive heat dissipation, SAM offers insights into their effects on battery efficiency and lifespan [242]. Accurate thermal modelling helps prevent issues like thermal runaway, significantly enhancing battery safety and reliability [243]. This capability allows users to develop more efficient and durable battery systems, ensuring optimal performance under diverse conditions [240].

SAM's versatility also extends to simulating both automatic and manual dispatch strategies, which is critical for effective thermal management. Automatic dispatch can be used for applications like peak shaving or responding to time-varying power prices, while manual dispatch allows users to specify charging and discharging schedules [242]. These features help evaluate the thermal impacts of various operational strategies, providing a comprehensive understanding of the trade-offs between enhanced thermal regulation and associated costs [244]. For instance, SAM can simulate the effects of different cooling strategies during peak usage, offering valuable insights into maintaining thermal stability [240,245]. This detailed analysis aids with developing battery systems that are not only efficient but also have extended lifespans, enhancing their overall economic viability [246].

SAM is scalable and is suitable for a wide range of renewable energy projects, from small residential systems to large utility-scale installations, including those that incorporate battery storage [247]. Known for its user-friendly interface and comprehensive support resources, SAM provides extensive tutorials and forums to assist users with designing and evaluating energy systems that include batteries. The software's graphical interface is intuitive, allowing users to easily model and simulate various renewable energy systems, including the integration of battery storage to enhance system reliability and efficiency [247]. SAM integrates effectively with other renewable energy tools and databases, facilitating comprehensive analyses and adaptability to different scales of projects. This integration capability is essential for evaluating the economic viability and performance of battery storage systems, optimizing their configuration and determining their impact on overall system performance [247]. SAM is designed to run efficiently on standard computing hardware, with moderate computational demands even for detailed renewable energy simulations [240]. It can typically operate effectively on systems with a dual-core processor, 8–16 GB of RAM and a standard graphics card. It integrates seamlessly with a variety of renewable energy tools and databases, making it highly adaptable to different technological contexts [247].

4.9. SimSES

Simulation of Stationary Energy Storage Systems (SimSES) is an open-source modelling framework crafted to replicate stationary energy storage systems. Initially created in MATLAB, the tool was later migrated to Python and was further enhanced and collaborated on by a group of researchers at the Technical University of Munich, Germany. SimSES empowers comprehensive assessment and economic modelling of stationary storage sys-

tems across different applications. Unique features of this tool include it being a modular, flexible and abstract energy storage model, which enables a user to define the combination of system structure and technology for the energy storage systems [248,249].

In essence, it might be essential to configure and simulate a sufficiently intricate model of a storage system to predict internal conditions like SoC, state-of-health (SOH) or internal losses. Moreover, these simulations should align with the operational requirements specific to the application, ensuring they yield compatible outcomes tailored for a particular setup and forecast the storage system's state accurately. Before proceeding with project acquisition, implementation and operation, it is crucial to conduct comprehensive sensitivity and optimisation analyses using a holistic techno–economic model from the investor's viewpoint. This ensures the most cost-effective integration of storage systems into power grids that are heavily reliant on variable renewable energy sources (vRESs). Additionally, Table 8 offers a quantitative comparison of the technical and economic modelling tools for stationary storage systems discussed in this section. Various parameters affecting deep-cycle batteries, such as the temperature, end-of-discharge voltage, discharge current and state-of-health, which significantly impact battery capacity, have also been explored.

SimSES is designed to be scalable, supporting the simulation of both small-scale and large-scale energy storage systems [250]. The tool is user-friendly, with a focus on ease-of-use for both novice and experienced users, which is crucial for widespread adoption in academic research and industry. Its interface is intuitive and guides users through the simulation process with clear instructions and visual aids, making it particularly useful for modelling the performance and lifecycles of different battery technologies [250]. SimSES integrates well with other simulation tools and energy management systems, enhancing its applicability in various contexts and its adaptability to different project scales. This integration capability allows users to conduct detailed analyses of battery systems, including their efficiency, degradation and economic impact, providing valuable insights for the design and optimisation of energy storage solutions in both grid-tied and off-grid applications [250]. SimSES requires moderate to high computational resources, particularly for detailed performance and lifecycle simulations of battery storage systems [250]. Optimal performance typically necessitates a multi-core processor, 16 GB of RAM and a dedicated graphics card. It integrates well with other simulation tools and energy management systems, though its specialised focus may require some adaptation for broader applications.

Table 8. Characteristics of technical and economic simulation tools for energy storage applications.

Simulator	Open Source	Web Based	Code Availability	GUI Based	User Manual	Economic Market Analysis	Application	Developer	SoC Estimation
MATLAB	✓	✓	✓	✓	✓	✓	✓	MathWorks	✓
StorageVET	✓	✓	×	×	✓	✓	✓	EPRI	✓
DER-VET	✓	×	✓	✓	✓	✓	✓	EPRI	✓
HOMER Pro	×	✓	×	✓	✓	✓	×	Homerenergy	×
PerModAC	✓	×	✓	×	✓	✓	×	htw	×
BLAST	×	×	×	✓	✓	✓	✓	NREL	×
GridLab-D	✓	×	×	×	✓	✓	×	PNNL	×
SAM	✓	×	×	✓	✓	✓	×	NREL	×
SimSES	✓	×	✓	×	✓	✓	✓	TUM	✓

5. Conclusions and Future Research Directions

In efforts to replace fuel-based electricity generation with renewable energy sources, implementing energy storage systems has become a promising research area amongst the researcher community to provide stable, available and reliable energy with respect to supply and demand. Battery management systems have become the preferred energy storage system due to their high power density and low self-discharging. A comprehensive analysis and evaluation of energy storage technologies, particularly focusing on electrochemical and battery-based storage, is presented. The discussion emphasises the role of battery energy storage systems in storing energy for photovoltaic (PV) applications, highlighting the

diverse characteristics of the batteries used in these setups. Various methods for estimating the SoC are explored and are categorised into different groups, each possessing unique attributes. Additionally, a concise comparison and assessment of different technical and economic modelling tools for energy storage applications is outlined, considering that no single tool suits every application scenario.

Renewable energy sources exhibit significant variability depending on the location. For instance, solar energy availability heavily relies on the latitude and climate conditions. Furthermore, even within a specific location, renewable resources can fluctuate significantly on a seasonal and hourly basis. The behaviour and economic feasibility of renewable power systems are directly influenced by the nature of available resources, impacting the quantity and timing of renewable power generation. Therefore, accurately modelling renewable resources is crucial in system analysis and planning. Renewable energy sources will continue to be more pervasive in the energy sector and are envisaged to positively provide an eco-friendlier, reliable and sustainable power supply, especially in austere and remote locations where the possibility of national-grid electrification is always a major issue to be addressed. The intermittent nature of many renewable energy sources is challenging to the daily operation and maintenance of the electric grid. Renewable intermittency refers to unforeseen fluctuations and variations in output power from wind and solar sources. This erratic output power of wind and solar power, which are subject to wind speed and solar irradiance variations, affect power system reliability and the stability in the distribution network. However, microgrids are an enabling technology for utilising renewable energy sources. The inherent intermittency and the variability associated with renewable energy sources become more complicated for microgrid operations. Since renewable energy sources (solar irradiance and wind speed, which are the major consequences of the volatile nature of wind and solar energy) will continue to disrupt the operation of the grid as a result of intermittency and uncertainty, it is critical to take into consideration an efficient energy storage system to store energy for future use.

Simulation and modelling tools for energy storage cannot universally cover all the essentials for designing, modelling and analysing systems due to the specificity of each application's needs. Consequently, it is crucial to scrutinise system approaches meticulously, aligning them with the mechanisms and objectives of the particular application in question. Applications vary in terms of scale, technology requirements and operational parameters, demanding tailored approaches to effectively capture their nuances and to address their unique challenges. This necessitates a thoughtful evaluation of methodologies to ensure they align with the intricacies and goals of the given use-case, thus enhancing their applicability and relevance.

SoC estimation is seen as an important parameter in every application related to energy storage systems. This is because it assists with monitoring batteries and protecting them from deep-charging and overcharging. Having an idea of the actual SoC gives proper information on the real-time energy status of batteries, thereby giving assurance of a reliable operation process. From the study, it is observed and evident that some of the SoC estimation approaches, like the neural network technique, though effective, require a lot of training data for accuracy. Also, network convergence is slow, making it difficult to achieve the global optimum. These issues are also similar with the different SoC estimation approaches discussed in this study. Therefore, it is recommended that novel approaches are modelled and implemented to solve the present challenges of these existing SoC estimating methods in confronting PV application use-cases for reliable and sustainable power demand in austere and remote locations.

Despite advancements in SoC estimation techniques, certain gaps persist. One notable area is the need for improved accuracy, especially under diverse operating conditions. Current methods might struggle with accurately estimating the SoC in extreme temperatures, varied charge/discharge rates or with aged batteries. There is a necessity for robust algorithms that can adapt to these conditions more effectively. Additionally, achieving real-time estimation methods that are both precise and computationally efficient remain

an ongoing challenge. Balancing accuracy with computational complexity is crucial for practical implementation, yet achieving this balance is an area that requires further exploration. Furthermore, the development of standardised validation methodologies for comparing and benchmarking SoC estimation techniques across various battery chemistries and system configurations is an area that requires attention.

In the realm of energy storage technologies, several gaps exist. While lithium–ion batteries dominate the market, their limitations in terms of safety, lifespan and environmental impact highlight the need for alternative technologies. Research in this area often focuses on enhancing the performance and safety of existing technologies. However, there is a gap in the development of entirely new, disruptive technologies that could potentially surpass the limitations of current options. Additionally, there is a need for scalability and cost-effectiveness, especially for grid-scale applications. Finding solutions that balance performance, scalability and cost across different energy storage technologies remains a challenge. Exploring novel materials, alternative chemistries and innovative storage concepts could address these gaps.

Current simulators for energy storage systems often lack comprehensive integration of various components, hindering their accuracy and applicability. There is a gap in creating simulation platforms that accurately capture the complex interplay between energy storage components, control strategies and external factors like grid dynamics or variable renewable energy sources. Integration of real-time data and control algorithms into simulation models for accurate real-world scenarios is also an area needing attention. Moreover, there is a lack of standardised and open-source simulation platforms that can facilitate collaboration and benchmarking across the research community. Developing such platforms would enable researchers to validate and compare their models, fostering innovation and improvement within the field.

Addressing these research gaps will significantly contribute to advancing the reliability, efficiency and applicability of SoC estimation methods, energy storage technologies and state-of-the-art simulators, which are crucial for the future development and deployment of efficient energy storage systems.

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Abbreviations

The following abbreviations are used in this article:

AC	Alternating Current
AGM	Absorbent Glass Mat
AI	Artificial Intelligence
Ah	Ampere-Hours
BESS	Battery Energy Storage System
BMS	Battery Management System
BSS	Battery Storage System
Cd	Cadmium
CC	Coulomb Counting

CPCS	Control and Power Conditioning System
DoD	Depth of Discharge
DC	Direct Current
DERVET	Distributed Energy Value Estimation Tool
EAP	Electrode Ageing Parameter
EMF	Electromotive Force
EV	Electric Vehicle
EKF	Extended Kalman Filter
HEMS	Home Energy Management System
HOMER	Hybrid Optimisation Model for Multiple Energy Resources
KF	Kalman Filter
KOH	Alkaline Potassium Hydroxide
LFP	Lithium Iron Phosphate
Li-ion	Lithium–Ion
LM	Levenberg–Marquardt
LSA	Lightning Search Algorithm
LMO	Lithium Manganese Oxide
LTO	Lithium Titanate
ML	Machine Learning
NN	Neural Network
NMC	Lithium Nickel Manganese Cobalt Oxide
NaS	Sodium Sulfur
NiCd	Nickel–Cadmium
OCV	Open-Circuit Voltage
PbA	Lead–Acid
PV	Photovoltaic
RMSE	Root Mean Square Error
RV	Recreational Vehicle
SCG	Scaled Conjugate Gradient
SLA	Sealed Lead–Acid
SoC	State-of-Charge
SoH	Sate-of-Heath
SoL	State-of-Life
SoP	State-of-Power
VRLA	Valve-Regulated Lead–Acid

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