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Review

Battery Energy Storage Systems: A Review of Energy Management Systems and Health Metrics

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Abstract: With increasing concerns about climate change, there is a transition from high-carbon-emitting fuels to green energy resources in various applications including household, commercial, transportation, and electric grid applications. Even though renewable energy resources are receiving traction for being carbon-neutral, their availability is intermittent. To address this issue to achieve extensive application, the integration of energy storage systems in conjunction with these resources is becoming a recommended practice. Additionally, in the transportation sector, the increased demand for EVs requires the development of energy storage systems that can deliver energy for rigorous driving cycles, with lithium-ion-based batteries emerging as the superior choice for energy storage due to their high power and energy densities, length of their life cycle, low self-discharge rates, and reasonable cost. As a result, battery energy storage systems (BESSs) are becoming a primary energy storage system. The high-performance demand on these BESS can have severe negative effects on their internal operations such as heating and catching on fire when operating in overcharge or undercharge states. Reduced efficiency and poor charge storage result in the battery operating at higher temperatures. To mitigate early battery degradation, battery management systems (BMSs) have been devised to enhance battery life and ensure normal operation under safe operating conditions. Some BMSs are capable of determining precise state estimations to ensure safe battery operation and reduce hazards. Precise estimation of battery health is computed by evaluating several metrics and is a central factor in effective battery management systems. In this scenario, the accurate estimation of the health indicators (HIs) of the battery becomes even more important within the framework of a BMS. This paper provides a comprehensive review and discussion of battery management systems and different health indicators for BESSs, with suitable classification based on key characteristics.

Keywords: battery energy storage system (BESS); battery management system (BMS); lithium-ion batteries (LIBs); battery health monitoring; health indicators (HIs); renewable energy resources

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1. Introduction

With the increasing power load demand and considering load characteristics, more energy resources are needed given the changing generation mix. Fossil-fuel-based resources result in emission and environmental pollution [1]. To reduce their environmental impact and ensure sustainable energy, renewable energy resources, such as solar and wind energies, are being integrated into our energy system infrastructure [2]. The key challenge with these renewable energy systems is their intermittent nature: they cannot continuously provide energy in a dispatchable manner. Integrating an energy storage system with renewable energy provides one possible solution to this key challenge [3].

With the growth of the electric vehicle (EV) sector and their wide deployment, batteries in EVs provide energy storage not only to drive the vehicle but also to possibly connect to the grid bidirectionally for both charging (grid to vehicle) or discharging (vehicle to grid) for grid services. In these cases, battery management systems (BMSs) have a key role in ensuring reliable and safe operations for both users and the power grid [4].

The battery energy storage systems (BESSs) used in EVs undergo many charge and discharge cycles during their life, and, as they age, performance degradation evolves, and their reliability becomes questionable. The aging mechanism can be measured by estimating battery health indicators and battery state of health (SOH). So, SOH estimation is critical, and other health indicators (HIs) are used to determine battery degradation. This paper explores the state of the art for estimating HIs and other battery states [5].

Battery technologies are evolving rapidly as a result of innovative materials and methodologies of battery management systems. HI and state estimations were proposed by the research community in [6]. The research focus on the SOH and remaining useful life (RUL) estimation of batteries is rapidcly increasing, amounting to around 1850 research articles in 2023 [7], as shown in Figure 1.

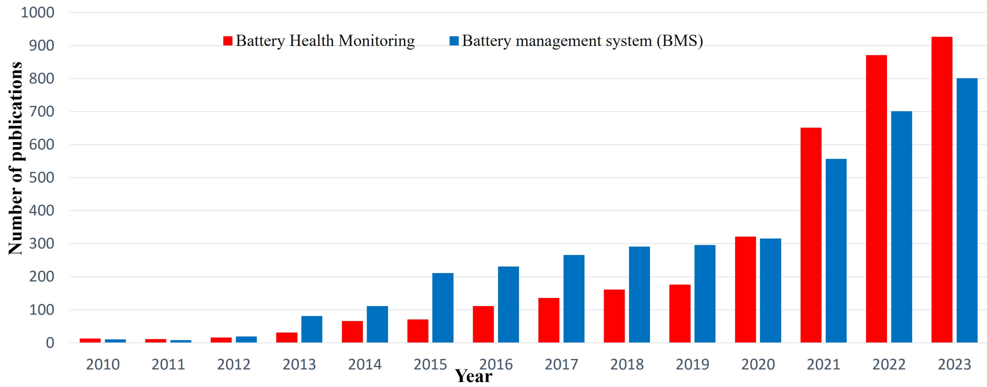

Figure 1. Progress of research on BMS and battery health monitoring in recent years.

The expanding research footprint of battery-related publications makes a comprehensive review of BMS essential for characterizing the research landscape and charting future research directions. The review of BMSs in [8] covers the functionality of BMSs from the perspective of cell balancing and limited state estimation, e.g., SOH and state of charge (SOC) only. Advances in BMSs are drive technology to include additional functionality that is essential for safe and extended battery use. RUL estimation methods, as a function of BMS, are covered in [9], categorizing existing approaches into physics-based, hybrid, statistical, and machine learning methods. However, limited methods for state estimation are mentioned, which are important for computing the RUL. Some of the new approaches like digital twins and cloud computing are also not covered in [9]. Extensive machine learning approaches are covered in [10] for the estimation of the RUL, with an end goal of formulating a battery degradation model. The impact of SOH and a few other battery use parameters like available capacity, internal resistance, and battery power are important when designing a battery degradation model.

Methods of evaluation of SOH covering data-driven methods and SOC are listed in [11]. A detailed classification of the available methods for SOH is also missing in the context of SOH estimation. Nonprobabilistic machine learning methods like linear regression, support vector machine (SVM), artificial neural network (ANN), random forest, and some of their variations for estimating SOH are listed in [12]. A comprehensive classification of the different SOH estimation methods is covered in [13], with special emphasis on its relationship to smart BMS development. Some methods related to ANN, gradient boosting, and SVM for the estimation of SOC and SOH are covered in [14] without HIs and their relation to BMS functionality. Model-based, data-driven, and ML-based estimation methods of SOH and RUL are covered in [15] with special emphasis on onboard technique. Critical reviews of BMS functionality are covered in [16] listing all major computation applications running in BMS. SOH and RUL estimation focusing on techniques based on deep learning like recursive neural network (RNN), long short-term memory (LSTM), gated recurrent units (GRUs), convolution neural network (CNN), and generative adversarial network (GAN) are covered in [17]. Transfer learning like LSTM, CNN, and GRU methods for the estimation of battery states like state of temperature (SOT), SOC, and SOH are covered in [18], with a study of their limited impact on aging prognosis. Different methods are available for battery modeling, including physics-based models, electrical-circuit-based models, and data-driven models, as covered in [19] for estimating battery states like state of power (SOP), SOC, and SOH. Popular battery chemistry types for electrical vehicle applications with significant emphasis on modeling, SOT estimation, and SOH estimation are discussed in [20], relating these metrics to BMS functionality. EV-specific battery types covering new battery types like flow batteries, high-temperature batteries, and metal air batteries are listed in [21]. Emerging BMS functionality for state estimation based on cloud computing and digital twins is covered in [21]. Methods related to data-driven and cloud computing frameworks for battery SOH estimation are proposed in [22]. A comprehensive classification of SOH estimation methods is performed in [23], which establishes its relationship to BMS functionality.

The optimal scheduling of isolated microgrids with BESSs under load and renewable generation uncertainties is described in [24]. The objective function considers (a) fuel costs of MT units, (b) spinning reserve costs, and (c) charge–discharge costs. The performance of the scheduling is evaluated for (a) different levels of renewable generation forecasting, (b) different values of charge–discharge cost of BESS, (c) different levels of available spinning reserves, (d) different sizes of BESSs, (e) different levels of load fluctuations, and (f) different solution steps of the optimization. The allocation and sizing of BESSs in weak grids with a high penetration of RESs to improve voltage and frequency stability were performed in [25]. The planning of distributed generation and energy storage by minimizing the annual cost of grid operation and daily operation optimization of the energy storage effectively alleviates the fluctuation caused by renewables, which improves the voltage profile, peak shaving, and minimizes network loss i [26].

1.1. Research Gap

Many studies on battery types and their performance comparison are available in the literature. Reviews of battery performance based on cost, performance, and strength have been performed in past work. The battery types covered in most of the papers are limited to traditional and lithium-ion batteries. Some papers are available on emerging battery technologies, with few comparisons of these with traditional technologies. BMS functionality is also evolving, with multiple functionalities added as the batteries and load demands advance. Comprehensive BMS functionality and its latest trends need to be revisited to provide at a holistic review of BMSs. Identifying and computing HIs are two of the main functions of BMSs. Reviews of HIs with systematic classification are scarce, with almost no graphical description for computation provided in the literature. A systematic classification and a graphical description of HIs are required to cover key aspects of battery health.

1.2. Objectives and Key Contributions

This paper comprehensively reviews the architecture of BMSs and reviews HIs as some of the functions of BMS. The objectives of this study are as follows:

1. Comprehensively review battery characteristics for a wide range of batteries with focus on lithium-based batteries.
2. Review of battery management system (BMS) functionality and latest trends.
3. Simplified classification of health indicators (HIs) based on electrical and temperature indicators and graphical description of HIs based on the proposed classification.

This paper provides a comprehensive view of BMS functionality along with key critical HIs. An analysis for comprehensive battery state estimation including SOH, SOC, state of safety (SOS), state of function (SOF), SOP, state of energy (SOE), SOT, and the final assessment of RUL are also discussed. Diverse metrics of HIs related to voltage, current, and temperature are extensively covered in this paper, placing each method in the appropriate category as computed by the BMS. All the major HIs are classified because BMSs dedicate significant computation effort in estimating these metrics.

This paper is organized as follows: Section 2 covers different BESS technologies with their characteristics, advantages, and limitations. Section 3 provides a comprehensive review of BMS functionality. Section 4 lists all the key HIs and classifies them based on estimation methods, which is followed by conclusions in Section 5.

2. BESS Classifications and Characteristics

Energy storage devices with recharging capabilities are used extensively in applications ranging from high-throughput electrical grids to portable low-power devices, because they overcome the problem of renewable energy intermittency and reuse over a long period. Variations in the weather, season, and time of day determine the power output of wind and solar farms [3]. The deployment of rechargeable batteries is extensive, as renewable energy sources are becoming cost-effective for supplying carbon-neutral electric power [2]. When surplus power is generated, these batteries are charged, and during its absence and connected to load, they are discharged when powered by a charging system [27]. However, for portable applications like EVs, mobile phones, and drones, the device needs to be taken out of operation and connected to the charging system. Batteries gradually degrade over time on repeated charging and discharging. The degradation is accelerated in the presence of temperature fluctuations, excessive variation in charging duration, deep discharges, and cycling partly without fully recharging [1]. A review of the basic chemistry of rechargeable batteries with an overview of characteristics is shown in Table 1 [28]. The characteristics of mature battery technology like lead acid, nickel-based, and lithium-based technology are reviewed in [20,29]. The technology and performance of future battery chemistry like sodium batteries, flow batteries, high-temperature batteries, and fuel cell batteries are covered in [20,30]. Similar cost, life cycle, energy density, power density, and efficiency of lead-acid, nickel cadmium, and lithium-ion batteries are compared in [31], listing lithium-ion as the best performing at the expense of cost.

Table 1. Common BESS types and examples of characteristics.

Battery Type	Lead-Acid	Ni-Cd	Ni-MH	Zn-Br	Fe-Cr	lithium-ion	NaS	NaNiCl	VRFB	ZBFB
Energy Density (Wh/L)	50–80 [29]	60–150 [29]	40–80 [32]	65–75 [20]	20–35 [33]	200–400 [29]	140–300 [29]	160–275 [29]	25–33 [29]	55–65 [29]
Power Density (W/L)	10–400 [29]	80–600 [29]	250–1000 [34]	60–110 [20]	70–100 [33]	1500–10,000 [29]	140–300 [29]	150–270 [29]	1–2 [29]	1–25 [29]
Cell Nominal Voltage (V)	2 [29]	1.3 [29]	1.2 [32]	1.67 [33]	1.18 [33]	4.3 [29]	2.08 [29]	2.85–3.1 [35]	1.4 [29]	1.8 [29]
Round Trip Efficiency	82% [29]	83% [29]	70%	70–80%	97.4%	95% [29]	80% [29]	84% [29]	70% [29]	70% [29]
Depth of Discharge	50% [29]	85% [29]	100%	100%	100%	95% [29]	100% [29]	100% [29]	100% [29]	100% [29]
Operating Temperature	−20–60 [33]	−40–60 [33]	−20–60 [33]	−20–60 [33]	−40–60 [33]	−20–60 [33]	300–350 [36]	−70–100 [37]	10–40 [38]	20–50 [39]
Charge Efficiency	79% [33]	70%	70%	73%	97.4%	100% [33]	90%	80–95%	97% [40]	70–80%
Energy Efficiency	70% [33]	69–90% [33]	75% [33]	80% [33]	66% [33]	80% [33]	90% [41]	95% [33]	72.3% [40]	82% [42]
Voltage Efficiency	80%	75%	70%	80%	82% [33]	98%	87%	80.9%	74.5% [40]	83%
Life Cycle	1500 [29]	2500 [29]	800–1200 [32]	200–400 [20]	300 [43]	10,000 [29]	5000 [29]	3000 [29]	13,000 [29]	10,000 [29]
Estimated Cost (USD/kWh)	105–475 [29]	400	100–500	170–580	290	200–1260 [29]	263–735 [29]	315–488 [29]	315–1050 [29]	525–1680 [29]

Lithium battery research [44] started in 1912, long before lithium-ion batteries became prominent in 1976 [20]. By that time, metallic lithium anodes and nonaqueous electrolytes were employed in the initial lithium-metal batteries (LMBs), resulting in substantial enhancements in specific energy and energy density. When Whittingham [45] developed intercalation materials in 1976, research and development of rechargeable LMBs became popular [46]. Rechargeable LMBs have low working potential and high specific capacity, making them candidates for electric vehicle (EV) propulsion despite the fact that safety concerns have impeded commercialization [15]. The merits of lithium nickel cobalt aluminium oxide (NCA) in terms of longevity, power density, energy storage, cost, and safety are listed in [15]. A comparison of the major lithium battery chemistries on the basis of cost, life span, performance, safety, power density, and energy density is provided in [16]. The most cost effective lithium battery chemistry is lithium titanate oxide (LTO), while lithium phosphate, lithium manganese, and NMC are equally expensive [16]. NMC and LTO have the maximum life span, whereas LTO has the maximum performance. A summary of the above characteristics for different lithium-based batteries is shown in Figure 2, with the individual pros and cons of each battery type.

An application-specific battery degradation study considering three applications, i.e., frequency containment reserve, increased self-consumption, and peak power shaving, was carried out in [47]. The study in [47] showed that battery degradation affects most of the peak power shaving applications. The component reliability of BESS was studied in [47] using a life cycle bathtub curve, and it was derived that the highest chance of failure is the DC link capacitor among the the components of the BESS. Lithium-ion battery failure modes were classified and studied in [48]. The failures were classified into anode degradation, cathode failures, separator failures, and current collector failures. The anode failures were further classified into failures of the solid–electrolyte interface, lithium plating, active material, anode structures, and electrolyte decomposition. Cathode failures consisted of failures in cathode structures, active material dissolution, active material isolation, and electrolyte decomposition due to oxidation. Regarding the contribution of the degradation modes to the overall reliability of lithium-ion batteries, loss of active anode and cathode material contributes to nearly 50% of the total capacity and power fades. This contribution increases to 70% after including the loss of lithium inventory. In [48], it is also shown that the solid–electrolyte interface growth with more rate and graphite exfoliation with less rate are significant contributors to the reliability and safety of lithium-ion batteries. A similar classification of lithium-ion degradation was performed in [49], considering the impact of cell level and pack level aspects of batteries on reliability. The chemical and electrical aspects were observed to have the highest impact compared to the mechanical and thermal aspects on battery reliability. The reliability evaluation of thermal management systems and electrical energy storage systems of lithium-ion batteries is proposed in [50]. Redundancy-driven improvement in the reliability of lithium-ion battery packs has been suggested in [51,52], which demonstrated that a suitable configuration enhances the battery reliability in EV applications.

The wide range of BESS characteristics cater to the diverse requirements of various applications, depending on the characteristics of the load it is driving. This makes some types of battery suitable for a specific application, while other batteries perform better for other application types. This results in the need to customize the threshold, charging profile, estimation algorithm, computation metric, etc., of the BMS for battery-specific management. Hence, the following section provides a review of BMS functionality and architecture for smart battery management.

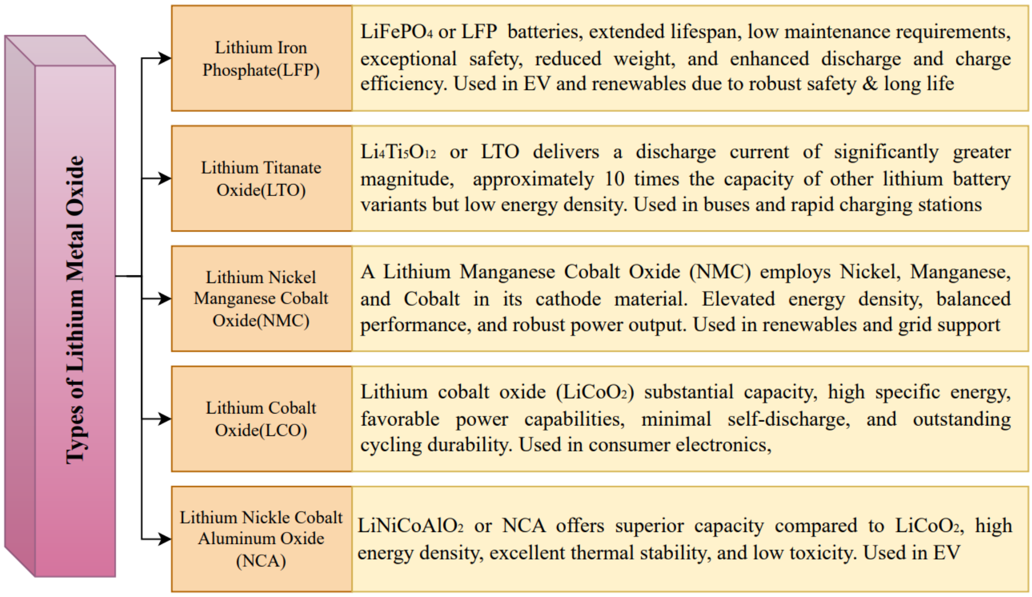

Figure 2. Different types of lithium metal oxides and key characteristics [15,16].

3. Battery Management System (BMS)

The battery management system is an electronic device that act as an interface with the battery pack and the load/charger [3,4]. An efficient BMS is primarily responsible for enhancing battery performance, ensuring safe battery operation, and extending battery life. A BMS is an integrated system that comprises both hardware and software modules, as demonstrated in Figure 3. A BMS monitors cell voltage, line current, and temperature to estimate battery stress, charge–discharge cycles, and faults. BMS functionalities are broadly segregated into temperature regulation, cell charge balancing, overvoltage, overcurrent and overcharging protection, battery degradation assessment, and usage time prediction [3,27]. The hardware components of a BMS include microcontrollers for computation, actuators for control and protection, sensors for data acquisition, and ports for communication. Its main functionalities are as follows [53]:

1. Measurement Functionality: The input cell voltage, battery chassis temperature, and line current signals are acquired by the sensors and digitized with an analog-to-digital converter (ADC). Voltage, current, and temperature values are sampled at a fixed interval, which are then digitized to analog values, scaled to the required level, and stored in memory. Then, time series data are formulated, and metrics and trends are extracted.
2. Protection Functionality: The BMS acts as a first line of defense for a battery against extreme operating scenarios. A battery can be subjected to overcharge with overvoltage and overcurrent, leading to degradation, or it can be overdischarged with high current, resulting in the battery being unusable. Extreme electrical conditions also result in battery temperature rising to dangerous levels, leading to fire hazards. The BMS prevents extreme electrical operating conditions as well as high-temperature variations in the battery. The BMS also monitors for any system faults and dead cells in the battery pack, with the possibility of isolating them if suitable circuit is in place. With the occurrence of faults and damage, the BMS indicates the specific anomaly on the visual alarms and display unit (if present).
3. Computational Functionality: All the computational functions, like charge management, cell voltage balancing, state estimation of the battery, and cooling control, are part of the output functionality of a BMS. Switching the charging mode from constant current to constant voltage is performed by the BMS based on monitoring the voltage and the current measurement functions. Differences in the electrical parameters of individual cells may lead to internal circuit loops, resulting in damage to the cells

when operated in series and parallel. The voltage balancing and charge balancing of each cell are important to prevent circulating current loops in the battery. Monitoring HIs and estimating battery states like the SOC, SOH, SOP, SOE, SOF, SOS, etc., are the computations performed by a BMS to maintain high battery performance.

4. Communication Functionality: BMS are typically equipped with communication ports like serial, controller area network (CAN), distributed network protocol (DNP3), and USB ports to connect with the host computer. New BMSs may also have wireless communication capabilities like Bluetooth, WiFi, etc. Communication with BMS smay be required for diagnostics, data downloading, and system updates.

The data acquisition module of a BMS samples the electrical and temperature signal at a rate higher than the Nyquist rate. However, this conventional strategy is inadequate when dealing with signals that fluctuate rapidly, including battery voltage and current. Event-driven ADCs (EDADCs) based on event-driven sensing (EDS) dynamically modify their sampling frequency to reduce the memory requirement and power consumption, enhancing system efficiency and increasing the speed of postprocessing [27]. In [54], the author presents a primary–secondary architecture [53] of battery management that is suitable for EVs. Thermal management, high-voltage protection, and CAN bus communication for data retrieval are some of the BMS functionalities implemented in [54]. A battery management integrated circuit (BMIC) fabricated using 0.18 μm high-voltage bipolar Cmos Dmos technology was tested in this study. The low-power BMIC was effective and compact. The BMIC could monitor a battery pack of 16 cells with sigma–delta ADC and had modules for control, data storage, and fault reporting. In [29], the author provides the comprehensive framework for a BMS consisting of a main fuse as a safety unit, a charging system unit, a balancing control module, a communication module, an internal power supply module, general digital outputs, voltage and current measurement units, a temperature control unit, a global clock module, a general analog, and a digital input. The communication module includes a calibration channel and supports the CAN bus protocol. The general digital output consists of cell balance indicators, SOH indicators, SOC indicators, and fault alarms.

SOC, SOH, SOE, SOP, SOT, SOS, and SOF are the key factors assessed by a BMS. The main focus is monitoring these metrics, leading to improved reliability and ensuring safety [55,56]. SOC, SOH, and SOP estimation; cell balancing; overvoltage protection; and thermal protection are the main functionalities of the BMS presented in [57]. An accurate SOC estimation helps a BMS to ensure better battery charging and discharging control. An extensive battery thermal management system is proposed in [20,58], with cooling and preheating functionalities for BMS applications. The BMS functions in [59] include protection, high-voltage control, diagnostics for battery state estimation and fault detection, performance management, and interface operation. A review of BMS technology, including battery modeling, battery state estimation, and charging optimization using current, voltage, and temperature sensors, is provided in [34]. A combination of phase-change materials (PCMs) and liquid cooling was used for the purpose of optimized coolant flow and enhanced cooling effect. Three categories of cell balancing methodology were implemented, which were voltage uniformity methods, capacity uniformity method, and an SOC uniformity method. Sensor faults, internal/external short-circuit faults, battery thermal management system faults, overcharge/overdischarge faults, and actuator faults were considered in the BMS's functionality. AI-powered cyber–physical platforms based on digital twins have also been explored for online large-scale fault detection [20,21]. The state estimations such as SOC, SOH, SOT, SOF, and overcharging and discharging protection functionalities of BMSs are reviewed in [60]. Improving rechargeable battery efficiency using a active energy balancing system with integrated SOC and SOH estimation is proposed in [61]. An application of a BMS in a house subscribed to demand-side management (DSM) is proposed in [3]. The data on the battery's status are transmitted to the load management system to optimize the usage patterns of appliances with variable power requirements, such as washing machines, HVAC, and boilers to improve energy efficiency and save costs [3]. A BMS assists with power supply fluctuations and hthe igh evening demand to optimize device scheduling and battery charging [27].

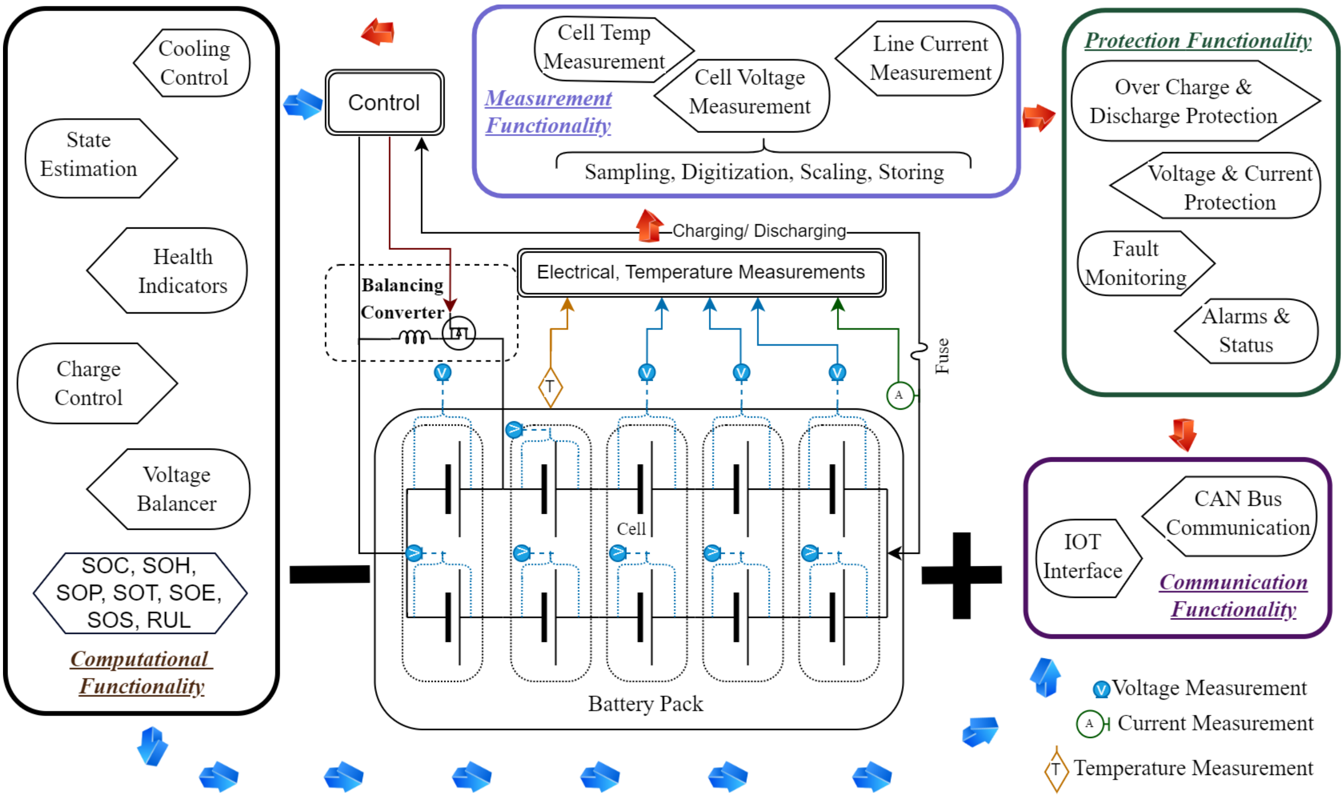

Figure 3. Battery management system (BMS).

A hierarchical architecture of a BMS is proposed in [53], in which centralized distributed and modular topologies are considered. The centralized BMS is more cost-effective and the least expandable, while the distributed BMS is the most expensive but easy to assemble. The study also demonstrated a primary–secondary configuration of a centralized BMS with multiple secondary BMSs connected to a serial interface for electric transportation applications. A comprehensive BMS architecture is presented in [53,62], in which charging/discharging control, voltage monitoring, battery balancing, temperature control, and fault diagnosis functionalities are implemented.

In [8,63], the concept related to cell balancing is proposed, which is vital to the functionality of BMSs for an extended battery life. Cell balancing is classified into two main categories, passive and active methods. In passive balancing techniques, shunt and bypass resistors are used; on the other hand, active balancing methods use energy transfer of elements like R, L, C, and a semiconductor switch. Between these two methods, active balancing is much better due to its faster cell balancing time, economic use, and higher efficiency. The active balancing circuit uses a charge shuttle and firing capacitors to transfer energy among cells. Inductor-based balancing circuits take less cell balancing time via storing energy in inductors. A detailed cell balancing comparison is provided in [8], covering simple cell balancing methods like shunt resistors to multi-inductor active charge/discharge methods. The shunt-based methods are high in power loss and low in efficiency, at the benefit of being low cost. High-performance methods with switches, inductors, and diodes are significantly more expensive. The BMS presented in [31] has all the major functionalities like charging, cell balancing, state estimation, thermal management, and fault detection. The functionality of traction motor control is also discussed extensively with a cost performance analysis. A performance comparison of EV motor configurations is also described in [31]. In [19], the author presents the future trends in BMSs, which should include increasing accuracy and meeting real-time demands, considering vehicle-to-grid (V2G) technology and emerging technologies such as 5G, increasing BMS bandwidth, and using big data and cloud computing [64,65]. A vulnerability study and the means of mitigating cyber-attacks are mentioned in [66]. Defending against false data injection attacks, random delay attacks, confidentiality and availability attacks via model-based, data-driven, and pseudo-measurement generation is the primary focus in [66]. An adversarial reinforcement learning agent is proposed to detect false-reporting attacks of SOC [66]. In [67], the author presented a field-programable gate array (FPGA) implementation of a BMS with a centralized and decentralized architecture. The centralized BMS version is cost-effective but less expandible. In contrast, the decentralized BMS using a primary–secondary architecture is robust and more flexible. The secondary module handles temperature measurement, voltage, and current measurements, and implements cell balancing; the primary module manages communication and battery state estimation. A practical BMS for unmanned aerial vehicles (UAVs) is presented in [68] using the ESP32 microcontroller platform. The proposed BMS uses machine learning and the IoT for real-time data exchange and control through mobile applications. Another FPGA implementation of a BMS is presented in [67,69]. State estimation is performed by an FPGA-based BMS design using a Matlab HDL coder. In [70], the author presents the concept of a smart battery consisting of self-reconfigurable multicell batteries (SRMBs) and self-regulated smart cells (SRSCs). The SRMBs use a matrix of switches and sensors for monitoring and controlling the cells in a battery pack, while the SRSC monitors individual cells of the battery, leading to a more expensive solution. A BMS using a digital twin with an extended Kalman filter (EKF) and XGBoost was implemented in [71] for improved state estimation. In [72], a similar digital twin for battery health monitoring is presented with stable hardware, software, and a diagnostic algorithm as advantages. In [73], the author presents a review with the main focus on cloud-based smart BMSs, considering their potential for removing limitations, improving battery algorithms, and enabling advanced BMS functionalities. Blockchain, cloud computing, artificial intelligence, and digital twins have been used to efficiently estimate battery chemical behavior using a BMS in [73–75]. In [76], the author presents a digital twin framework for EV batteries. The physical system has an on-vehicle BMS that gathers real-time data and transmits them to the Azure cloud. The digital model in the cloud estimates the SOH, including incremental fine-tuning of a deep learning network on new data.

In [9], the author presents a review focusing on BMSs, mainly focusing on the remaining useful life (RUL) of batteries, considering the advantages of and challenges ahead for different methods. Estimation of RUL using adaptive filter technologies provided the best estimation measure using an unscented particle filter (UPF), and its variation with estimation error in the range of 0–2% was achieved within 30–32 cycles of charging/discharging. Similar accuracy was also achieved using a combination of empirical mode decomposition, DNN, and LSTM within 30 cycles.

The high penetration of batteries with renewable energy sources poses new challenges and additional requirements for BMSs. A comprehensive list of supplementary tasks of BMS installed for managing batteries in grid energy storage is covered in [77]. The authors in [77] point out that mechanical hazard protection, thermal isolation, and battery pressure release are some of the safety functions of BMSs in batteries used for grid storage systems. Several specialized functionalities of BMSs related to grid management are also listed in [77,78], like (a) participation of the grid assets in primary and secondary control, (b) participation in energy arbitrage, (c) optimizing renewable energy supply to daily load demand curves, (d) responding to demand response programs, and (e) improving grid resiliency by minimizing blackouts. The inclusion of life cycle operating and storage cost as optimization objectives in BMSs for renewable energy sources is proposed in [79]. Extending the battery life and improving power quality in the grid are advanced functionalities included in BMS operation in [79]. Large arrays of cells and battery packs are common in grid energy storage systems to obtain rated output voltage and current levels. The reconfiguration functionality of battery packs to achieve balancing, healing, and optimization is proposed in [80]. Grid-scale application requires functionalities like supplying peak power demand, load following, improved stability, power quality, parallel operation, and fulfilling renewable intermittency, which is mentioned in [81]. In [82], BMS functionalities are expanded to cover economic operation, minimizing power loss, and hourly battery scheduling, as well as achieving user-defined objectives. Optimizing the objectives of demand response, minimizing intermittency, and minimizing power loss is demonstrated in [83]. A solar PV was interfaced with a smart grid with a goal of maximizing revenue in a variable tariff market [84].

Recommendations for extending the battery life are listed as controlling four battery features in [85], which are temperature-related features, like (a) minimizing exposure to high temperature during discharge and low temperature during charging; (b) maintaining the SOC at 90% and not at 100% or 0% for a long time; (c) avoiding fast charging and discharging current; (d) prevening moisture exposure, mechanical damage, and follow calibration. Apart from these restrictions, several other goals are considered in [86] for formulating objective functions like (a) cost of operation when connected to a microgrid; (b) cost of storage and expansion considering the time shifting of application to ease grid operation; (c) life cycle cost including installation, operation, and maintenance; (d) degradation cost of battery. A similar cost function minimization is also presented in [87]. Optimal life cycle battery planning is presented in [88] considering (a) fixed revenue obtained from frequency-regulation services, (b) operation and maintenance cost is proportional to the power capacity of a BESS, (c) BESS degradation cost and penalty cost for uncompensated power, (d) BESS second-life operation and maintenance cost, and (e) BESS depreciation cost. An optimized real-time BESS schedule considering total life loss and facilitating economic operation and security of microgrids under stochastic conditions is demonstrated in [89]. The consideration of aging and maximizing lifetime battery profitability is demonstrated in [90,91]. A summary of the BMS trends discussed in this paper is presented in Table 2.

Table 2. BMS functionality summary.

BMS Trends	Works
Event-driven ADCs	[27]
Primary, secondary architecture, FPGA centralized and decentralized architecture	[53,54,67,69]
Cell balancing, overvoltage protection, and thermal protection, liquid cooling, Charging/discharging control, fault diagnosis and detection, battery state estimation, thermal isolation, and battery pressure release	[8,9,20,29,31,34,54–62,77]
Mitigating cyber attacks	[66]
Unmanned Aerial Vehicles (UAVs)	[68]
Blockchain, cloud computing, artificial intelligence, digital twins, vehicle-to-grid (V2G), big data	[20,21,64,65,71–76]
Reconfiguration, self-reconfigurable multicell batteries	[70,80]
Demand response, demand-side management, grid management	[3,78,81,83]
Economic operation and security, energy arbitrage, battery operation cost minimization, minimizing power loss, battery scheduling, life cycle operating and storage cost optimization	[79,82,84–91]

Amongst the many functionalities of BMSs, computing HIs and states of the battery provides important metrics for healthy operation and improving battery longevity. Hence, the selection of the HIs to be computed and the different states to be estimated drives the innovation path of BMSss. In the following section, a review of HIs and battery states and a detailed classification of the methods are provided under suitable groups and subgroups.

4. BESS Health Indicators (HIs)

The health indicators (HIs) are parameters used to quantify the degradation of a battery. These parameters are further used to estimate the state of health (SOH) of batteries, which indicates the (1) capacity, denoting the battery's ability to hold energy; (2)iInternal resistance, demonstrating the battery's ability to deliver current; and (3) self-discharge, offering data regarding the mechanical integrity and stress events of the battery [92]. HIs are determined using a set of fundamental parameters like voltage, current, and temperature [93,94] to ascertain the performance of the electrochemical process, and these markers are used to estimate the SOH. Simple HIs like open-circuit voltage (OCV) and instantaneous temperature are used for portable appliances, while complex HIs are preferred in EV and grid-support applications. A broad classification of HIs is shown in Figure 4, with primarily measured and calculated HIs as the types of HIs. The measured HIs consist of voltage- and current-based HIs, and the second type is the temperature-based HIs. The voltage and current plots of a [95] battery starting from the discharged state, charging initially with a constant current, followed by constant voltage, and finally discharged with a constant current are shown in Figure 5. The voltage- and current-based HIs in the measured HIs segment are the following [93,94,96]:

1. CCCT, constant-current charge time: The time interval for charging at a constant current from a discharged state, shown in Figure 5.
2. CVCT, constant-voltage charge time: The time interval for charging at a constant voltage post-constant-current charging, shown in Figure 5.
3. TECD, time of equal current drop: Time of charging current reduction by the same value for multiple charging cycles during constant-voltage charge.
4. TEVR, time of equal voltage rise: Time of charging voltage rise by same value for multiple charging cycles during constant-current charge.
5. VRET, voltage rise of equal time: Voltage rises in the same time interval for multiple charging cycles during constant-current charge.
6. CDET, current drop of equal time: Current drop in the same time interval for multiple charging cycles during constant-voltage charge.
7. CCDT, constant-current discharge time: The time interval for discharging at constant-current from full charge to discharge state.
8. VDET, voltage drop of equal time: Voltage drop in the same time interval for multiple discharging cycles during constant-current discharge.
9. TEVD, time of equal voltage drop: Time of discharging voltage drop by same value for multiple discharging cycles during constant-current discharge.

The voltage- and current-based calculated HIs are as follows:

1. RCCCV, ratio of constant current to constant voltage: The ratio of the time interval of constant current to constant voltage.
2. SCC, slope of charge current: SCC = dI/dt at the constant-voltage charging interval.
3. SCV, slope of charge voltage: SCC = dV/dt at the constant-current charging interval.
4. SDV, slope of discharge voltage: SCC = dV/dt at the constant-current discharging interval.

The temperature plot of constant-current charging followed by constant-voltage charging and constant-current discharging for a [95] battery is shown in Figure 6. The temperature-based HIs in the measured HIs segment are as follows:

1. HCCCT, LCCCT: highest and lowest constant-current charge temperature: The highest and lowest values of temperature in the constant-current charging interval.
2. HCT, LCT: highest and lowest charge temperature: The highest and lowest valuesof temperature in the entire charging interval.

3. HT, LT: highest and lowest temperature: Highest and lowest values of temperature in the entire charging and discharging interval.
4. TETR, time of equal temperature rise: Time of equal value of rise in temperature for multiple cycles during constant-current discharging.
5. TRET, temperature rise of equal time: Temperature rise in the same time interval for multiple cycles during constant-current discharging.
6. HCVCT, LCVCT: highest and lowest constant-voltage charge temperature: Highest and lowest values of temperature in the constant-voltage charging interval.
7. HDT, LDT: highest and lowest discharge temperature: Highest and lowest values of temperature in the discharging interval.

The temperature-based HIs in the calculated HIs segment are as follows:

1. SDT, slope of discharge temperature: SDT = dT/dt in the constant-current discharging interval.
2. MDT, mean discharge temperature: Mean value of temperature in constant-current discharging interval.
3. MCT, mean charging temperature: Mean value of temperature in the entire charging interval.
4. MCCCT, mean constant-current charge temperature: Mean value of temperature in the constant-current charging interval.
5. MT, mean temperature: Mean value of temperature in the entire charging and discharging cycle.
6. MCVCT, mean constant-voltage charge temperature: Mean value of temperature in the constant-voltage charging interval.

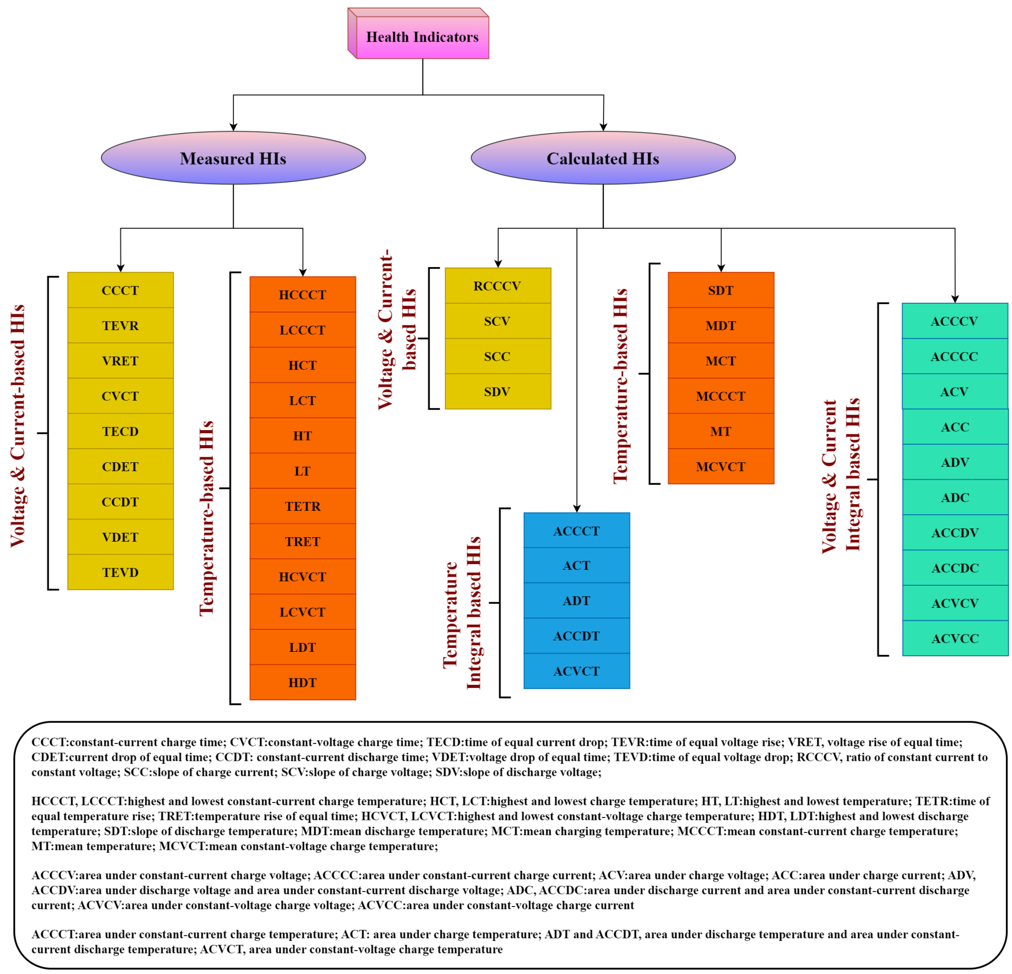

Figure 4. Classification of health indicators.

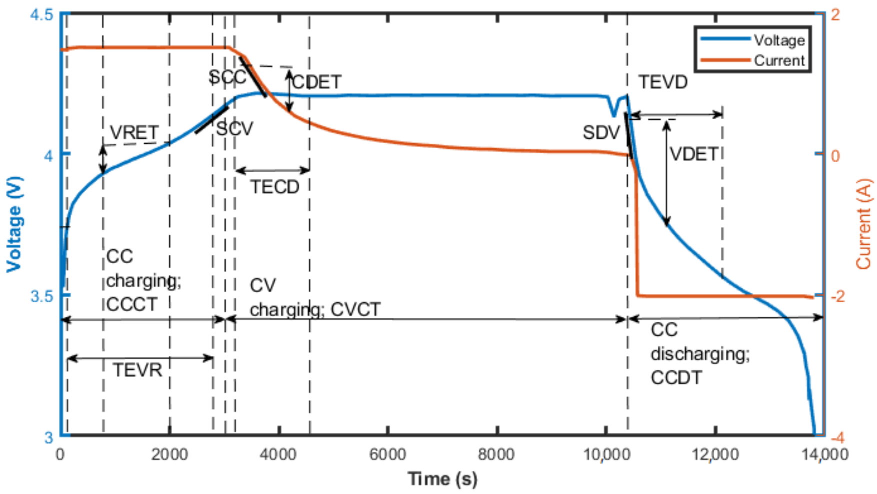

Figure 5. Voltage- and current-based HIs.

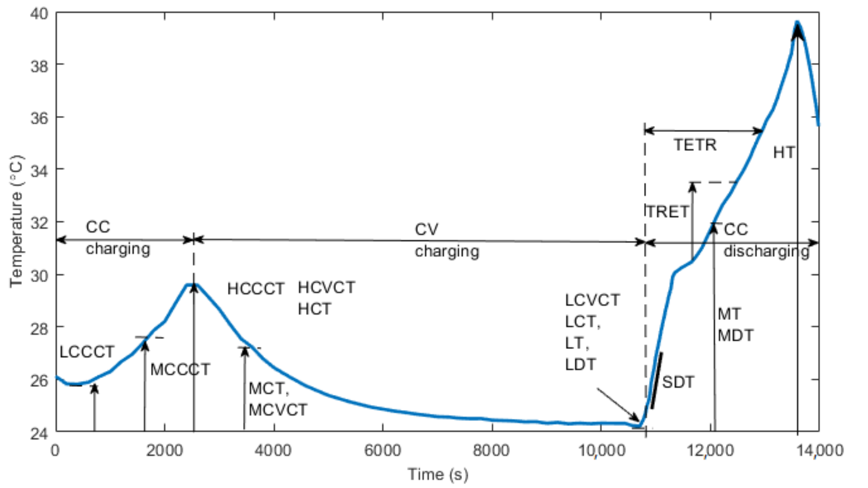

Figure 6. Temperature-based HIs.

The calculated HIs, consisting of the integral of a combination of voltage and current signals, are proposed in [97]. The integral of the voltage and current plots results in area components are shown in Figure 7. The integral voltage- and current-based HIs are as follows:

1. ACCCV, area under constant-current charge voltage: Area under the voltage in the interval of constant-current charging, shown as A2 in Figure 7.
2. ACCCC, area under constant-current charge current: Area under the current in the interval of constant-current charging, shown as A1 + A2 in Figure 7.
3. ACV, area under charge voltage: Area under the voltage in the entire charging interval, shown as A2 + A4 + A5 in Figure 7.
4. ACC, area under charge current: Area under the current in the entire charging interval, shown as A1 + A2 + A3 + A5 in Figure 7.
5. ADV and ACCDV, area under discharge voltage and area under constant-current discharge voltage: Area under voltage in the constant-current discharging interval, shown as A7 + A8 in Figure 7. These are the same, as only constant-current discharge is considered.
6. ADC and ACCDC, area under discharge current and area under constant-current discharge current: Area under current in the constant-current discharging interval, shown as A6 + A8 in Figure 7. These are the same in this case, as only constant-current discharging is considered.

7. ACVCV, area under constant-voltage charge voltage: Area under the voltage in the interval of constant voltage charging, shown as A4 + A5 in Figure 7.
8. ACVCC, area under constant-voltage charge current: Area under the current in the interval of constant-voltage charging, shown as A3 + A5 in Figure 7.

The calculated HIs, consisting of the integral of temperature resulting in area under temperature, are shown in Figure 8 and are follows:

1. ACCCT, area under constant-current charge temperature: Area under temperature in the interval of constant-current charging, shown as A1 in Figure 8.
2. ACT, area under charge temperature: Area under temperature in the interval of entire charging, shown as A1 + A2 in Figure 8.
3. ADT and ACCDT, area under discharge temperature and area under constant-current discharge temperature: Area under temperature in the interval of constant current discharging, shown as A3 in Figure 8. These are the same, as constant-current discharging is considered in this case.
4. ACVCT, area under constant-voltage charge temperature: Area under temperature in the interval of constant-voltage charging, shown as A2 in Figure 8.

The combination of CCCT, CVCT, and a new metric called fixed segment (FST) is a specific duration within CCCT, where a battery experiences a fixed voltage interval, as proposed in [98]. This enhanced HI is a linear combination of the three HIs, where a , b, and c are feature parameters to be obtained after performing optimization when learning SOH estimation. The expression of enhanced HI is given as $EnhancedHI = aCCCT + b(1 - CVCT) + cFST$. In [99], the author introduced a new HI, duration of equal charging voltage difference (DECVD), which is evaluated as a time difference between the specified low voltage and high voltage during the constant-current charging interval. DECVD was used for estimating the SOH in [99] using extreme learning machines. A Box–Cox transformation, normalization, and correlation analysis of VDET was used to estimate the RUL of a battery in [100]. The transformed HIs were observed to have a greater impact on the battery degradation for estimating the RUL. Incremental capacity analysis (ICA), given by $IC = \frac{dQ}{dV} = \frac{\Delta dQ}{\Delta V}$, is an effective HI for estimating battery SOH, as demonstrated in [94,101,102]. Further insights into the application and usability of HIs in real-world applications are obtained based on the trends in and ease of computation of HIs. The usability of the HIs depends on their variations as the battery ages. The operation reliability and lifespan of a BESS improve when controlling the charging and discharging patterns based on the deterioration of the battery health as computed using HIs. The variation in the HIs with battery cycles is shown in Table 3, which shows that the HIs that change more during the later life of the battery are particularly more useful in tracking a battery's health.

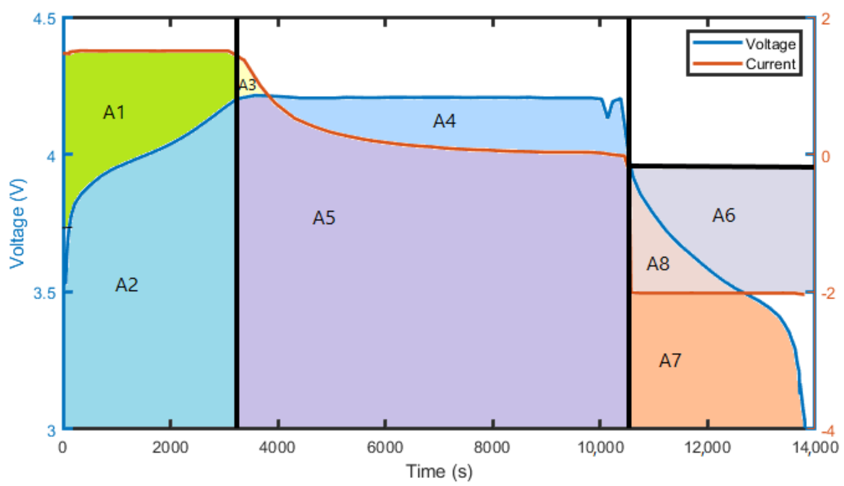

Figure 7. Voltage- and current-integral-based HIs.

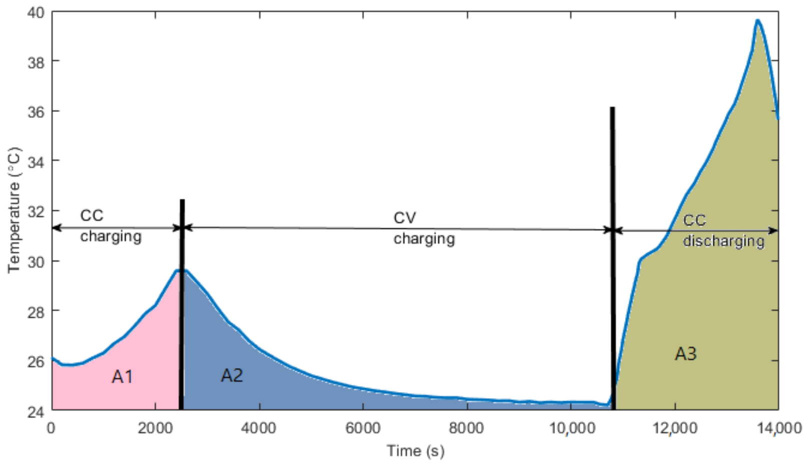

Figure 8. Temperature-integral-based HIs.

Table 3. Variations in HIs with battery deterioration.

Name of HIs	Trend as Battery Ages	Impact on Early Life	Impact on Later Life	Works
CCCT	Decrease	Less	High	[94,103]
CCDT	decrease	Less	High	[94]
CVCT	increase	Less	High	[94,104]
LCCCT	increase	Less	High	[94]
HCVCT	increase	Less	Less	[94]
LCVCT	increase	Less	Less	[94]
HT	increase	Less	Less	[94]
(dQ/dV vs. V) peak	decrease	High	Less	[94,102]
SCC	decrease	Less	Less	[94]
SCV	increase	Less	Less	[94]
SDV	Same	Less	Less	[94]
VRET	increase	Less	High	[96]
TEVR	decrease	Less	High	[96]
CDET	decrease	Less	Less	[105]
TECD	increase	Less	Less	[105]
VDET	increase	Less	High	[106]
TEVD	increase	Less	High	[106]
TRET	increase	Less	High	[107]
TETR	decrease	Less	High	[107]

5. Future Trends in BMS Development

In the era of interconnected devices with multiple access points in a BMS, the issue of cyber threats is an important consideration for future research. Robust threat identification and isolation are important features that are indispensable for future BMSs. The interconnectivity of BMSs is also required to form a platform for solving distributed optimization problems considering multiple objectives for computational efficiency and improving storage resiliency. Implementing high-computing physics-informed neural networks is also a future trend that has the potential to improve the accuracy of battery state estimation and predict faults in the battery packs of BMSs. Remedial action schemes using different communication channels are important for addressing the intermittent nature and ensuring the secure grid operation of renewables, as described in [108]. The trends in future BMS are listed in [109], which include (a) smart sensing of multiple battery parameters like electrochemical, mechanical, acoustical, and optical behavior; (b) employing big data technology to process large and high-fidelity measurements; (c) blockchain technology for energy society data management; (d) high intelligence like attention transformers.

6. Conclusions

This paper provided (a) a review of battery technologies with a focus on lithium-ion BESSs, (b) a comprehensive review of battery management systems (BMSs) and functionality, and (c) a review and classification of health indicators (HIs) as one of the functionalities provided by BESS BMSs. An extensive review of the wide range of battery characteristics in terms of performance, and capacity was provided. The typical cell-level operating parameters of the batteries were also compared. When selecting a battery for a load-specific application, specific characteristics must be considered to appropriately match the requirements. The advantages and limitations of the recently developed Li-metal batteries were also covered as they are the blocks that are supporting EVs and grid-connected renewable sources. The application-specific relationships among BMS functionality and HIs are shown in Table 4, in which the required BMS functionality for different applications is presented depending on the available computing resources, criticality, and protection requirement. Similarly, the computed HIs were also selected based on the application requirement.

Table 4. BMS and HIs requirements for common applications.

Application	BMS Functionality	Battery HIs	Key Considerations
Electric Vehicles (EVs)	Cell balancing, thermal management, SOC monitoring, protection, fault detection, and communication with vehicle electronic control unit (ECU)	Measured voltage and current HIs, measured temperature HIs	High power density, fast charging capability, robust thermal management.
Renewable energy storage	SOC monitoring, cell balancing, protection, cooling, and communication with EMS	Measured voltage and current HIs, measured temperature HIs, calculated voltage and Current HIs, calculated temperature HIs, voltage and current integral HIs, temperature integral HIs	Scalability, and grid integration capabilities.
Consumer Eeectronics	SOC monitoring, protection, thermal management,	OCV, HT	Compact size, low power consumption
Uninterruptible power supplies (UPSs)	Voltage monitoring, balancing, protection, fault detection, cooling, communication with power management systems.	Measured voltage and current HIs, measured temperature HIs, calculated voltage and current HIs, calculated temperature HIs,	High reliability, quick response to power interruptions, long service life.
Medical devices	Reliable SOC monitoring, protection, fault detection,	OCV	Safety-critical, compact design, low power consumption.
Aerospace	Cell balancing, thermal management, fault detection, communication with the flight control system, and adherence to strict safety standards.	Measured voltage and current HIs, measured temperature HIs, calculated voltage and current HIs, calculated temperature HIs, voltage and current integral HIs, temperature integral HIs	Lightweight, high reliability, wide operating temperature range.
Electric grid support	SOC monitoring, cell balancing, cell reconfiguration, cooling, meeting grid demands, communication with energy management systems.	Measured voltage and current HIs, measured temperature HIs, calculated voltage and current HIs, calculated temperature HIs, voltage and current integral HIs, temperature integral HIs	Grid compatibility, scalability, and bidirectional power flow.

The development of advanced batteries is also fostering innovations in BMSs, as discussed in this work. Computing requirements are driven by estimating HIs and battery states for different battery types, finally impacting the estimation of RUL. This paper highlighted the functional components of BMSs in great detail and the architectures of BMSs. The HIs are one of the modules of BMSs, which were also reviewed based on different categories and methodologies. The basis of categorizing HIs is measurement-based and calculation-based, which were further subclassified depending on the associated phenomenon of the battery under study. In view of the extensive classification of BMSs and

HIs discussed in this paper, the trends and accuracy performance of major technologies were analyzed.

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References

1. Wang, Z.; Feng, G.; Zhen, D.; Gu, F.; Ball, A. A review on online state of charge and state of health estimation for lithium-ion batteries in electric vehicles. *Energy Rep.* **2021**, *7*, 5141–5161. [CrossRef]
2. Cheng, M.; Zhang, X.; Ran, A.; Wei, G.; Sun, H. Optimal dispatch approach for second-life batteries considering degradation with online SoH estimation. *Renew. Sustain. Energy Rev.* **2023**, *173*, 113053. [CrossRef]
3. Tian, J.; Xiong, R.; Shen, W. A review on state of health estimation for lithium ion batteries in photovoltaic systems. *eTransportation* **2019**, *2*, 100028. [CrossRef]
4. Song, K.; Hu, D.; Tong, Y.; Yue, X. Remaining life prediction of lithium-ion batteries based on health management: A review. *J. Energy Storage* **2023**, *57*, 106193. [CrossRef]
5. Weng, C.; Feng, X.; Sun, J.; Ouyang, M.; Peng, H. Battery SOH Management Research in the US-China Clean Energy Research Center-Clean Vehicle Consortium. *IFAC-PapersOnLine* **2015**, *48*, 448–453. [CrossRef]
6. Liu, X.; Li, J.; Yao, Z.; Wang, Z.; Si, R.; Diao, Y. Research on battery SOH estimation algorithm of energy storage frequency modulation system. *Energy Rep.* **2022**, *8*, 217–223. [CrossRef]
7. Ge, M.F.; Liu, Y.; Jiang, X.; Liu, J. A review on state of health estimations and remaining useful life prognostics of lithium-ion batteries. *Measurement* **2021**, *174*, 109057. [CrossRef]
8. Habib, A.K.M.A.; Hasan, M.K.; Issa, G.F.; Singh, D.; Islam, S.; Ghazal, T.M. Lithium-Ion Battery Management System for Electric Vehicles: Constraints, Challenges, and Recommendations. *Batteries* **2023**, *9*, 152. [CrossRef]
9. Hasib, S.A.; Islam, S.; Chakrabortty, R.K.; Ryan, M.J.; Saha, D.K.; Ahamed, M.H.; Moyeen, S.I.; Das, S.K.; Ali, M.F.; Islam, M.R.; et al. A Comprehensive Review of Available Battery Datasets, RUL Prediction Approaches, and Advanced Battery Management. *IEEE Access* **2021**, *9*, 86166–86193. [CrossRef]
10. Rauf, H.; Khalid, M.; Arshad, N. Machine learning in state of health and remaining useful life estimation: Theoretical and technological development in battery degradation modelling. *Renew. Sustain. Energy Rev.* **2022**, *156*, 111903. [CrossRef]
11. Tian, H.; Qin, P.; Li, K.; Zhao, Z. A review of the state of health for lithium-ion batteries: Research status and suggestions. *J. Clean. Prod.* **2020**, *261*, 120813. [CrossRef]
12. Sui, X.; He, S.; Vilsen, S.B.; Meng, J.; Teodorescu, R.; Stroe, D.I. A review of non-probabilistic machine learning-based state of health estimation techniques for Lithium-ion battery. *Appl. Energy* **2021**, *300*, 117346. [CrossRef]
13. Xiong, R.; Li, L.; Tian, J. Towards a smarter battery management system: A critical review on battery state of health monitoring methods. *J. Power Sources* **2018**, *405*, 18–29. [CrossRef]
14. Manoharan, A.; Begam, K.; Aparow, V.R.; Sooriamoorthy, D. Artificial Neural Networks, Gradient Boosting and Support Vector Machines for electric vehicle battery state estimation: A review. *J. Energy Storage* **2022**, *55*, 105384. [CrossRef]
15. Elmahallawy, M.; Elfouly, T.; Alouani, A.; Massoud, A.M. A Comprehensive Review of Lithium-Ion Batteries Modeling, and State of Health and Remaining Useful Lifetime Prediction. *IEEE Access* **2022**, *10*, 119040–119070. [CrossRef]
16. Hannan, M.A.; Hoque, M.M.; Hussain, A.; Yusof, Y.; Ker, P.J. State-of-the-Art and Energy Management System of Lithium-Ion Batteries in Electric Vehicle Applications: Issues and Recommendations. *IEEE Access* **2018**, *6*, 19362–19378. [CrossRef]
17. He, W.; Li, Z.; Liu, T.; Liu, Z.; Guo, X.; Du, J.; Li, X.; Sun, P.; Ming, W. Research progress and application of deep learning in remaining useful life, state of health and battery thermal management of lithium batteries. *J. Energy Storage* **2023**, *70*, 107868. [CrossRef]
18. Liu, K.; Peng, Q.; Che, Y.; Zheng, Y.; Li, K.; Teodorescu, R.; Widanage, D.; Barai, A. Transfer learning for battery smarter state estimation and ageing prognostics: Recent progress, challenges, and prospects. *Adv. Appl. Energy* **2023**, *9*, 100117. [CrossRef]
19. Wang, Y.; Tian, J.; Sun, Z.; Wang, L.; Xu, R.; Li, M.; Chen, Z. A comprehensive review of battery modeling and state estimation approaches for advanced battery management systems. *Renew. Sustain. Energy Rev.* **2020**, *131*, 110015. [CrossRef]
20. Liu, W.; Placke, T.; Chau, K. Overview of batteries and battery management for electric vehicles. *Energy Rep.* **2022**, *8*, 4058–4084. [CrossRef]
21. Waseem, M.; Ahmad, M.; Parveen, A.; Suhaib, M. Battery technologies and functionality of battery management system for EVs: Current status, key challenges, and future prospectives. *J. Power Sources* **2023**, *580*, 233349. [CrossRef]

22. Yang, K.; Zhang, L.; Zhang, Z.; Yu, H.; Wang, W.; Ouyang, M.; Zhang, C.; Sun, Q.; Yan, X.; Yang, S.; et al. Battery State of Health Estimate Strategies: From Data Analysis to End-Cloud Collaborative Framework. *Batteries* **2023**, *9*, 351. [CrossRef]
23. Yang, B.; Qian, Y.; Li, Q.; Chen, Q.; Wu, J.; Luo, E.; Xie, R.; Zheng, R.; Yan, Y.; Su, S.; et al. Critical summary and perspectives on state-of-health of lithium-ion battery. *Renew. Sustain. Energy Rev.* **2024**, *190*, 114077. [CrossRef]
24. Li, Y.; Yang, Z.; Li, G.; Zhao, D.; Tian, W. Optimal Scheduling of an Isolated Microgrid With Battery Storage Considering Load and Renewable Generation Uncertainties. *IEEE Trans. Ind. Electron.* **2019**, *66*, 1565–1575. [CrossRef]
25. Ramos, A.F.; Ahmad, I.; Habibi, D.; Mahmoud, T.S. Placement and sizing of utility-size battery energy storage systems to improve the stability of weak grids. *Int. J. Electr. Power Energy Syst.* **2023**, *144*, 108427. [CrossRef]
26. Li, Y.; Feng, B.; Wang, B.; Sun, S. Joint planning of distributed generations and energy storage in active distribution networks: A Bi-Level programming approach. *Energy* **2022**, *245*, 123226. [CrossRef]
27. Qaisar, S.M.; AlQathami, M. Event-Driven Sampling Based Li-Ion Batteries SoH Estimation in the 5G Framework. *Procedia Comput. Sci.* **2021**, *182*, 109–114. [CrossRef]
28. Sobon, J.; Stephen, B. Model-Free Non-Invasive Health Assessment for Battery Energy Storage Assets. *IEEE Access* **2021**, *9*, 54579–54590. [CrossRef]
29. Ali, M.U.; Zafar, A.; Nengroo, S.H.; Hussain, S.; Junaid Alvi, M.; Kim, H.J. Towards a Smarter Battery Management System for Electric Vehicle Applications: A Critical Review of Lithium-Ion Battery State of Charge Estimation. *Energies* **2019**, *12*, 446. [CrossRef]
30. Olabi, A.; Abdelghafar, A.A.; Soudan, B.; Alami, A.H.; Semeraro, C.; Al Radi, M.; Al-Murisi, M.; Abdelkareem, M.A. Artificial neural network driven prognosis and estimation of Lithium-Ion battery states: Current insights and future perspectives. *Ain Shams Eng. J.* **2024**, *15*, 102429. [CrossRef]
31. Thangavel, S.; Mohanraj, D.; Girijaprasanna, T.; Raju, S.; Dhanamjayulu, C.; Muyeen, S.M. A Comprehensive Review on Electric Vehicle: Battery Management System, Charging Station, Traction Motors. *IEEE Access* **2023**, *11*, 20994–21019. [CrossRef]
32. Karkuzhali, V.; Rangarajan, P.; Tamilselvi, V.; Kavitha, P. Analysis of battery management system issues in electric vehicles. In *IOP Conference Series: Materials Science and Engineering*; IOP Publishing: Bristol, UK, 2020; Volume 994, p. 012013. [CrossRef]
33. Leonardi, S.G.; Samperi, M.; Frusteri, L.; Antonucci, V.; D'Urso, C. A Review of Sodium-Metal Chloride Batteries: Materials and Cell Design. *Batteries* **2023**, *9*, 524. [CrossRef]
34. Liu, K.; Li, K.; Peng, Q.; Zhang, C. A brief review on key technologies in the battery management system of electric vehicles. *Front. Mech. Eng.* **2019**, *14*, 47–64. [CrossRef]
35. Lemaire-Potteau, E.; Perrin, M.; Genies, S. BATTERIES | Charging Methods. In *Encyclopedia of Electrochemical Power Sources*; Garche, J., Ed.; Elsevier: Amsterdam, The Netherlands, 2009; pp. 413–423. [CrossRef]
36. Xu, X.; Zhou, D.; Qin, X.; Lin, K.; Kang, F.; Li, B.; Shanmukaraj, D.; Rojo, T.; Armand, M.; Wang, G. A room-temperature sodium–sulfur battery with high capacity and stable cycling performance. *Nat. Commun.* **2018**, *9*, 3870. [CrossRef]
37. Li, Z.; Zhang, Y.; Zhang, J.; Cao, Y.; Chen, J.; Liu, H.; Wang, Y. Sodium-Ion Battery with a Wide Operation-Temperature Range from −70 to 100 °C. *Angew. Chem. Int. Ed.* **2022**, *61*, e202116930. [CrossRef]
38. Rao, P.; Jayanti, S. Physics-Based Electrochemical Model of Vanadium Redox Flow Battery for Low-Temperature Applications. *Batteries* **2023**, *9*, 374. [CrossRef]
39. Johnson, S.C.; Todd Davidson, F.; Rhodes, J.D.; Coleman, J.L.; Bragg-Sitton, S.M.; Dufek, E.J.; Webber, M.E. Chapter Five-Selecting Favorable Energy Storage Technologies for Nuclear Power. In *Storage and Hybridization of Nuclear Energy*; Bindra, H., Revankar, S., Eds.; Academic Press: New York, NY, USA, 2019; pp. 119–175. [CrossRef]
40. Karrech, A.; Regenauer-Lieb, K.; Abbassi, F. Vanadium flow batteries at variable flow rates. *J. Energy Storage* **2022**, *45*, 103623. [CrossRef]
41. Sheelam, A.; McLeod, W.T.; Badam, R.; King, M.; Bell, J.G. Chapter 27—Comparison between supercapacitors and other energy storing electrochemical devices. In *Smart Supercapacitors*; Hussain, C.M., Ahamed, M.B., Eds.; Elsevier: Amsterdam, The Netherlands, 2023; pp. 673–712. [CrossRef]
42. Wu, M.; Zhao, T.; Jiang, H.; Zeng, Y.; Ren, Y. High-performance zinc bromine flow battery via improved design of electrolyte and electrode. *J. Power Sources* **2017**, *355*, 62–68. [CrossRef]
43. Skyllas-Kazacos, M.; Menictas, C.; Lim, T. 12 - Redox flow batteries for medium- to large-scale energy storage. In *Electricity Transmission, Distribution and Storage Systems*; Melhem, Z., Ed.; Woodhead Publishing Series in Energy; Woodhead Publishing: Cambridge, UK, 2013; pp. 398–441. [CrossRef]
44. Lewis, G.N.; Keyes, F.G. The potential of the lithium electrode. *J. Am. Chem. Soc.* **1913**, *35*, 340–344. [CrossRef]
45. Whittingham, M.S. Electrical energy storage and intercalation chemistry. *Science* **1976**, *192*, 1126–1127. [CrossRef] [PubMed]
46. Berecibar, M.; Gandiaga, I.; Villarreal, I.; Omar, N.; Van Mierlo, J.; Van den Bossche, P. Critical review of state of health estimation methods of Li-ion batteries for real applications. *Renew. Sustain. Energy Rev.* **2016**, *56*, 572–587. [CrossRef]
47. Bakeer, A.; Chub, A.; Shen, Y.; Sangwongwanich, A. Reliability analysis of battery energy storage system for various stationary applications. *J. Energy Storage* **2022**, *50*, 104217. [CrossRef]
48. Gandoman, F.H.; Jaguemont, J.; Goutam, S.; Gopalakrishnan, R.; Firouz, Y.; Kalogiannis, T.; Omar, N.; Van Mierlo, J. Concept of reliability and safety assessment of lithium-ion batteries in electric vehicles: Basics, progress, and challenges. *Appl. Energy* **2019**, *251*, 113343. [CrossRef]

49. Gandoman, F.H.; Ahmed, E.M.; Ali, Z.M.; Berecibar, M.; Zobaa, A.F.; Abdel Aleem, S.H.E. Reliability Evaluation of Lithium-Ion Batteries for E-Mobility Applications from Practical and Technical Perspectives: A Case Study. *Sustainability* **2021**, *13*, 11688. [CrossRef]
50. Ren, Y.; Jin, C.; Fang, S.; Yang, L.; Wu, Z.; Wang, Z.; Peng, R.; Gao, K. A Comprehensive Review of Key Technologies for Enhancing the Reliability of Lithium-Ion Power Batteries. *Energies* **2023**, *16*, 6144. [CrossRef]
51. Liu, Z.; Tan, C.; Leng, F. A reliability-based design concept for lithium-ion battery pack in electric vehicles. *Reliab. Eng. Syst. Saf.* **2015**, *134*, 169–177. [CrossRef]
52. Xia, Q.; Wang, Z.; Ren, Y.; Sun, B.; Yang, D.; Feng, Q. A reliability design method for a lithium-ion battery pack considering the thermal disequilibrium in electric vehicles. *J. Power Sources* **2018**, *386*, 10–20. [CrossRef]
53. Gabbar, H.A.; Othman, A.M.; Abdussami, M.R. Review of Battery Management Systems (BMS) Development and Industrial Standards. *Technologies* **2021**, *9*, 28. [CrossRef]
54. Zhu, G.; Qian, L.; Li, Y.; Guo, W.; Ding, R.; Yang, Y. 16-Cell stackable battery monitoring and management integrated circuit for electric vehicles. *Microelectron. J.* **2023**, *136*, 105782. [CrossRef]
55. Hu, X.; Feng, F.; Liu, K.; Zhang, L.; Xie, J.; Liu, B. State estimation for advanced battery management: Key challenges and future trends. *Renew. Sustain. Energy Rev.* **2019**, *114*, 109334. [CrossRef]
56. Shen, M.; Gao, Q. A review on battery management system from the modeling efforts to its multiapplication and integration. *Int. J. Energy Res.* **2019**, *43*, 5042–5075. [CrossRef]
57. Selvaraj, V.; Vairavasundaram, I. A comprehensive review of state of charge estimation in lithium-ion batteries used in electric vehicles. *J. Energy Storage* **2023**, *72*, 108777. [CrossRef]
58. Darwish, M.; Ioannou, S.; Janbey, A.; Amreiz, H.; Marouchos, C.C. Review of Battery Management Systems. In Proceedings of the 2021 International Conference on Electrical, Computer, Communications and Mechatronics Engineering (ICECCME), Wolmar, Mauritius, 7–8 October 2021; pp. 1–6. [CrossRef]
59. Khawaja, Y.; Shankar, N.; Qiqieh, I.; Alzubi, J.; Alzubi, O.; Nallakaruppan, M.; Padmanaban, S. Battery management solutions for li-ion batteries based on artificial intelligence. *Ain Shams Eng. J.* **2023**, *14*, 102213. [CrossRef]
60. Park, S.; Ahn, J.; Kang, T.; Park, S.; Kim, Y.; Cho, I.; Kim, J. Review of state-of-the-art battery state estimation technologies for battery management systems of stationary energy storage systems. *J. Power Electron.* **2020**, *20*, 1526–1540. [CrossRef]
61. Ren, H.; Zhao, Y.; Chen, S.; Wang, T. Design and implementation of a battery management system with active charge balance based on the SOC and SOH online estimation. *Energy* **2019**, *166*, 908–917. [CrossRef]
62. See, K.; Wang, G.; Zhang, Y.; Wang, Y.; Meng, L.; Gu, X.; Zhang, N.; Lim, K.; Zhao, L.; Xie, B. Critical review and functional safety of a battery management system for large-scale lithium-ion battery pack technologies. *Int. J. Coal Sci. Technol.* **2022**, *9*, 36. [CrossRef]
63. Rey, S.O.; Romero, J.A.; Romero, L.T.; Martínez, F.; Roger, X.S.; Qamar, M.A.; Domínguez-García, J.L.; Gevorkov, L. Powering the Future: A Comprehensive Review of Battery Energy Storage Systems. *Energies* **2023**, *16*, 6344. [CrossRef]
64. Wen, S.; Lin, N.; Huang, S.; Wang, Z.; Zhang, Z. Lithium battery health state assessment based on vehicle-to-grid (V2G) real-world data and natural gradient boosting model. *Energy* **2023**, *284*, 129246. [CrossRef]
65. Augello, A.; Gallo, P.; Sanseverino, E.R.; Sciabica, G.; Sciumè, G. Certifying battery usage for V2G and second life with a blockchain-based framework. *Comput. Netw.* **2023**, *222*, 109558. [CrossRef]
66. Kharlamova, N.; Hashemi, S.; Træholt, C. Data-driven approaches for cyber defense of battery energy storage systems. *Energy AI* **2021**, *5*, 100095. [CrossRef]
67. Kim, M.; So, J. VLSI design and FPGA implementation of state-of-charge and state-of-health estimation for electric vehicle battery management systems. *J. Energy Storage* **2023**, *73*, 108876. [CrossRef]
68. Shibl, M.M.; Ismail, L.S.; Massoud, A.M. A machine learning-based battery management system for state-of-charge prediction and state-of-health estimation for unmanned aerial vehicles. *J. Energy Storage* **2023**, *66*, 107380. [CrossRef]
69. Kumar, B.; Khare, N.; Chaturvedi, P. FPGA-based design of advanced BMS implementing SoC/SoH estimators. *Microelectron. Reliab.* **2018**, *84*, 66–74. [CrossRef]
70. Pradhan, S.K.; Chakraborty, B. Battery management strategies: An essential review for battery state of health monitoring techniques. *J. Energy Storage* **2022**, *51*, 104427. [CrossRef]
71. Jafari, S.; Byun, Y.C. Prediction of the Battery State Using the Digital Twin Framework Based on the Battery Management System. *IEEE Access* **2022**, *10*, 124685–124696. [CrossRef]
72. Li, W.; Rentemeister, M.; Badeda, J.; Jöst, D.; Schulte, D.; Sauer, D.U. Digital twin for battery systems: Cloud battery management system with online state-of-charge and state-of-health estimation. *J. Energy Storage* **2020**, *30*, 101557. [CrossRef]
73. Tran, M.K.; Panchal, S.; Khang, T.D.; Panchal, K.; Fraser, R.; Fowler, M. Concept review of a cloud-based smart battery management system for lithium-ion batteries: Feasibility, logistics, and functionality. *Batteries* **2022**, *8*, 19. [CrossRef] [PubMed]
74. Li, S.; He, H.; Zhao, P.; Cheng, S. Health-Conscious vehicle battery state estimation based on deep transfer learning. *Appl. Energy* **2022**, *316*, 119120. [CrossRef]
75. You, H.; Zhu, J.; Wang, X.; Jiang, B.; Sun, H.; Liu, X.; Wei, X.; Han, G.; Ding, S.; Yu, H.; et al. Nonlinear health evaluation for lithium-ion battery within full-lifespan. *J. Energy Chem.* **2022**, *72*, 333–341. [CrossRef]
76. Eaty, N.D.K.M.; Bagade, P. Digital twin for electric vehicle battery management with incremental learning. *Expert Syst. Appl.* **2023**, *229*, 120444. [CrossRef]

77. Byrne, R.H.; Nguyen, T.A.; Copp, D.A.; Chalamala, B.R.; Gyuk, I. Energy Management and Optimization Methods for Grid Energy Storage Systems. *IEEE Access* **2018**, *6*, 13231–13260. [CrossRef]
78. Stecca, M.; Elizondo, L.R.; Soeiro, T.B.; Bauer, P.; Palensky, P. A Comprehensive Review of the Integration of Battery Energy Storage Systems Into Distribution Networks. *IEEE Open J. Ind. Electron. Soc.* **2020**, *1*, 46–65. [CrossRef]
79. Hannan, M.; Wali, S.; Ker, P.; Rahman, M.A.; Mansor, M.; Ramachandaramurthy, V.; Muttaqi, K.; Mahlia, T.; Dong, Z. Battery energy-storage system: A review of technologies, optimization objectives, constraints, approaches, and outstanding issues. *J. Energy Storage* **2021**, *42*, 103023. [CrossRef]
80. Viswanathan, V.; Palaniswamy, L.N.; Leelavinodhan, P.B. Optimization techniques of battery packs using re-configurability: A review. *J. Energy Storage* **2019**, *23*, 404–415. [CrossRef]
81. Lawder, M.T.; Suthar, B.; Northrop, P.W.C.; De, S.; Hoff, C.M.; Leitermann, O.; Crow, M.L.; Santhanagopalan, S.; Subramanian, V.R. Battery Energy Storage System (BESS) and Battery Management System (BMS) for Grid-Scale Applications. *Proc. IEEE* **2014**, *102*, 1014–1030. [CrossRef]
82. Yang, Y.; Bremner, S.; Menictas, C.; Kay, M. Modelling and optimal energy management for battery energy storage systems in renewable energy systems: A review. *Renew. Sustain. Energy Rev.* **2022**, *167*, 112671. [CrossRef]
83. Erenoğlu, A.K.; Şengör, İ.; Erdinç, O.; Taşcıkaraoğlu, A.; Catalão, J.P. Optimal energy management system for microgrids considering energy storage, demand response and renewable power generation. *Int. J. Electr. Power Energy Syst.* **2022**, *136*, 107714. [CrossRef]
84. Nge, C.L.; Ranaweera, I.U.; Midtgård, O.M.; Norum, L. A real-time energy management system for smart grid integrated photovoltaic generation with battery storage. *Renew. Energy* **2019**, *130*, 774–785. [CrossRef]
85. Woody, M.; Arbabzadeh, M.; Lewis, G.M.; Keoleian, G.A.; Stefanopoulou, A. Strategies to limit degradation and maximize Li-ion battery service lifetime - Critical review and guidance for stakeholders. *J. Energy Storage* **2020**, *28*, 101231. [CrossRef]
86. Apribowo, C.H.B.; Sarjiya, S.; Hadi, S.P.; Wijaya, F.D. Optimal Planning of Battery Energy Storage Systems by Considering Battery Degradation due to Ambient Temperature: A Review, Challenges, and New Perspective. *Batteries* **2022**, *8*, 290. [CrossRef]
87. Comello, S.; Reichelstein, S. The emergence of cost effective battery storage. *Nat. Commun.* **2019**, *10*, 2038. [CrossRef]
88. Zhang, Y.; Xu, Y.; Yang, H.; Dong, Z.Y.; Zhang, R. Optimal Whole-Life-Cycle Planning of Battery Energy Storage for Multi-Functional Services in Power Systems. *IEEE Trans. Sustain. Energy* **2020**, *11*, 2077–2086. [CrossRef]
89. Xue, X.; Ai, X.; Fang, J.; Cui, S.; Jiang, Y.; Yao, W.; Chen, Z.; Wen, J. Real-Time Schedule of Microgrid for Maximizing Battery Energy Storage Utilization. *IEEE Trans. Sustain. Energy* **2022**, *13*, 1356–1369. [CrossRef]
90. Collath, N.; Cornejo, M.; Engwerth, V.; Hesse, H.; Jossen, A. Increasing the lifetime profitability of battery energy storage systems through aging aware operation. *Appl. Energy* **2023**, *348*, 121531. [CrossRef]
91. Zhang, L.; Yu, Y.; Li, B.; Qian, X.; Zhang, S.; Wang, X.; Zhang, X.; Chen, M. Improved Cycle Aging Cost Model for Battery Energy Storage Systems Considering More Accurate Battery Life Degradation. *IEEE Access* **2022**, *10*, 297–307. [CrossRef]
92. Merrouche, W.; Trari, M.; Djellal, L.; Mammeri, M.; Tebibel, H.; Blaifi, S.; Chong, L.W.; Ould-amrouche, S.; Boussaha, B. Improved model and simulation tool for dynamic SOH estimation and life prediction of batteries used in PV systems. *Simul. Model. Pract. Theory* **2022**, *119*, 102590. [CrossRef]
93. Hu, X.; Che, Y.; Lin, X.; Onori, S. Battery health prediction using fusion-based feature selection and machine learning. *IEEE Trans. Transp. Electrif.* **2020**, *7*, 382–398. [CrossRef]
94. Ma, Y.; Shan, C.; Gao, J.; Chen, H. A novel method for state of health estimation of lithium-ion batteries based on improved LSTM and health indicators extraction. *Energy* **2022**, *251*, 123973. [CrossRef]
95. Saha, B.; Goebel, K. *"Battery Data Set", NASA Prognostics Data Repository*; NASA Ames Research Center: Mountain View, CA, USA, 2007.
96. Li, Y.; Stroe, D.I.; Cheng, Y.; Sheng, H.; Sui, X.; Teodorescu, R. On the feature selection for battery state of health estimation based on charging–discharging profiles. *J. Energy Storage* **2021**, *33*, 102122. [CrossRef]
97. Jiang, N.; Zhang, J.; Jiang, W.; Ren, Y.; Lin, J.; Khoo, E.; Song, Z. Driving behavior-guided battery health monitoring for electric vehicles using machine learning. *arXiv* **2023**, arXiv:2309.14125.
98. Liu, Z.; Zhao, J.; Wang, H.; Yang, C. A New Lithium-Ion Battery SOH Estimation Method Based on an Indirect Enhanced Health Indicator and Support Vector Regression in PHMs. *Energies* **2020**, *13*, 830. [CrossRef]
99. Gou, B.; Xu, Y.; Feng, X. State-of-Health Estimation and Remaining-Useful-Life Prediction for Lithium-Ion Battery Using a Hybrid Data-Driven Method. *IEEE Trans. Veh. Technol.* **2020**, *69*, 10854–10867. [CrossRef]
100. Liu, D.; Zhou, J.; Liao, H.; Peng, Y.; Peng, X. A Health Indicator Extraction and Optimization Framework for Lithium-Ion Battery Degradation Modeling and Prognostics. *IEEE Trans. Syst. Man, Cybern. Syst.* **2015**, *45*, 915–928. [CrossRef]
101. Krupp, A.; Ferg, E.; Schuldt, F.; Derendorf, K.; Agert, C. Incremental Capacity Analysis as a State of Health Estimation Method for Lithium-Ion Battery Modules with Series-Connected Cells. *Batteries* **2021**, *7*, 2. [CrossRef]
102. Pan, W.; Luo, X.; Zhu, M.; Ye, J.; Gong, L.; Qu, H. A health indicator extraction and optimization for capacity estimation of Li-ion battery using incremental capacity curves. *J. Energy Storage* **2021**, *42*, 103072. [CrossRef]
103. Yun, Z.; Qin, W. Remaining Useful Life Estimation of Lithium-Ion Batteries Based on Optimal Time Series Health Indicator. *IEEE Access* **2020**, *8*, 55447–55461. [CrossRef]
104. Sun, Y.; Hao, X.; Pecht, M.; Zhou, Y. Remaining useful life prediction for lithium-ion batteries based on an integrated health indicator. *Microelectron. Reliab.* **2018**, *88–90*, 1189–1194. [CrossRef]

105. Wang, R.; Feng, H. Remaining useful life prediction of lithium-ion battery using a novel health indicator. *Qual. Reliab. Eng. Int.* **2021**, *37*, 1232–1243. [CrossRef]
106. Huang, Z.; Xu, F.; Yang, F. State of health prediction of lithium-ion batteries based on autoregression with exogenous variables model. *Energy* **2023**, *262*, 125497. [CrossRef]
107. Jia, J.; Liang, J.; Shi, Y.; Wen, J.; Pang, X.; Zeng, J. SOH and RUL Prediction of Lithium-Ion Batteries Based on Gaussian Process Regression with Indirect Health Indicators. *Energies* **2020**, *13*, 375. [CrossRef]
108. Yu, F.R.; Zhang, P.; Xiao, W.; Choudhury, P. Communication systems for grid integration of renewable energy resources. *IEEE Netw.* **2011**, *25*, 22–29. [CrossRef]
109. Dai, H.; Jiang, B.; Hu, X.; Lin, X.; Wei, X.; Pecht, M. Advanced battery management strategies for a sustainable energy future: Multilayer design concepts and research trends. *Renew. Sustain. Energy Rev.* **2021**, *138*, 110480. [CrossRef]