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Review

Digital Technology Implementation in Battery-Management Systems for Sustainable Energy Storage: Review, Challenges, and Recommendations

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Abstract: Energy storage systems (ESS) are among the fastest-growing electrical power system due to the changing worldwide geography for electrical distribution and use. Traditionally, methods that are implemented to monitor, detect and optimize battery modules have limitations such as difficulty in balancing charging speed and battery capacity usage. A battery-management system overcomes these traditional challenges and enhances the performance of managing battery modules. The integration of advancements and new technologies enables the provision of real-time monitoring with an inclination towards Industry 4.0. In the previous literature, it has been identified that limited studies have presented their reviews by combining the literature on different digital technologies for battery-management systems. With motivation from the above aspects, the study discussed here aims to provide a review of the significance of digital technologies like wireless sensor networks (WSN), the Internet of Things (IoT), artificial intelligence (AI), cloud computing, edge computing, blockchain, and digital twin and machine learning (ML) in the enhancement of battery-management systems. Finally, this article suggests significant recommendations such as edge computing with AI model-based devices, customized IoT-based devices, hybrid AI models and ML-based computing, digital twins for battery modeling, and blockchain for real-time data sharing.

Keywords: energy storage systems; battery-management system; artificial intelligence; digital twin; blockchain; edge computing

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Citation: Krishna, G.; Singh, R.; Gehlot, A.; Akram, S.V.; Priyadarshi, N.; Twala, B. Digital Technology Implementation in Battery-Management Systems for Sustainable Energy Storage: Review, Challenges, and Recommendations. *Electronics* **2022**, *11*, 2695. https://doi.org/10.3390/electronics11172695

Academic Editors: Stefano Feraco, Angelo Bonfitto and Nicola Amati

Received: 29 July 2022
Accepted: 24 August 2022
Published: 27 August 2022

1. Introduction

The United Nations (UN) has emphasized implementing renewable energy for minimizing carbon emissions. As part of this, renewable energy is being widely adopted by many countries. Prior to this, the implementation of ESS has gained wide attention [1]. However, monitoring of these ESS has paved a way for implementing battery-management systems to detect abnormalities and allow fault detection in ESS [2]. Figure 1 illustrates the global market for battery-management systems for different applications, in which a compound annual growth rate (CAGR) of 54.8% is anticipated due to wireless bifurcation based on connection [3]. Wireless battery-management systems are quickly gaining traction with the need to reduce wires and the usage of the IoT.

Additionally, a battery-management system ensures that unusual circumstances in the architecture of a device will have pre-configured remedial measures. A battery-management system further validates the proper method for controlling a gadget's temperature because the temperature has an impact on the power-intake profile. In comparison to conventional battery technology, lithium-ion batteries charge faster because they have a higher energy density and provide a higher power density for longer battery life in a more compact package [4]. When compared to nickel-based batteries, their self-discharge is less than half as great, and they do not require prolonged priming (priming is a conditioning cycle used as a service to improve battery performance during usage or after long periods of storage) [5]. Li-ion batteries are also becoming more affordable, which makes them an attractive option for electric vehicles and other applications [6].

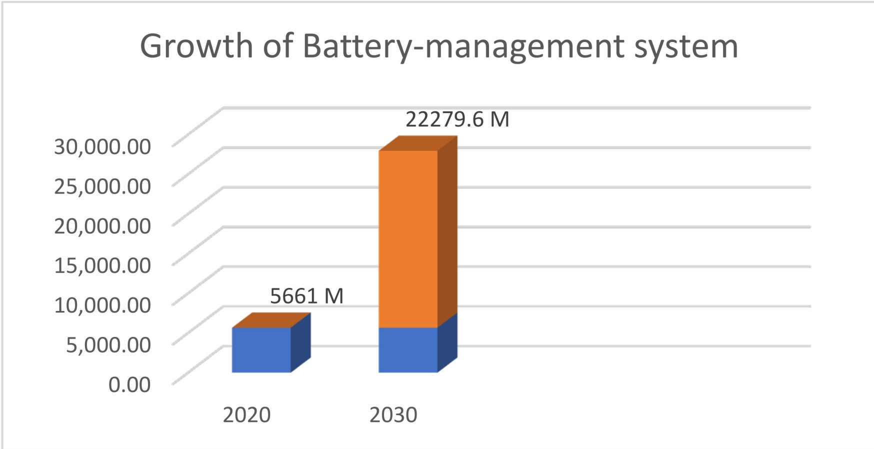

Figure 1. Growth of Battery-management systems from 2020 to 2030 [3].

There are various traditional charging methods, such as constant current (CC), constant voltage (CV), constant-current-constant-voltage (CCCV), and multi-stage constant current (MCC) charging. CC charging is a charging method that uses a constant current to charge the battery. The CV charging approach is environmentally friendly for fast charging; the approach depends upon the battery's technologies, but such charging harms the battery's capabilities. The CCCV charging method is a hybrid strategy that incorporates both CC and CV [7]. The MCC charging technique consists of several phases with CC, and the current progressively declines as the terminal voltage approaches a preset voltage threshold. The battery is charged up to the point at which the conditions of the terminal are met [8]. The dangers associated with conventional battery charging techniques include overheating, overvoltage, deep discharge, overcurrent, pressure, and mechanical stress. A supervisory system that makes sure batteries work properly in the intended application is necessary to prevent battery failure and reduce potentially dangerous circumstances. A battery-management system is the name of this monitoring device [9]. Nowadays, there are many features available in BMS that help the battery operate more efficiently and safely. Monitoring, battery protection, assessment of the state of health (SOH), state of charge (SOC), mobile balancing, charging control, and thermal management are a few of these functions.

A well-designed battery-management system is essential since there are issues about the safety, dependability, and overall performance of lithium-ion battery systems, particularly in stand-alone systems [10]. Currently, digital technologies such as WSN, IoT, cloud computing, AI, ML, NN, deep learning, blockchain, big data, cyber security, etc., have gained attention for real-time sensing, monitoring, fault detection, fault diagnosis, real-time alert generation, and real-time analytics with prediction.

The cost of storing electricity is still high, and charging a battery fully takes a long time. The cost of a battery also depends on the components that build up the battery. Infrastructure for public charging is still lacking. A battery-management system has many technologies applied to it, but there are still certain restrictions, such as cell balancing, temperature control, charge control, environmental influence on the system, exact reading of State of Health (SoH), State of Charge (SoC), and logbook functions, among others [11–21]. Studies have also conducted different systematic reviews of battery-management systems, such as the [22] study, which carried out an extensive literature review on state-of-health estimating approaches, and [23] presented a comprehensive review of the most widely used battery modeling and state estimation methodologies for battery-management systems. Recently, a study [24] examined the evolutions and problems of cutting-edge battery technologies and battery-management systems. Moreover, in data-driven electrothermal models, data-driven technologies such as AI, cloud computing, and blockchain technologies are examined. From this, it concluded that previous studies have focused on discussing the review of individual technology implementation in battery-management systems.

With the motivation from the above aspects, this study discussed and reviewed the progress and implementation of these technologies in battery-management systems, which empowers an inclination towards industry 4.0. The novelty of this study is that in previous studies it has been observed that the exploration of digital technology's impact on battery-management systems is discussed separately. Even though numerous approaches have been offered, only a few kinds of literature have attempted a comprehensive assessment of strategies for monitoring battery-management systems with multiple digital technologies The authors of this work aim to present clearly and discuss the impact of digital technology on battery-management systems by combining literature of digital technologies (WSN, IoT, cloud computing, AI, ML, NN, deep learning, blockchain, big data, cyber security). From the literature, we have concluded and discussed the vital recommendation that can be applied as a part of the future research direction. The main contribution of the study is as follows:

- The basic concept of battery-management systems with different technical terms and architecture is discussed in detail.
- In order to analyze the impact of these technologies on battery-management systems, we discussed various digital technologies such as WSN, IoT, Cloud Computing, AI, ML, NN, deep learning, blockchain, big data, and cyber security for battery-management systems using tabular and pictorial representation.
- Finally, from the analysis, the article discusses the limitations and presents vital recommendations for future work.

The structure of the paper: Section 2 discusses an overview of battery-management systems; Section 3 covers the technologies used in battery-management systems; Section 4 includes recommendations; Section 5 presents the conclusion.

2. Methodology for Review

In this section, we discuss the methods utilized to carry out and check the progress of wireless technology implementation in battery-management systems. The methods are provided in the following order: search strategy and selection criteria, data collection and extraction, and data analysis. This review is largely concerned with the progress of the various technologies involved in establishing a battery-management system.

The main research question is: "Which technologies are employed in battery management systems for sustainable energy resources?" Based on the discussed question, we collected research articles from several databases such as the web of science and Scopus. During the search of articles, the following keywords were primarily applied in the database. "Wireless monitoring of battery management system", real-time monitoring of battery management system "; "IoT and battery management system", WSN and battery management system", cybersecurity and battery management system", "digital technologies and battery management system", artificial intelligence and battery management system"; "intelligent monitoring and battery management system", "machine learning and battery management system", "deep learning and battery management system"

To decide whether an item should be included or removed from this review, the following criteria were used.

- We did not select evaluation studies with identical results that used the same data sets, methods, or algorithms.

- Reviews were not accepted for research that discussed methods but did not conduct experiments or validate results.
- Diploma theses and dissertations in bachelor's and master's programs were not evaluated.
- Scientific articles that were non-peer-reviewed were not reviewed.

The authors have analyzed the articles that were considered for review. Based on the analysis, this review presents the statistics of different papers that were utilized to study the different technologies implemented for automated feedback systems. Figure 2 illustrates a pie chart that shows the percentage of the technologies used in this literature survey. The major parts of the technology reviewed were WSN at 11%, IoT is at 13%, Cloud Computing at 8%, AI/ML, NN and DL at 37%, Big Data at 4%, Blockchain at 7%, and Expert System at 4%. Based on this conclusion, this study aims to discuss the progress and significance of these technologies' implementation in battery-management systems. This study considers certain parameters to address the different technologies' applications with algorithms, techniques, and advantages.

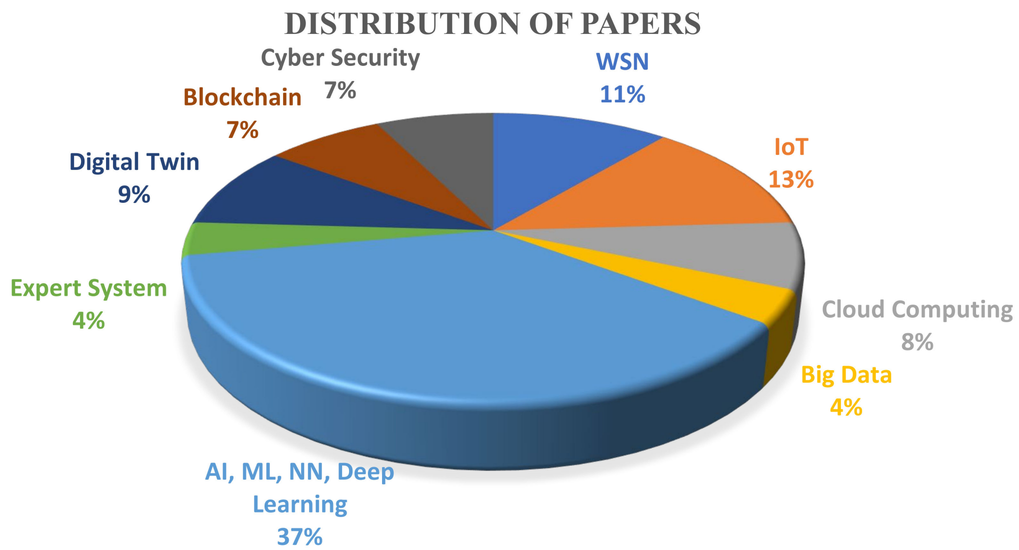

Figure 2. Bar Chart to show the percentage of technologies in the literature.

3. Overview of Battery-Management Systems

In this section, we discuss the overview of battery-management systems which is addressed in detail, and a comparison of the environmental and technical efficiency impact in tabular form is conducted. The battery-management system is a broad area with many applications (Figure 3) and implementations that are both sophisticated and diverse. An electrical power garage device's several battery modules can have their total performance monitored, managed, and optimized by a battery-management system. In the event of abnormal circumstances, BMS can detach modules from the apparatus.

a. Structure of Elements and Arrangements

A battery-management system cannot be used as a stand-alone system in a machine infrastructure. A smart electrical automation machine includes modules for managing batteries, an interface for connecting the machine to the power grid, packs for storing energy, and a system for supervising the battery and regulating energy usage [25]. Battery-management system implementations come in a range of styles, including centralized, distributed, and modular approaches. Multiple cables link the manipulator unit and battery cells in a centralized structure. A modular BMS puts together the strengths and weaknesses of the other two topologies and requires additional hardware and programming work. Figures 4 and 5 show the battery-management system implementation topology. Lastly, with a modular topology, a certain battery-moving device corresponds to several operating devices, but the operating devices are linked [26]. A component-based battery-management system requires more programming coders and components (hardware), but it simplifies troubleshooting and optimization for various network topologies.

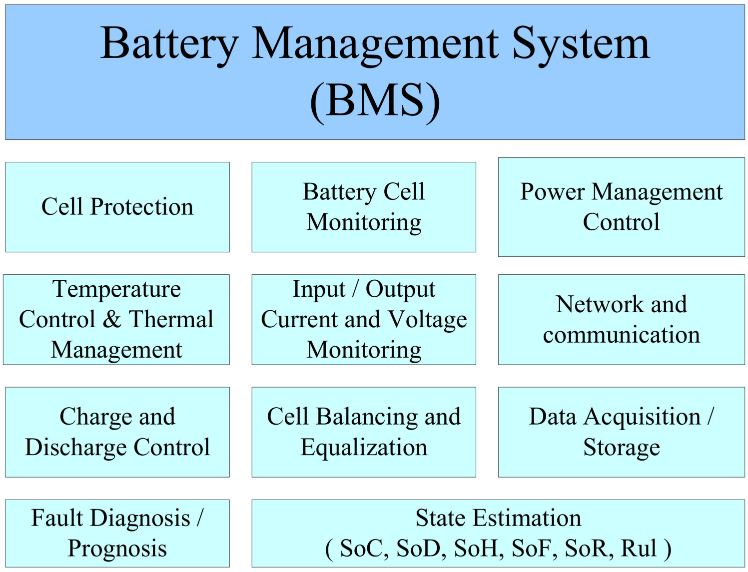

Figure 3. Applications of battery-management systems.

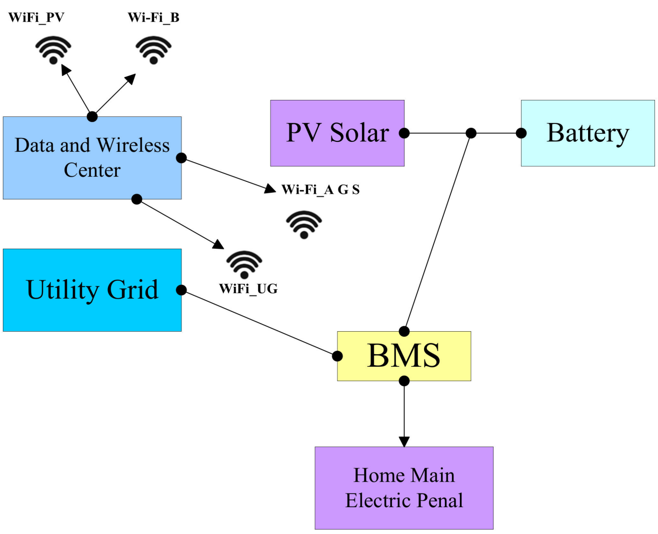

Figure 4. Connections of a battery-management system and its integration [27].

b. Structure of Battery-management system

The software for managing a battery is created to make multitasking simple since it is effective at identifying activities fast, as shown in Figure 6 [28]. Previously, it had been impractical to continue both extraordinary commitments concurrently; one mission had to be postponed in order to sustain the other mission. Battery-management systems of the back-state can't perform multi-tasking at the same time, but the current battery-management system software architecture offers this capability. Now, new architectures of battery-management systems represent that they can perform multiple tasks without any barrier. The initial tasks are defined by the architecture of the battery-management system, such as reading and calculation of voltage and current, over-current and voltage protection, reading and calculation of the battery-management system, protective relay actuation, etc. It must be performed promptly to ensure the safety of the battery-management system. A Common Microcontroller Software Interface Standard (CMSIS) and a Hardware Access

Layer (HAL) are connected to the microcontroller. For real-time functionalities, a real-time operating system (RTOS) is introduced into the BMS software architecture [12].

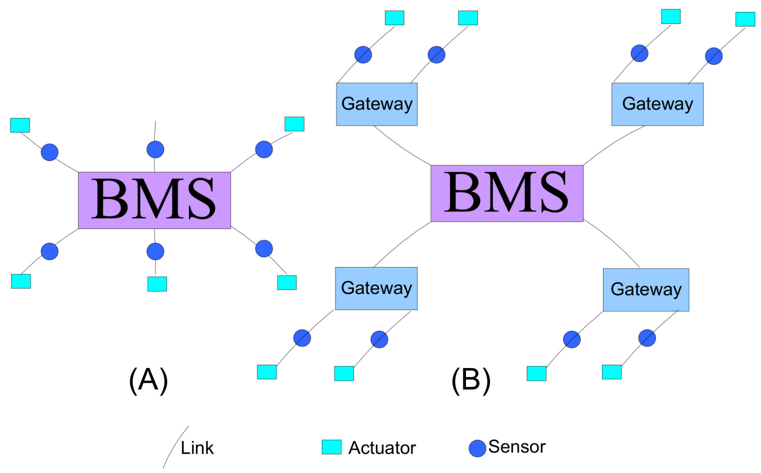

Figure 5. Implementation topology for a battery-management system. (**A**) Centralized (**B**) Distributed.

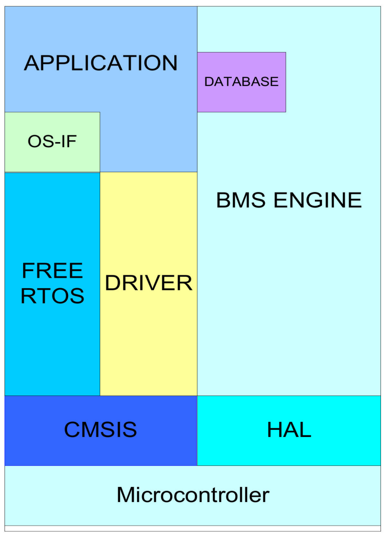

Figure 6. Battery-management system software architecture.

c. Functionalities of Battery-management systems

There are lots of functionalities of a battery-management system. For the capacity estimation of the battery, it calculates the current, temperature, and voltage percentage. Temperature control devices can be operated via the IoT using controlling devices. These measures also aid in extending the life of the battery [29].

d. Impacts of Battery-management systems

There are two types of impacts that can affect battery-management systems: environmental and technical efficiency. This study discusses the electrochemical methods used by EES structures, including batteries. Power terminals and batteries can be dangerous if not used correctly. The environmental effects of small-scale power garage facilities were examined in this paper. This investigation uncovered the causes of animal extinction as well as soil and water pollution caused by cadmium. This paper also discusses other compounds used in state-of-the-art electrochemical batteries and any shielding techniques that could be used to make them secure and with a low environmental impact [30]. These movements have the potential to cut emissions from software networks and electric flows, successfully lowering air pollution and enhancing other policies and effects on people.

Our gadgets and technology are powered by electricity, which transforms chemical energy into electric energy. Electricity can flow to a digital device through a battery's electrical circuit, which is formed by the anode and cathode. Batteries must be properly disposed of once this electric circuit is exhausted, however, tens of thousands of batteries are thrown away every year [31]. Even while disposing of batteries can seem innocuous, doing so might have disastrous effects on the environment. Each battery includes dangerous, lethal, and corrosive elements including lead, lithium, cadmium, and mercury. Here are five facts regarding batteries you should be aware of if you are worried about their impact on the environment. Battery-management system concerns related to efficiency, the environment, and other operational characteristics are presented and summarized in Table 1.

Table 1. Environmental and technical efficiency impact of battery-management systems.

Environmental Impact	**Impact of Technical Effectiveness**
CO_2 emissions reduction:	Estimation of the real-time SoC:
In addition to adopting a battery-management system to store off-height electricity to meet height demand, we think a fee of 40% might cut CO_2 emissions.	In addition to implementing a battery-management system to store electricity generated off-height to satisfy the demand for height.
Benefits of greenhouse gases (GHG):	Optimal Charging:
If we employ more battery-management systems and smooth off-top electricity rather than surges, the benefits of batteries for reducing greenhouse gas emissions may be doubled.	The target is a layout that is mostly based on layout characteristics and is exceptionally time-efficient, secure, and optimal.
Effects of metal depletion:	Fast Characterization:
BMS could be an excellent option for charging and discharging batteries since it can manage charging and discharging cycles as well as the operating frequency. On compounds with high environmental and power impacts, this substance has a considerable impact.	Accurate SOC and SOH characterizations are available from BMS. While SOH characterization is mostly focused on the range of cycles of data, SOC models its conclusions using a single full cycle of data.
Impacts of temperature regulation:	Self-Evaluation:
A BMS may be used to control two separate temperatures: the electrochemical response temperature and the ambient temperature of the battery.	BMS represents intricate battery functions, such as capacity, power, hysteresis effects, and temperature effects using mathematical formulae.

4. Technological Review of Battery-Management Systems

In this section, we discuss the distinct digital technologies that have been identified through the analysis. Here, the individual technologies of battery-management systems are addressed in detail. To show the representative battery operating states in electric vehicle (EV) applications, battery modeling and the assessment of battery internal states and characteristics initially play a significant role. After identifying these crucial factors, a suitable battery charging strategy may be created to safeguard the battery, increase energy conversion efficiency, and prolong battery life. It is challenging to ensure modeling, estimating, and charging performance in actual applications, which might differ from test settings or in a worst-case scenario. To tackle this difficult problem, it is necessary to study the constraints or to establish a confidence interval for the methods that are described [32].

4.1. WSN in Battery-Management Systems

A battery pack with several separate cells contains many wire terminations that can fail. To address the wiring issue, a wireless battery-management system relies on the ZigBee communication protocol with voltage, temperature, and SOC sensors [33]. The Battery-management system monitors runtime statistics, keeps a data log, and manages load switching between photovoltaic power systems and utility. The current and voltage sensors are connected to the FPGA through an Analogue-to-Digital Converter [34].

Table 2 gives a comparative evaluation of the evaluation research primarily based totally on battery-management systems, along with sensors and a set of rules with the prevailing study. Little research offers the dialogue of wi-fi sensor community technology as much as LoRa technology and wi-fi information acquisition. However, this text gives a complete dialogue of lots of wireless sensor communities with information and communication technology (ICT), along with IoT and battery-management systems [35–38]. The article also depicts the notion of IoT implementation in a battery-management system using a wireless sensor network. Finally, this essay discusses the benefits and ideas for improving battery-management systems using an advanced methodology and advises building the architecture in WSN using 5G technology.

Table 2. A detailed survey of WSN in battery-management systems.

Ref.	Objective	Sensor Used	Algorithm Used	Advantage
[33]	Enhancement of battery life	Voltage, current, temperature, and SOC	Battery electrochemistry (lifepo4)	The study describes a wireless battery control device that uses both the wi-fi architecture and the Zigbee conversation protocol to connect with other devices.
[34]	Improvement of energy efficiency	Current sensors, voltage sensors, CT and PT sensors	Smart energy management system algorithm	The voltage and current sensors are connected to an FPGA using an Analog-to-Digital Converter (ADC). An FPGA and strength control and tracking center are two examples of equipment connected to a network using the wireless communication protocol Zigbee.
[35]	Increase the battery lifetime	Wireless sensor	E-power management algorithm.	A hybrid-strength garage machine can aid in preventing damage to the Wi-Fi sensor's typical battery during the process of rapid discharge.
[36]	Fulfillment of battery-based power demand	Current and voltage sensor.	-	The study discussed presents a conceptual design for a LoRa-based Private Server Network-mode battery energy storage monitoring system.
[37]	LSTM-based battery voltage prediction	Current sensor	-	The gadget that is the subject of the study discussed helps to avoid sudden battery failure and poor functioning and is beneficial in speeding up the repair and lowering restoration expenses.

4.2. IoT in Battery-Management Systems

The state-of-charge parameters of a battery can be measured using different techniques and this state of charge measures the amount of charge it can store or can show the current charging status of the battery [38]. Overcharging the battery will not be a possibility if the percentage is calculated correctly. However, because each has its restrictions, there may be times when the battery is overcharged. The alternators will include a built-in voltage regulator that can deliver steady voltage even when charging automobile batteries. Failure might have several dangerous repercussions. Gases like hydrogen and oxygen, among others, may be released as a result of overcharging. They are created by the electrolyte's aqueous solution evaporating [39]. The study discussed the progress of smart cells and battery-management systems from various points of view using the possible integration of sensing techniques, design, and innovation in battery-management systems [40]. The study examines sensor noise estimation methodologies and error boundaries and finishes with a look ahead at the research that will be required to enable quick charging, battery repurposing for degradation prediction, grid energy storage, and defect-recognition [41] by thoroughly analyzing the extant literature on the status of health estimating methods.

There are two sorts of estimation methods: experimental and model-based estimation approaches. In this work, thorough literature analysis and the methods for assessing the health condition of the battery are presented in greater detail, and their respective merits and weaknesses are evaluated [42].

The physical and digital embodiments of a battery interact closely in this cyber-physical system, allowing for smarter control and longer battery life. The state-of-the-art in-vehicle diagnostic tools, battery modeling, data-driven modeling methodologies, and how these aspects might be merged into a framework for generating a battery digital twin are all presented in these viewpoints [43]. Fiber optic sensors are being used more and more in battery monitoring as a result of the growing demand for advanced battery control structures with accurate reputation estimations. The purpose of this evaluation is to include the advancements that have made it possible to use measurements of battery internal parameters, along with the nearby pressure, strain, temperature, and refractive index for renowned processes, as well as outside dimensions, along with the temperature gradient and a gasoline sensor, to detect thermal runaway. Fiber optic sensors are characterized in terms of battery structures of three different sizes including grid-scale battery structures, battery packs for heavy-duty electric trucks, and electric cars [44].

The large current peaks during the data transmission method are one feature of the LoRa technology. Thus, a hybrid energy storage device is implemented in preventing the typical battery of a wireless sensor from degrading during rapid draining [35]. The study discussed and detailed the abstract approach of employing a camera server network-mode LoRa camera-powered energy-storage observation system [36]. The study discussed offers a prediction approach for forecasting the subterranean management system's battery capacity evaluation. The technology guards against the improper operation and unexpected battery failure [22]. With a 5G advanced battery-management system structure, the classic BMS mostly uses comprehensive laboratory data to calibrate parameters, which makes it challenging to satisfy the needs of extreme precision and real-time performance. The study described the abstract design of the camera server network using a LoRa-based battery energy-storage observation system. The trend for the future is a fact-based architecture of personalized battery control systems, as seen in Figure 7.

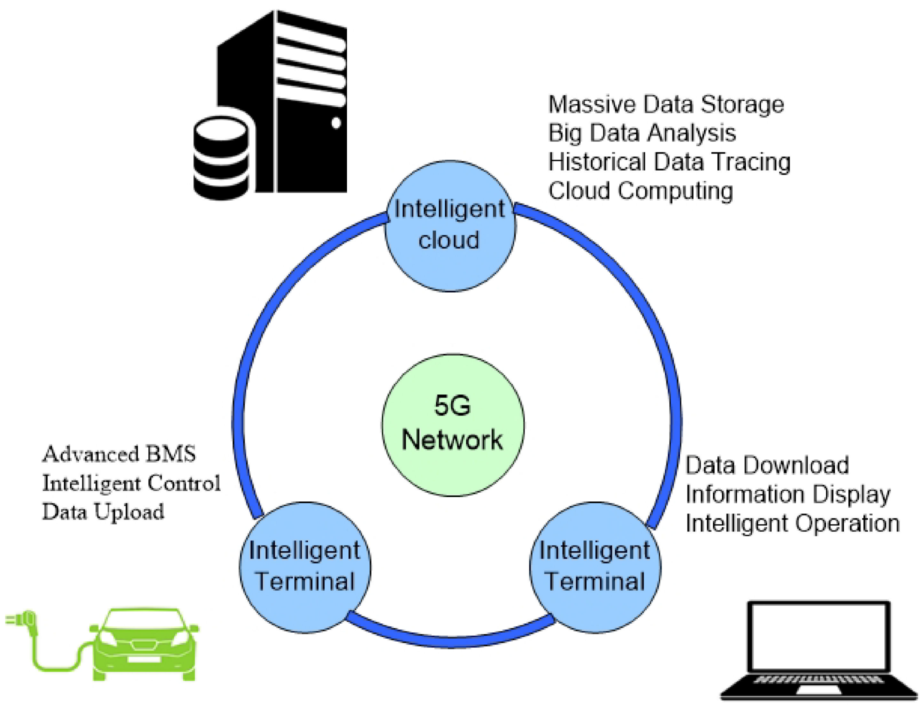

Figure 7. Advanced battery-management system architecture with 5G.

Table 3 depicts earlier research that used IoT in a wireless sensor network. The prior research included in the table was largely concerned with error detection, fault tolerance, and increasing energy density. The integration of IoT and battery-management system is used to obtain the most efficient and sustainable solution.

Table 3. A detailed survey of IoT in battery-management systems.

Ref.	Objective	Sensor Used	Algorithm Used	Advantage
[38]	Calculate the SoC	Current sensor	NN (Neural Network) Algorithm	The percentage error is less using the NN algorithm, as compared to without a NN algorithm.
[39]	Calculate the Soc and SoH	Current sensor	Temperature calculation algorithm	Establishment of a fault diagnosis system
[40]	SoC, SoH progresses of smart cell	Current sensor	Estimation and control algorithms	The work on the optical FBG sensor yields some positive results and demonstrated its ability to assess surface/inner pressure and temperature in situ and operando.
[41]	Battery SOH estimation	Current sensor	Data optimization	Increasing energy density and associated vehicle range.
[42]	Battery SOH estimation	High-precision current sensor	Adaptive filtering or data-driven algorithm	The method utilized to evaluate the battery health level is based on real needs.
[43]	Estimation of fast charging algorithm	Hall Effect sensor or Shunt resistor	k-nearest neighbors' algorithm	Many scientific works use a combination of spectroscopic, physical, and electrochemical methodologies to improve the understanding of how batteries work.
[44]	Estimation of a sensing system for optical fiber.	Temperature, low-cost fiber optic sensors	Equivalent-circuit-model-based SOC estimation algorithms	The predicted sensing system costs for standard fiber optic sensors, and one of the restrictions in their practical deployment into batteries is the expensive interrogation cost.

4.3. Cloud Computing in Battery-Management Systems

Bluetooth 4.0 module usage, and subsequently Bluetooth network protocol usage, results in larger battery energy savings, that is, a longer battery lifespan in all circumstances, when contrasted with the results of the energy consumption calculation performed using the XBee ZigBee antenna [45]. This is due to the module lacking different energy values when transmitting and receiving data, and also lower module expenditure values when active in contrast to ZigBee and Wi-Fi XBee antennae. End sensing, edge computing, cloud computing, and a knowledge repository are all part of a layered cloud-to-things system, such as a cloud-based battery management solution with status estimation capabilities. Data visualization from the cell-battery vehicle transportation system at various scales can be conducted. A hierarchical functional display is created using the Cyber Hierarchy and Interactional Network (CHAIN) architecture [46].

In order to raise the processing power and data storage capacity of cloud computing, the study offers a cloud-based battery-management system. All battery-related data is monitored and wirelessly uploaded to the cloud via the Internet of Things to create a digital replica of the battery system. The data is then analyzed by battery diagnostic algorithms, which expose the battery state and aging window [47]. This is also the first study to show that the battery's capacity and power degrade concurrently. Figure 8 shows the architecture of a cloud-connected battery-management system. The system's functionality and methods of diagnosis were tested with prototypes of a cloud battery-management system in the field.

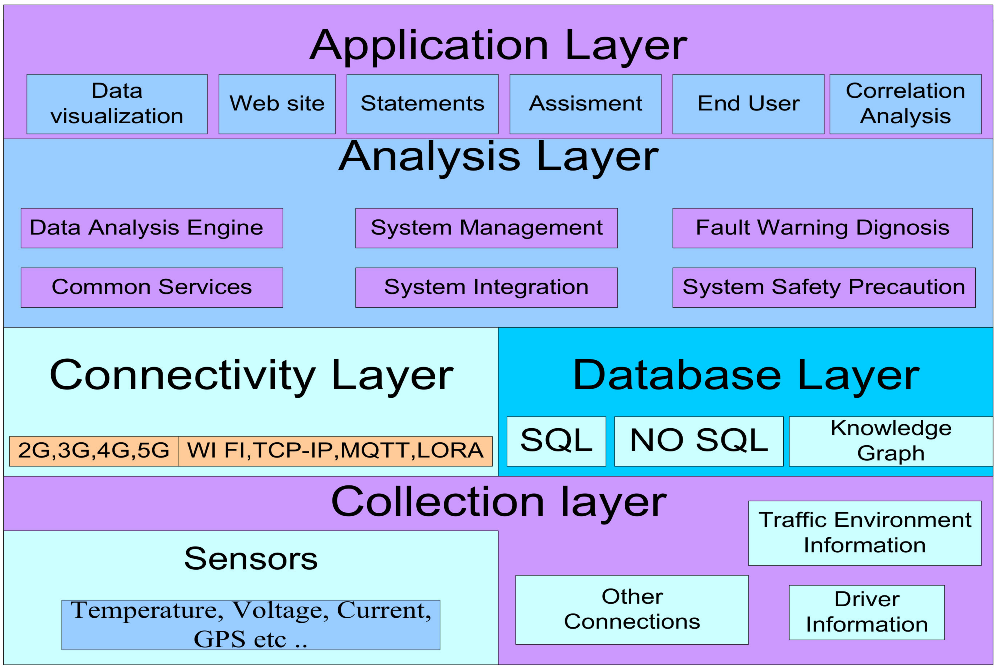

Figure 8. The architecture of a cloud-connected battery-management system.

Techniques of ML will be ready in the future based on data received from cloud-based battery-management systems for exact lifespan forecasting and system improvements [48]. Table 4 provides the detailed function of cloud computing in wireless sensor networks. The prior research included in the table contains the different types of sensors with display systems, algorithms, and improved scheduling services for better battery energy management.

Table 4. A survey on cloud computing in battery-management systems.

Ref.	Objective	Sensor Used	Display System	Algorithm Used	Advantage
[45]	Calculation of sleep-time	Current sensor	Numerous display types	Parameter identification, meta-heuristics, SOCs, cloud-suited battery diagnostic algorithms.	A cloud-based digital twin for battery systems improves the computing power, data storage capacity, and dependability of the battery-management system.
[46]	Functions of state estimation	Air, humidity, temperature, MQ-2 gas, smoke flame	Numerous displays	NA	Improved battery energy savings offered by the Bluetooth network protocol.
[47]	New intelligent BMS	Current sensor	-	IIS, PVE Algorithm	For managing battery energy, the intelligent scheduling service charging model is more effective than the conventional scheduling service.
[48]	Monitoring the battery cells	Current sensor	-	AEKF, PSO algorithm	A framework for a cloud-based battery-management system is proposed that makes use of an end-edge-cloud architecture.

4.4. Big Data in Battery-Management Systems

Cyber-Physical System (CPS) technology and battery big data platforms are the foundations of the study’s uniquely flexible and dependable battery management strategy. The proposed GRNN algorithm and cross-validation technology-driven data cleaning technique may effectively fix corrupt data in the cloud battery database under temperature changes [49]. A machine learning-based data cleaning technique is proposed that is relevant to the properties of huge data from electric car batteries. The work presented a deep learning-enabled lithium battery model that can adapt to a big data environment.

The data cleaning method, which is based on a machine-learning algorithm, produces favorable results when a terminal voltage is absent, for example, when the mean absolute percentage error of filling is less than 4%, which has a greater impact on improving the overall quality of the dataset [50].

Information is gathered using big data technologies, which include N.N., machine learning, and deep-learning algorithms. However, after going through the data cleaning procedure, one can obtain the most accurate data, which is crucial for the battery's lifespan. Table 5 gives a thorough analysis of big data in battery-management systems.

Table 5. A detailed survey on big data in battery-management systems.

Ref.	Objective	Sensor Used	Algorithm Used	Advantage
[49]	SoC error estimation	Current Sensor	ELM, deep learning, conventional data mining.	Accurately restore the cloud battery database's corrupt data.
[50]	Simulation of the battery characteristic	Current Sensor	SVR, deep learning, machine learning, neural network.	The method for cleansing data produces positive outcomes using the ML algorithm.

4.5. AI—ML, NN, and Deep Learning in Battery-Management Systems

We will see an increased role of battery-management systems with next-generation batteries. A model that evolves as it investigates a chemical area may be created using a machine learning inverse design, allowing for the expansion of a model in areas of extreme uncertainty and the identification of molecular space regions with desired attributes as a role of composition. The challenges of modeling the links between material properties and intricate physical parameters have been handled in recent years by ML approaches [51]. For cell-level capacity estimation, a deep-learning technique using deep convolutional neural networks (DCNN) is used, which is based entirely on the current, voltage, and price capability measurements throughout a half-charge cycle. With these aims in mind, this is one of the first attempts to use deep learning to estimate the capacity of a Li-ion battery online [52]. The major focus of this research is the creation of new deep learning (DL) with a SOC estimation model for safe renewable energy management (DLSOC-REM) for HEVs. Since battery damage from excessive charging and discharging is unavoidable, the BMS should provide an accurate SOC calculation [53].

Today's technology concentrates on the creation of clever algorithms for estimating inaccuracy, SOC, SOE, SOH, centered structure, access characteristics, advantages, and downsides. According to the study, clever algorithms have demonstrated improved overall performance in terms of precision, flexibility, robustness, and battery efficiency when using an estimate [54]. Because of their high electricity and energy density, lithium-ion batteries are widely employed in the automotive sector (in electric motors and hybrid electric motors). However, this creates more challenging protection and dependability scenarios that necessitate the advancement of cutting-edge battery-management systems. A BMS ensures a battery's safe and reliable functioning and understands that it requires solving a model. Modern BMSs, on the other hand, may not be able to deliver accurate results at real-time prices and some points, in a vast operation range, thus they are not designed to the specifications of the automotive sector [55].

The study looks at how battery-management systems have changed over time and suggest a tiered design architecture with three progressive levels for improved battery management. The algorithm layer aims to give full knowledge of the battery, while the application level provides a secure and effective battery method through correct supervision.

The foundation layer concentrates on the system's theoretical underpinnings and physical foundations [23]. By thoroughly analyzing the extant literature on the status-of-health estimating methods, the study discussed seeks to act as a valuable resource for scholars and practitioners. There are two types of these techniques: methods of estimation based on experiments and models [56].

One study implemented a battery life forecast model that is geared towards operational battery management optimization. The methodology has been developed for lithium-ion (Li-ion) cells to take into account five operational factors: discharging and charging currents, maximum and minimum cycling constraints, and operating temperature [57]. The proposed SoC and SoH calculations are utilized to build an algorithm that can accurately estimate the battery state. The SoC may be appropriately computed by applying the battery efficiency to the open circuit voltage to minimize the initial fault of the Coulomb counting method (CCM). The internal resistance of a battery increases while charging and discharging, while the CC charging time decreases [58].

This work calculates the SoC of Li-battery systems for any applications like EV using a variety of ML techniques such as support vector machines (SVM), artificial neural networks (ANN), linear regression (LR), ensemble bagging, and Gaussian process regression (GPR) (Figure 9). The model's error analysis is used to optimize the battery's performance parameters. Finally, performance indexes are used to compare all six algorithms [59]. Energy storage systems (ESSs) need a battery-management system algorithm that can control the battery's condition since getting older causes a battery's internal resistance to increase and its capacity to diminish. To manage the battery status, this research presents a battery-efficiency calculation formula. The proposed formula for calculating the battery efficiency takes into account charging current, charging time, and battery capacity [60].

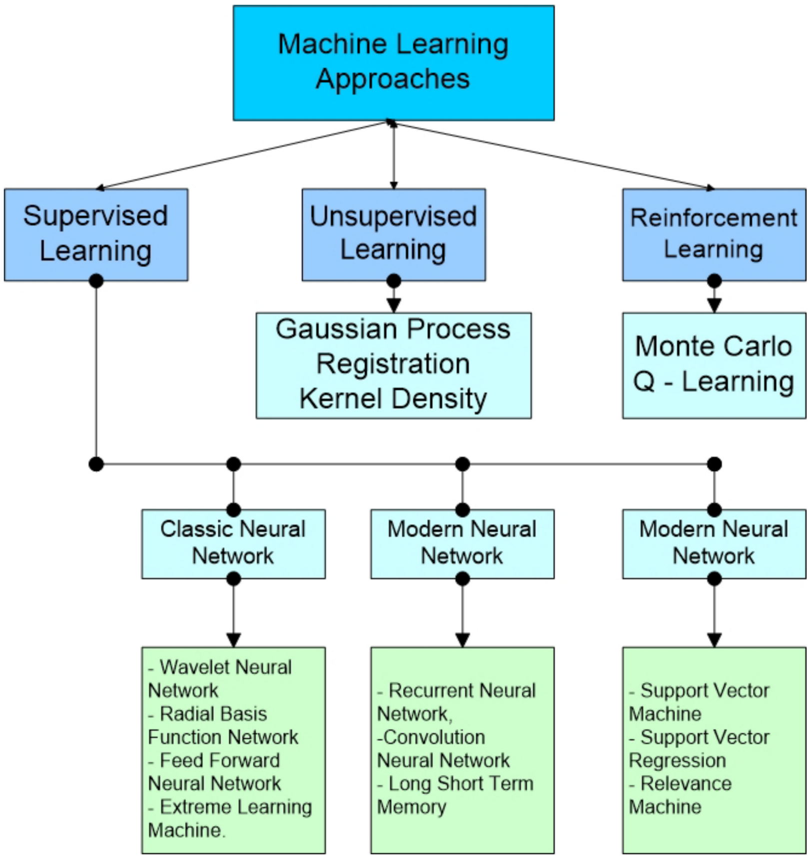

Figure 9. ML approaches in battery management.

The multipurpose control and planning (MCP) approach using three indices to define the best BESS location and category: BESS capacity, OLTC and SVR tap operations, and

PVP curtailment. In the simulated case study, BESSs were used for power smoothing of the substation/PVPs and RPF prevention at the substation, simulating the needs of Japanese power utilities [61]. The review begins with an introduction to machine learning's conceptual framework and general application process, followed by a review of ML progress in both enlightening battery material design and precise battery state estimation. ML is thought to help accelerate the use and improvement of lithium-ion batteries on a big scale [62].

The method for calculating the necessary parameters depends on the simulation of the temperature from the battery measurements presented in the study discussed. A set of rules first looks at the relationship between current steps and the terminal voltage that was determined, using the assumption that a certain load is present in both the present and the past. Second, by combining the Gauss-Newton approach and particle swarm optimization, the first-predicted parameters from the primary methodology are appropriate for the dimension data. Then, it is estimated how each simulation parameter depends on the battery temperature and market reputation [63]. The five most extensively researched types of device-learning techniques for estimating battery SOH are thoroughly examined. The ML-assisted SOH estimation strategies are evaluated from three angles: the assessment performance of several procedures using five performance indices, and training modes based entirely on feature extraction and choice strategies [64].

In order to test lithium batteries, the educational data is divided using a special evolutionary algorithm based entirely on the fuzzy C-approach clustering method. With the help of the clustering findings, the antecedent parameters and the model's topology are found. The parameters are extracted using the recursive least-squares method, and the antecedent and subsequent portions are then optimized simultaneously using the backpropagation learning method. Studies have shown that the suggested estimator is accurate and performs better than those produced using traditional fuzzy modeling techniques [65]. Table 6 makes a distinction between different methodologies based on the concept, kind, structure, and performance evaluation. Smart grids (SGs) and electric cars are two examples of high-power applications that employ lithium-ion battery packs and need a battery-management system.

Table 6. A detailed survey on AI-ML-NN and deep learning in battery-management systems.

Ref.	Objective	Sensor Used	Algorithm Used	Advantage
[51]	SoC calculation	Current sensor	Ml algorithm, support vector regression synced cross-validation simplex algorithm, and ANN algorithm are all examples of algorithms.	Active learning in the domain of objective functions may lead to a better knowledge of the appropriate rewards to pursue when performing ML.
[52]	Accuracy in SoC and SoH	Current sensor	The adaptive-observer algorithm, SVM, RVM, KNN regression, and lazy-learning algorithm.	The proposed DL technique demonstrates significant efficiency in capacity estimation, highlighting that a method is a suitable tool for online Li-ion battery health management.
[53]	SoC estimation	Current sensor	Bmo algorithm, SoC-rem algorithm, hybrid metaheuristic optimization algorithms	The dlsoc-rem technique can be used to estimate SoCs in an accurate and timely manner.
[66]	Safety of battery	Current, stress, fiber, Bragg grating,	Intelligent algorithms	The future of data-driven and intelligence-based battery management is examined.

Table 6. *Cont.*

Ref.	Objective	Sensor Used	Algorithm Used	Advantage
[58]	SoC and SoH estimation	Current sensor	Ocv, ccm, and proposed soc algorithm	Accurate SoC and SoH estimations were proposed by applying battery efficiency to the estimation process. The estimated SoC and SoH were used to improve not only the performance of the BMS but also the battery safety via a fault diagnosis algorithm with accurate SoH estimation.
[59]	SoC estimation	Current sensor	ANN, SVM, LR, Gaussian process regression.	Analyzing the voltage and current in the SoC estimation.
[60]	SoH estimation	High-precision current sensor	Adaptive filtering or data-driven algorithm	This method is chosen to evaluate the battery health level based on real demands.
[61]	SoC, voltage, and current estimation	Current sensor	SVM, ANN, linear, GPR, ensemble boosting, ensemble bagging	An analysis is conducted based on voltage and current.
[62]	SoC, SoH estimation	Current sensor	Ml algorithms, clustering algorithms, naïve Bayes, logistic regression, linear regression	ML can be used for knowing the battery state.
[63]	SoC, voltage, and current estimation	Current sensor	The deep-learning algorithm,	Calculations and modern material design demonstrate improved battery performance.
[64]	Accuracy estimation	High-precision current measurement sensors	LR, KNN, SVM, ANN, and EL ALGORITHM	The new method shows the input characteristics and the estimation accuracy.
[65]	SoC and SoH estimation	High-precision Hall current sensor, current-sensor	The least-squares algorithm, subtractive clustering, fuzzy clustering, direct search algorithm, genetic algorithm, and ANN	The learning mechanism works using the genetic fuzzy-clustering technique and the direct search algorithm leveraged to realize the antecedent parameters.
[49]	Charging and discharging estimation	Current sensors	BMS algorithms, optimal charging algorithms, constant-current charging algorithm, genetic algorithm, BFG algorithms	Battery impedance, capacity estimation, optimal charging strategies, and strategies to evaluate battery-management systems.
[67]	SoH estimation	Current sensor	MD, ANN, SVM, KNN, RF, ERT, DNN, SVR, KRR, PLS	This worked for the safety of the battery of the EV.
[68]	Performance estimation of model	Current sensor	Swarm optimization algorithm, kernel-based learning algorithm, gradient descent algorithm,	Compared to other models, the CNN model performs better.
[69]	Cost estimation using models	Current sensor	A fast recursive algorithm, adaptive filtering algorithms, least-squares algorithm	Model size and computational cost are much lower than those of the original convolutional neural network model
[70]	SoC, SoH estimation	Current sensor	SVM, ANN, LR, GP and ANN	Probability distribution has improved the state-of-charge estimation.

A battery-management system requires a combination of software and hardware to complete functions such as battery-state estimation, problem detection, monitoring, and control [71]. The most recent research on the use of ML in battery development, involving electrodes and electrolytes, is summarized. Meanwhile, battery state prediction is available. Finally, numerous present issues are discussed, as well as a methodology for addressing them in the future development of ML for rechargeable lithium-ion batteries [67]. To increase the resilience and the projected 1D CNN network's accuracy, the partial hyperparameters of the neural network are optimized by employing a weighted particle-swarm optimization method that is linearly decreasing. To account for the unpredictability of charging behavior in practice, the 1D CNN model employs random sections of the charging-voltage curve, differential charging-voltage curve, and charging-current curve as input data. LDWPSO is also utilized to optimize the fundamental hyperparameters of the 1D CNN model [68]. The article provides a novel framework for building compact CNN models on a limited dataset with better-estimated performance that incorporates the ideas of transfer learning and network pruning [69]. According to the findings, if a DNN has enough retired layers, it can anticipate the SOC of unknown driving cycles during training. EVs and smart grids are two examples of high-power applications that frequently employ lithium-ion battery packs and a battery-management system which requires software and equipment combined to complete duties such as battery state estimation, problem discovery, monitoring, and control. The study discussed presents a thorough examination of the current level of ML approaches to battery-management systems. It creates the difference between the techniques based on concept, type, structure, and evaluation of performance [71].

4.6. Expert (Recommendation) Systems in Battery-Management Systems

A battery-powered device's safety, effectiveness, and dependability are all guaranteed by a device that controls the battery or battery-management systems. Numerous studies on battery-management systems have been conducted over the years, and they have largely improved the safety, effectiveness, and dependability of battery systems. However, there are still issues that need to be resolved. In this article, we outline such issues and discuss potential solutions. The difficulties of creating a battery-operated gadget that can be used in upcoming destiny projects are discussed in this article. It also talks about some of the responses that were given [4]. There are certain projects where you may find prototypes of various players, usually from universities or government programs. Additionally, there are a few duties for businesses that are participating in the market but are still in the prototype and market testing phases. We have to decide whether to publish asynchronous conversation modes based entirely on open specs and the well-known example of XML because it is difficult to find globally general specifications and requirements for data exchange, particularly with intelligent grid systems, public transportation systems, control systems, and batteries inside the power industry [72]. The studies in Table 7 address the sensors and advantages of implementing expert systems for battery-management systems. The various algorithm-like hybridized intelligent algorithms enable users to recommend a cost-effective and energy-saving strategy that can be executed in the customization of battery-management systems.

Table 7. A survey on expert systems in battery-management systems.

Ref.	Objective	Sensor Used	Algorithm Used	Advantage
[4]	Precise characterization, and reliable battery estimation	Current Sensor	BMS, optimal charging, constant-current charging, BFG algorithms	Battery impedance, capacity estimation, optimal charging strategies, and strategies to evaluate battery-management systems.
[72]	Precise characterization and reliable battery estimation	Temperature, Current thermal sensor	Hybridized intelligent algorithms, newly designed algorithms for eight-cell battery packs	A complete examination, evaluation, and advice for automotive engineers.

4.7. Digital Twins in Battery-Management Systems

The materials and management techniques employed determine the lifespan of li-battery-powered equipment. A digital twin of a battery is a digital variant of a battery that interacts intimately with a cyber-physical system, allowing for greater control and a longer lifespan [43]. Monitoring of the battery-management system is carried out to ensure the greatest level of reliability and safety. The meta-model, which permits the creation of domain-specific models, reflects the architecture as seen in Figure 10. The three basic layers of the idea are hardware, twin, and service level [73].

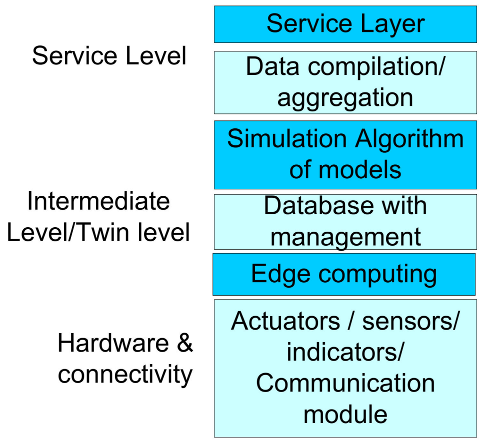

Figure 10. Layers of Architecture.

Based on the digital twin, we can conclude the many solutions for battery-management systems, such as real-time state estimation, digital modeling, dynamic charging control, dynamic equalization control, dynamic thermal management, etc., [74]. For developing the digital twin of a battery-management system, all the relevant data should be processed and stored on a cloud platform. The stage of each battery cell can be shown by the digital twin [75]. The studies in Table 8 address the study of digital twins in battery-management systems using IoT and cloud technology, and by inserting the SOC and SOH into the system for the digital twin, we can fit battery models to the data [76].

Table 8. A survey on digital twins in battery-management systems.

Ref.	Objective	Sensor Used	Display System	Algorithm Used	Advantage
[43]	Standard procedure on the database Management	Hall Effect and other sensors	-	SOC, SOAP, CC-CV charging algorithm	Intelligent control of battery systems using the ML approaches.
[73]	digital twin architecture for BMS	Integrated Sensor	-	Multi-discipline algorithm	The proposed design provides a roadmap for the life cycle of a BMS.
[74]	Application of digital twin in BMS	RFID, sensors	Soh display	Least squares algorithm	Summarizes recent methods of research for future enhancement.
[75]	Measurement of SoC, SoH.	Voltage, current, and temperature	Web front end	Open-loop, model-based, AEHF.	BMS was developed based on cloud computing and IoT
[76]	Inserting the SoC, and SoH in the cloud	Voltages, temperature, and current	Web front end	least-squares, Levenberg–Marquardt	Stored data shows the state of the battery with advancements.

4.8. Blockchain in Battery-Management System

Nowadays, a limited range of battery life is the major problem for electric vehicles. To address this, we can swap the batteries but there are few authorized battery-swapping stations. In this situation, a strong battery-management system or battery-swapping system (by station or driver) based on blockchain is required which can be continuously monitorable [77]. Blockchain has found wide use in the energy sector because of its underlying qualities of anonymity, decentralization, transparency, and dependability [78]. An upcoming battery-management system can be managed by critical activities and tasks involving the management of the battery, recovery, firmware security checks, patch generation, etc., [79]. Blockchain generation is used to defend an IoT-enabled battery control gadget from undesirable cyberattacks and make certain verbal exchanges and statistics security [80]. The studies in Table 9 address the sensors, algorithms, and advantages of implementing blockchain for battery-management systems.

Table 9. A survey on Blockchain in battery-management systems.

Ref.	Objective	Sensor Used	Algorithm Used	Advantage
[77]	Increase the reliability	-	Consensus algorithm (Hashing).	The user received either a battery or a charge/swap station.
[78]	Security enhancement	-	Charging scheduling algorithm, consensus algorithm.	The future generation of distributed energy solutions can be designed using blockchain.
[79]	Reverse engineering for security check and recovery	Current, voltage sensor	Embedded battery-management system algorithms.	Firmware checks and recovery are possible by blockchain.
[80]	Enhancing the Security	Current Sensor	Leader election algorithm, on-board control algorithms	Enhancing cybersecurity of the wbm in blockchain-based IoT network

4.9. Cybersecurity in Battery-Management System

The topic of cyber-physical security of battery-energy-storage systems is complicated because it not only involves information security principles but also calls for bridging the knowledge gaps between the effects of cyberattacks on industrial control systems [81]. Due to the constant network connectivity of IoT devices, there is an increasing risk of cyberattacks. There are lots of threats that can be possible such as unauthorized software updates, unauthorized access, Man-in-the-Middle attacks, insecure network protocols, unauthorized cloud access, SQL Injection, etc., [82]. For the detection of attacks, there are lots of methods such as manipulated system command attack detection, battery attack detection, training-set attack detection, etc. Protected IoT-cloud platforms will be made available to BMSs to encourage better cybersecurity and spur the adoption of Li-ion battery systems in cyber-physical settings [82]. Table 10 gives a comparative study based on the cyber security based on the battery-management systems.

Table 10. A survey on cyber security in BMS.

Ref.	Objective	Sensor Used	Algorithm Used	Advantage
[81]	Cyber-attacks and prevention	Current sensor	SoC estimation, EMS algorithms, voltage-based charge equalization algorithms	To enhance the risk assessment of these assets, threat models for BESS must be further developed.
[82]	Cyber-attacks and prevention	Current sensor	Health monitoring, IoT network, SHA256 hashing algorithm	IoT-cloud platforms will be applied to BMSs to increase cybersecurity and accelerate the proliferation of Li-ion battery systems in cyber-physical environments.
[82]	Cyber-attacks and prevention	Current sensor	ML and ANN	Battery SE such as SOC and SOH are forecasted using ML and ANN.

5. Recommendations

In the above, we have detailed and discussed the significance of battery-management systems and the integration of digital technologies in battery-management systems for achieving digital-based monitoring with advanced features. Based upon the analysis, we have discussed the challenges and suggested further recommendations for future enhancement below.

- Wide adoption of customized IoT sensor-based devices in the monitoring and obtaining of real-time data of battery-management systems [4]. Customization allows the user to include features that are very significant for their battery-management system. In addition to this, researchers need to adopt the materials in developing IoT devices for making them resistant to the environmental conditions of the battery-management system.
- The large amount of sensor data that is generated through IoT sensor-based devices can be effectively utilized for the prediction of charging and discharging time, SoC, SoH, aging, etc., [72]. Researchers need to focus on creating a hybrid model that can detect different anomalies under different environmental conditions with a high accuracy rate. To achieve this, AI-based computing units should also be integrated into IoT-based devices.
- Edge computing in battery-management systems is implemented limitedly. Edge computing needs to be integrated into IoT-based devices for processing the obtained sensor data at the edge network itself [43]. In addition to this, AI models can be loaded into the computing unit to perform prediction analytics on real-time data. This indeed can empower the enhancement of the latency and minimize the load on the server for performing the prediction.
- The digital twin is an emerging technology, and the integration of this technology will empower the creation of a replica of a battery-management system under different environmental conditions with customized features [73]. Few studies have already introduced state estimation and cloud-inspired equalization for batteries. Moreover, this study also enabled upgrading of the route of the battery with full life-cycle data.
- Blockchain technology in battery-management systems enables the securing of data and also connects different entities in the distributed network for real-time monitoring of the health of the battery-management system from any location [74]. In addition to this, blockchain enables the removal of the barrier of accessing and sharing data of battery-management systems among manufacturers, electricity consumers, and power grid operators.
- The evolution of big data with ML and DL has overcome the challenges of complicated modeling and insufficient data-feature extraction, making the extraction and life prediction of lithium battery health assessment features practicable [75]. Big data examines the effects of important elements on the use of batteries: current, voltage, and temperature. It focuses on the impact of charge-current fluctuations, high charge cut-off voltage, and temperature on the stability of lithium batteries based on an investigation of batteries of various materials.

6. Conclusions and Future Scope

Battery-management systems have gained significant attention due to the wide adoption of renewable energy generation for sustainability. The health monitoring of batteries is crucial for reliably storing energy. Along with this, the evolution of digital technologies has proven to be effective for monitoring the physical environment from any location. Based on this motivation, this article discussed the significance of battery-management systems and further discussed the implementation of these technologies in battery-management systems. From the review of different articles, it can be concluded that battery health estimation methodologies have been developed for monitoring the remaining capacity and energy estimation, capacity prediction, life and health prediction, and alternative essential indicators connected to battery balance and thermal management. Finally, this article suggests recommendations such as edge computing with AI model-based devices, customized IoT-based devices, hybrid AI models and ML-based computing, digital twins for battery modeling, and blockchain for real-time data sharing.

Author Contributions: Conceptualization, R.S. and G.K.; methodology, A.G.; formal analysis, S.V.A.; data curation, S.V.A.; writing—original draft preparation, G.K.; writing—review and editing, N.P.

and B.T.; visualization, R.S. and A.G.; funding acquisition, N.P. and B.T. All authors have read and agreed to the published version of the manuscript.

Funding: The APC was funded by Tshwane University of Technology, South Africa.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data sharing not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

ADC	Analog-to-Digital Converter
AI	Artificial Intelligence
ANN	Artificial Neural Network
BMO	Barnacles Mating Optimizer
BMS	Battery-management system
CAGR	Compound Annual Growth Rate
CC	Constant Current
CCCV	Constant-Current-Constant-Voltage
CMSIS	Common Microcontroller Software Interface Standard
CNN	Convolutional Neural Network
CPS	Cyber-Physical System
CT	Current Transformer
CV	Constant Voltage
DL	Deep Learning
ESS	Energy Storage Systems
EV	Electric Vehicle
FPGA	Field Programmable Gate Arrays
HAL	Hardware Access Layer
ICT	Information and Communication Technology
IoT	Internet Of Things
KNN	K-Nearest Neighbor
LDWPSO	Linearly Decreasing Weight Particle Swarm Optimization
LI	Lithium—Ion
L0RA	Long Range Radio
LSTM	Long Short-Term Memory
MCC	Modern Constant Current
ML	Machine Learning
NN	Neural Network
OCV	Optical Character Verification
PGD	Projected Gradient Descent
PV	Photovoltaic
REM	Energy Management
RTOS	Real-Time Operating System
RVM	Reverse Vending Machine
SGs	Smart Grid
SHA	Secure Hash Algorithm
SoC	State of Charge
SoD	State of Discharge
SoE	State of Emission
SoH	State of Health
UN	United Nations
Wi-Fi	Wireless Fidelity
WSN	Wireless Sensor Network

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