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Review

Optimization Consumption Power in Internet of Things Technology: A Systematic Review

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Abstract: This study reviews algorithms for battery optimization, focusing on estimation methods and State of Charge (SOC) algorithms, which are crucial components of Battery Management Systems (BMS) designed to reduce power consumption. With the increasing global demand for electricity driven by rapid population growth, optimizing energy use has become critical. Accurate estimation of battery capacity is essential for extending battery lifespan and ensuring efficient power delivery. To monitor, control, and deliver the battery's power at its maximum efficiency, the BMS is introduced. This systematic review focuses on three key research questions: What is the purpose of optimization? What is the type of algorithm estimation method? What is the type of algorithm of SOC? Following systematic review guidelines, 21 articles were selected from an initial 1721 based on inclusion and exclusion criteria. The findings reveal that most algorithms aim to minimize battery power consumption. Data-driven methods and hybrid algorithms demonstrate superior performance compared to others, although further modifications are necessary to enhance their effectiveness. This review emphasizes the imperative of advancing those algorithms to improve BMS efficiency and satisfy growing demands for optimum energy consumption in Internet of Things technologies.

Keywords: Battery, Battery Optimization, Battery Management System, State of Charge, Capacity, Estimation Method, Energy Optimization, Optimization Energy, Internet of Things

Introduction

This IOT can be interpreted in two ways either as the internet or as the things being connected (Reddy Maddikunta *et al*., 2020). The field of information and communication technology is fast evolving as advanced sensing and communication technologies emerge, allowing connectivity at any time, from any place, and between anything (Shah *et al*., 2019). IOT boasts enormous possibilities in various use cases, but it also faces significant communication issues with technology which have become a major concern in recent times (Shah *et al.*, 2019). Hence, researchers are committing significant time and effort to develop effective solutions for these challenges, striving to ensure that IOT-based networks can be reliably and effectively in a wide range of real-world environments and applications. Shah *et al*. (2019).

John Goodenough invented the first lithium-ion batteries in 1980, using cathodes made of lithium cobalt oxide and lithium manganese dioxide (Goodenough and Kim, 2010). It is a rechargeable power source that operates by moving ions of lithium between the "anode" and "cathode", throughout the charge-discharge process (Singh *et al*., 2024). Because of its outstanding effectiveness and capacity of battery, lithium-ion batteries are extensively utilized in electric and electronic devices. The moving of lithium ions is important to ensure the devices receive enough power for data transition to the cloud server.

One of the issues in Internet of Things applications is inefficient battery consumption power. To monitor, control, and deliver the battery's energy at its maximum efficiency, this study consists of a comprehensive literature on battery consumption optimization algorithms that are studied.

Energy storage that uses lithium-ion batteries is quickly rising across market share and attracting significant Research and Development (R&D) activities because of their benefits against other battery technologies (González *et al*., 2022). Nowadays, lithium-ion battery cells are extensively used because of their outstanding effectiveness, substantial open-circuit cell power, broad thermal operating range, and extended longevity (Zhang *et al*., 2018).

A part of lithium-ion batteries is the Battery Management Unit (BMU), which is created by the manufacturer and is also referred to as the Battery Management System (BMS). This system is vital in maintaining the battery securely and effectively by monitoring essential attributes such as "voltage", "current" and "temperature" (Teodorescu and Sui, 2024). It also balances the cells and manages the charge and discharge operations to ensure that the battery runs precisely throughout its lifespan. The manufacturer provides the Battery Management Unit (BMU) so that its operations and settings are not directly accessible to the user, who can only view specific attributes such as “current”, “voltage”, “temperature” and “State of Charge (SOC)” (González *et al*., 2022).

Lithium-ion batteries are lightweight, extremely reactive, and supply the highest possible energy density (Parameswari and Usha, 2024). Lithium-ion batteries have a faster charging and discharging rate compared to other battery types. Moreover, lithium-ion batteries must be operated within their safe voltage range to avoid issues such as chemical reactions, overheating, cell venting, and the risk of combustion. Therefore, to ensure that the battery runs effectively, a Battery Management System (BMS) is implemented (Ravi, 2021).

Moreover, accurately estimating the State of Charge (SOC) is a key function of the BMS in battery packs (Zhang *et al*., 2018). The key elements that affect the reliability and efficiency of SOC estimation are the features of the lithium-ion battery, the estimation method, the battery model, and cell unbalancing (Qahtan *et al*., 2022). Generally, the State of Charge (SOC) value serves as a foundation for battery estimation and energy management control. Improper SOC calculation due to over-charge and discharge might degrade the battery life.

A precise SOC estimate is essential to optimize battery capacity and performance. In short, the purpose of this research is to carry out a literature analysis on battery optimization to determine approaches for optimizing battery consumption in IOT technology.

Background and Related Work

This section discussed the features of lithium-ion batteries, Battery Management Systems (BMS), and energy optimization methods.

Lithium-Ion Battery

The battery life of IOT devices must be estimated. Rechargeable and non-rechargeable batteries have certain similarities. However, each type of battery offers its unique advantages and disadvantages (Reddy Maddikunta *et al*., 2020). When selecting a battery type for IOT, the three primary elements to examine include self-discharge, electrical discharge implementation, physical battery characteristics, and protection, all of which contribute to its longevity (Reddy Maddikunta *et al*., 2020). Advantages of lithium-ion batteries include Zhang *et al*. (2018):

- High energy density
- High power density
- Long cycle life
- Strong environmental adaptability
- High cell voltage

Based on the study, there are several types of lithium-ion batteries, each with its benefits and drawbacks, which comprise “Lithium Cobalt Oxide (LCO)”, “Lithium Nickel Oxide (LNO)”, “Lithium Manganese Oxide (LMO)”, “Lithium Nickel Manganese Cobalt Oxide (NMC)”, “Lithium Iron Phosphate (LFP)”, “Lithium Nickel Cobalt Aluminium Oxide (NCA)” and “Lithium Titanate (LTO)” (Biswal, 2023).

According to Fig. (1) the global market for lithium-ion batteries is predicted to reach 185 GWh in 2020 and 950 GWh in 2026 by Statista's Research and Markets statistics (Statista Projected Global Battery Demand from 2020 to 2030, by Application (in Gigawatt Hours), 2022). The statistic overview highlights the significant growth in the utilization of lithium-ion batteries, particularly in IOT technologies. These batteries have become increasingly essential to various industries, powering devices such as robotics, Automated Guided Vehicles (AGVs), and a broad range of consumer gadgets.

Lithium-ion batteries will play a vital part in the world's transition to a low-carbon economy, providing efficient energy storage to enable renewable energy and electric vehicles while lowering carbon emissions.

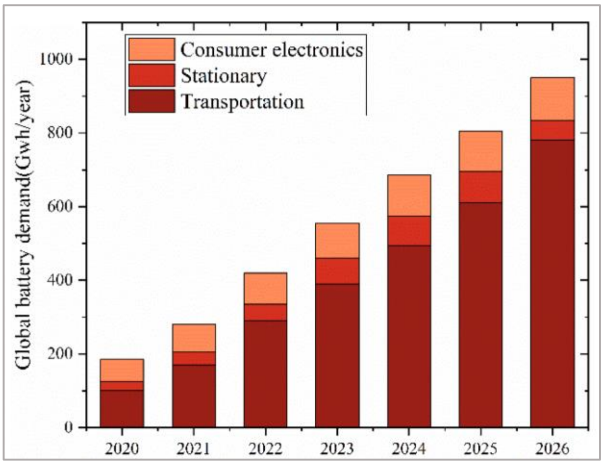

Fig. 1: A Global Battery Demand 2020-2026

Battery Management System (BMS)

The Battery Management System (BMS) is a key component in the IOT technology areas. BMS is crucial to prevent overcharging or over-discharging the batteries in electric vehicles to ensure their longevity and optimal performance. If such occurs, it can damage the battery, rise in temperature, shorten its lifespan and, in some cases, pose risks to the users of the device (Ravi, 2021). In this case, utilizing the energy that is stored in the vehicle, helps to increase the range of the vehicle. It is essential to ensure proper maintenance of the BMS for the reliability and durability of the battery. Thus, the usage of a BMS enables the battery to run within its safety zone.

Clean energy relies on battery storage systems and renewable resources to supply an environmentally friendly and innovative solution, meeting future energy demands while driving advancements in IOT technology (Hananda *et al.*, 2023). Battery energy storage systems are essential for supplying sustainable, pollution-free energy and enabling the continuous transition to renewable resources. As studied, lithium-ion batteries are currently the leading technology for energy optimization.

Figure (2) depicts the specific construction of a Battery Energy Storage System (BESS), which contains battery cells, a Power Conversion System (PCS), a Battery Management System (BMS), and other components (Teodorescu and Sui, 2024). The BMS is part of the Battery Energy Storage System (BESS) to make sure the cells operate securely. State estimation, voltage/temperature monitoring, and problem diagnosis and warning are all tasks of a BMS (Teodorescu and Sui, 2024). One of the components is the battery capacity, which defines the maximum amount of charge in Ah the battery can deliver at a specified time (Peng *et al.*, 2022).

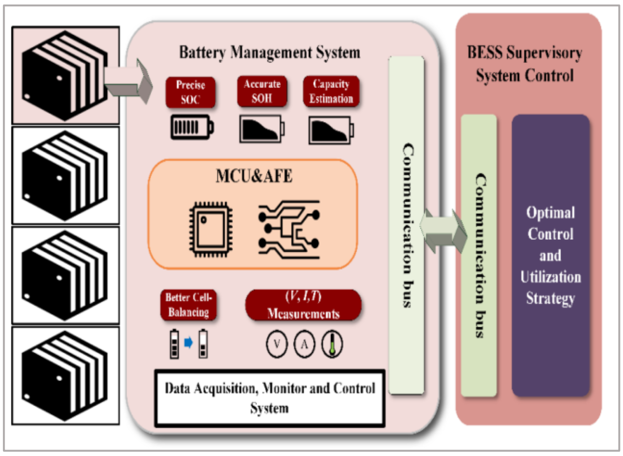

Fig. 2: Battery Energy Storage System (BESS)

A battery's capacity and specific energy depend on the number and energy of electrons (Wang *et al.*, 2022). The behavior of lithium ions has a significant influence on battery performance because almost all electrode materials in lithium-ion batteries involve the insertion and removal of lithium ions during electron gain and loss (Wang *et al.*, 2022). For BMS energy management decision-making, the battery capacity of a lithium-ion battery is crucial. For instance, the State of Charge (SOC) is a measure that compares the battery's capacity to its current Ah amount, indicating the remaining energy in the battery.

In the absence of battery capacity, determining the accuracy of the State of Charge (SOC) is challenging (Meng *et al.*, 2018). After gaining an accurate SOC, BMS may decide when to charge or discharge each cell (Peng *et al.*, 2022). The lithium-ion battery capacity should be clearly stated to prevent overuse. A key factor in the secondary use of a lithium-ion battery is its capacity. Battery capacity is essential for managing the longevity of cells in a BMS (Hossain Lipu *et al.*, 2021). Hence, it is anticipated that the rapid growth of IOT will enhance the techniques used for estimating BMS capacity.

The capacity of a battery is commonly viewed as a measure of its life expectancy and it is thought to achieve its End of Life (EOL) which capacity reaches 80% of its initial capacity value. This is because a precise capacity can increase the precision of SOC estimates which allows users to undertake charging and maintenance of batteries as necessary. Only a slight decrease in capacity would gradually impair the electrical battery and thermal properties, which can cause additional serious safety risks (Deyab and Mohsen, 2021).

Effective temperature control is vital in Battery Management Systems (BMS) to improve battery efficiency, and maintain reliability and longevity (Selimefendigil *et al.*, 2024). The performance of a battery management system is laboriously dependent on maintaining optimal operating temperatures. High temperatures can damage battery components, reduce efficiency, and limit lifespan, whereas insufficient cooling can lead to overheating and safety issues. Hence, enhanced cooling performance can lead to better temperature management, which helps in maximizing battery efficiency, extending its operational life, and improving overall system performance.

Besides that, one advanced approach using a hybrid system that incorporates Phase Change Materials (PCMs) along with liquid cooling channels can significantly enhance thermal management that crucial in Battery Management Systems (BMS). This combination maintains the energy source throughout its ideal temperature level, increasing reliability, longevity, and safety. This hybrid solution is particularly advantageous in high-performance computing and other applications where efficient and stable thermal management is crucial (Ortiz *et al.*, 2024).

Optimization Energy

Optimizing energy utilization is crucial for improving efficiency and minimizing consumption in various applications. Energy optimization algorithms such as improving Dynamic Programming (DP) techniques to enhance real-time performance are critical for effective energy management (Lü *et al*., 2024). Besides, the purpose of Model Predictive Control (MPC) in building energy management, demonstrates its ability to optimize operations through predictive modeling (Hernández *et al*., 2021). Additionally, Genetic Algorithms (GA) have been increasingly applied to complex energy systems which are effective in optimizing configurations for renewable energy systems (Gómez *et al*., 2023).

However, energy optimization still heavily relies on hardware solutions. For instance, smart meters provide users and utility providers access to real-time data on energy consumption, enabling improved management and adjustment of energy use. Recent advances in smart meter technology and applications were discussed by researchers (Mao and Zhu, 2024), who reviewed improvements in these devices and their impact on optimization energy management. Energy Storage Systems (ESS) have also evolved which reviewing recent advancements that enhance Energy Storage Systems (ESS) have also evolved which reviewing recent advancements that enhance the incorporation of sustainable power resources (Álvarez-Arroyo *et al*., 2024).

The optimization of the BESS must be built further to identify improved materials and compositions for the battery (Hananda *et al*., 2023). Based on the studies, the advancement of battery storage systems will improve from the optimization of BESS to facilitate the power flow with low self-discharge rates, high reliability, and quick responses (Hananda *et al*., 2023). Moreover, the reduction of emissions of ozone-depleting compounds during production is another benefit of battery optimization.

However, some factors including the battery cell life, cost-effectiveness, charges and discharges activities, energy oscillations, rapid load evolves, transmission system problems, and battery energy supply are some of the characteristics and aspects that are taken into consideration as system limitations of optimizing the battery storage system (Deyab and Mohsen, 2021). This is because, the battery's lifespan is influenced by its energy transmission methods, cell framework, and thermal conditions which are also influenced by the charges and discharges process that had been studied by the researchers (Deyab and Mohsen, 2021).

Based on Fig. (3) both estimation methods are related to the optimization energy process. The capacity estimation method is referred to the capacity that measures the amount of charge the battery can retain which is one of the most vital features of a battery. Generally, the three most prevalent units for measuring battery capacity are "Watt-hours (Wh)", "kilo Watt-hours (kWh)" and "Ampere-hours (Ah)". According to the study, battery capacity is usually estimated in Ampere-hours (Ah), which indicates how long a battery can produce a constant current before running out.

SOC is a measure of how much energy is currently available concerning a battery's nominal capacity. The SOC plays a key role in how much energy a battery can store and provide throughout its longevity. However, the energy management system requires particular knowledge of the SOC estimation approach of the battery to provide optimal and effective operation.

Related Work

The optimization of the production method for lithium-ion batteries is a key factor throughout the research and commerce battery industries (Drakopoulos *et al*., 2021). Based on the research studies, there are key points on battery SOC estimation through analyzing several existence estimation approaches. This is because the features of the lithium-ion battery and the approach to estimation method are the most vital elements influencing the preciseness and robustness of SOC estimation for battery optimization.

In one of the case studies, (Reddy Maddikunta *et al*., 2020) found results validated the proposed approach exceeds the performance of current advanced regression methods in achieving a 97% predictive by using the machine learning-based approach that used the random forest regression methods accuracy in terms of conserving the battery longevity of IOT devices. In this case study, the battery life of the IOT-based network is accurately estimated using PCA-based random forest regression techniques.

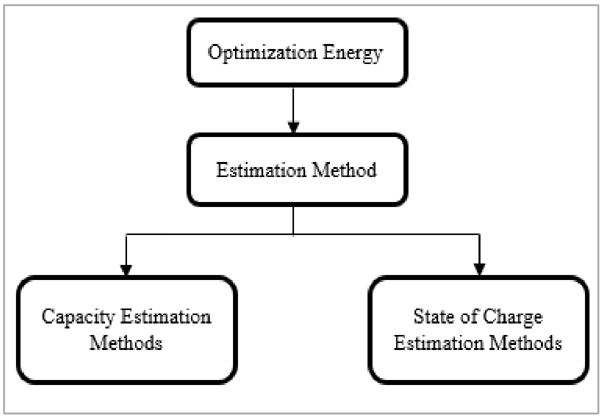

Fig. 3: Optimization energy estimation method

In other case studies by Vasanthkumar *et al*. (2022), the researchers presented a refined wild horse optimizer combined with an advanced learning-powered battery management system for Hybrid Electric Vehicles (HEVs). To accurately evaluate SOC in HEVs, they implement an attention-based bidirectional with short-term memory technique. Hence, the results in a more simplified and accurate representation of the input. A detailed simulation result showed that the deep learning method for the BMS model outperformed the other techniques in several measures.

In addition, the integration of Micro-Electro-Mechanical Systems (MEMS) technology has performed a major function in advancing the fields of IOE (Internet of Everything), IOT (Internet of Things), and 5G communication systems. Iannacci (2018) highlights the transformative potential of RF-MEMS (Radio Frequency MEMS) and energy-harvesting MEMS (EH-MEMS) in creating a unified vision that bridges these technologies. The importance of MEMS in the continuous growth of connected systems is highlighted by the confluence of MEMS technology with IOT and 5G, which not only optimizes energy utilization but also paves the way for more sustainable and scalable communication infrastructures.

The study by He (2024), provides a detailed examination of the periodic motion in Micro-Electro-Mechanical Systems (MEMS). This research highlights the critical importance of understanding the frequency-amplitude relationship, which can predict when a system transitions from stable periodic motion to instability. This research provides broader research on MEMS by presenting a robust analytical framework that can be employed in the design and analysis of advanced MEMS devices, ensuring their operational stability and reliability.

Another case studies by He *et al*. (2024) discuss a piezoelectric biosensor based on a highly sensitive MEMS system. The emergence of the SARS-CoV-2 virus highlighted the critical need for ultrasensitive biosensors to detect pathogens at the earliest stages of a pandemic. The study explores a piezoelectric biosensor focused on an ultrasensitive MEMS technology using Polyvinyl Li Dene Fluoride (PVDF) nanofibers with unsmooth surfaces. By incorporating these advanced MEMS technologies, IOT systems can provide real-time, accurate data for public health responses, offering a comprehensive approach to pandemic control and a deeper understanding of MEMS applications in healthcare.

Research studies by Zhao *et al*. (2024) discuss the growing significance of 5G communication technology and its associated challenges, particularly in thermal management and energy harvesting. The authors propose a thermodynamic approach that enhances thermal conductivity and this study emphasizes the importance of advanced materials such as nanofibers and nanofluids, which offer promising solutions for improving the thermal efficiency and reliability of 5G systems. This research is particularly relevant to the ongoing exploration of energy-efficient technologies in high-density networks and could provide a foundation for future developments in 6G and beyond.

Next, according to Chandran *et al*. (2021) studies, the use of probability distributions rather than point estimates in Gaussian Process Regression (GPR) and Artificial Neural Network (ANN) approaches leads to impressive improvements in State of Charge estimation. The optimized properties used in the machine learning framework determine the battery state of charge prediction, assisting stakeholders and researchers in determining the optimal battery for certain applications. Based on SOC estimates, GPR and ANN will assist in designing the best battery management system for electric vehicles.

Other than that, (Drakopoulos *et al*., 2021) used Artificial Intelligence (AI) to create graphite-based anode electrodes for lithium-ion batteries by connecting production processes to final electrochemical and battery life performance data. Based on the study, the researcher involves the machine learning methodology by determining the possible variables in training data and calculating by evaluating the estimated values with the data to ensure that the formulation that had been created using the algorithm can be proposed to meet the required targets.

Besides, Yang *et al*. (2021) introduce a SOC estimate approach utilizing an enhanced Extended Kalman Filter (EKF), known for being accurate and reliable. Hence, in the results of the studies, the research findings indicate that using the standard EKF methodology, advancements have been conducted with noise adaptability, a fading filter, and linear-nonlinear filtering. The strong mathematical proof was appropriately carried out to highlight the importance of the Battery Management System (BMS) which performs a variety of functions such as calculating residual power, estimating the status of power capacity, voltage monitoring, cell balancing, and lifespan estimations.

Other research on the Kalman filter algorithm was conducted by Chen *et al*. (2019) based on an Improved Unscented Kalman Filter (IUKF) approach that is composed of a model adaptive algorithm and a noise adaptive algorithm. Based on the SOC estimation analysis, the findings indicate the estimation error of the suggested approach is less than 1.79% based on suitable robustness and time complexity.

In other literature findings by Chen *et al*. (2019), the researcher proposes an alternative technique that combines the cost-effective Ampere-Hour Integral (AHI) method with the high-accuracy Adaptive Extended Kalman Filter (AEKF). Based on the investigation, the SOC estimation was computed by the time (in second) comparison between both methods which the result of the finding concluded that the alternate technique almost retains the same SOC accuracy as the AEKF method while reducing the greatest absolute SOC error by 50% when compared to the AHI method. In comparison to the AEKF approach, the proposed approach achieves almost the same estimation accuracy at a calculation cost comparable to the AHI approach.

Methodology

This section employs a Systematic Literature Review (SLR) to examine a research approach to assess and analyze the existing literature on the research topic. A Systematic Literature Review (SLR) is an alternative to a systematic literature analysis. Kitchenhand guidelines are more specific to conduct this SLR. These guidelines were chosen which offer detailed procedures for each stage of the review process, ensuring comprehensiveness and reproducibility. The SLR protocol for this research study is divided into the following subsections.

Research Questions

This study addresses key questions to map and analyze research on energy optimization in IOT and battery management. This comprehensive review aims to provide insights into current trends and advancements in the field.

The research questions were formulated based on gaps identified in the preliminary literature. These questions were designed to address specific aspects of battery optimization algorithms, focusing on the objective of the research, estimation methods, and SOC algorithms, as described earlier

Mapping Question

Mapping questions are used to categorize and map out the landscape of research related to battery optimization in BMS, particularly within the context of IOT. These questions help in systematically organizing the literature and identifying trends, clusters, and gaps. To develop the mapping, we proceeded to establish the following questions:

MQ1: How many studies have been published during the years 2017 -2023?
This period is critical as it aligns with significant advancements in IOT technology, Battery Management Systems (BMS), and optimization techniques. By focusing on this timeframe, this study can capture the most current research, ensuring that the review is relevant and reflects the latest developments

MQ2: What is the geographical distribution of publications in optimization energy in IOT?
The geographical distribution of publications can reveal where the most active research communities are located and how research on optimization energy in IoT varies across different regions
By mapping the geographical distribution, this study can identify potential regional gaps in the literature, encouraging more balanced global research efforts
Additionally, it helps to understand how regional factors, such as climate, energy infrastructure, and industry needs, might shape the research focus and methodologies used in different parts of the world.

MQ3: What are the main benefits of BMS in managing and controlling energy in IOT?
Identifying the primary benefits of BMS in managing and controlling energy in IOT systems is crucial for understanding the practical impact of these technologies
This mapping question is designed to summarize the key advantages reported in the literature, such as improved energy efficiency, extended battery life, enhanced reliability, and reduced operational costs.
Moreover, by mapping these benefits, this study can highlight areas where BMS has been particularly effective, as well as where further improvements or innovations might be needed to maximize their potential in IOT applications

Research Question

The choice of research questions was guided by the need to synthesize existing knowledge and identify areas requiring further investigation. Each research question targets a different dimension of the topic to ensure a holistic understanding of the subject matter. The following three-dimensional research questions were developed to create the systematic literature review:

RQ1: What is the purpose of optimization?
Optimization in battery management, particularly within the realm of IOT, is critical for enhancing efficiency, extending battery life, and reducing energy consumption. By addressing this question, this study seeks to clarify the specific objectives behind optimization in BMS within IOT, helping to align research and development efforts with the most pressing needs in the field.

RQ2: What is the type of algorithm estimation method?
Estimation methods are essential for accurately predicting battery state parameters and evaluating these methods to understand which are most effective in different scenarios. By exploring the types of algorithms used in estimation, this study can provide their strengths and weaknesses and also provide valuable recommendations for future research and development.

RQ3: What is the type of algorithm of SOC?
This research question addresses the need to identify and evaluate the different algorithms used for SOC estimation, particularly in the context of IOT, where factors like varying load conditions and intermittent power sources can complicate

SOC estimation. Accurate SOC estimation is fundamental for battery systems to operate safely and effectively, particularly in IOT applications where power management is crucial.

Search Strategy

In this section, we explore search terms, electronic resources, reference management tools, and the approach to conducting searches. Further steps are provided in the following subsections.

Search Keywords

The research questions served as the basis for the search keywords and strings. Synonyms keywords were added from relevant literature on energy optimization in IOT technology.

We show the following keywords in the following. “Battery optimization”, “Estimation method”, “State of Charge (SOC)”, “Battery Consumption Power” and “Battery Management System for Internet of Things”.

Electronic Source

The most significant digital libraries were utilized in searching for papers. These repositories are ACM, IEEE Explore, Science Direct, and Scopus. These digital libraries serve as the main repositories for publications related to the field of computer science.

Reference Management

By using various search terms, we uncovered numerous studies from the electronic sources mentioned earlier. To organize and manage the gathered materials efficiently, we utilized Endnote X9, which allows for the easy addition and removal of studies as needed.

Search Process

A comprehensive search was conducted in digital libraries to collect literature from conferences, journals, and e-books, which yielded over 77 studies. Endnote was subsequently used to organize the PDF documents with their references, making the papers more accessible. Afterward, we implemented a selection process to exclude irrelevant studies.

Studies Inclusion and Exclusion Criteria

To address varied questions raised, five Inclusion Criteria (IC) alongside five Exclusion Criteria (EC) have been defined, as outlined in Table (1).

Quality Assessment Criteria (QAC)

As the requirement of this study, the QAC criteria were applied to ensure the quality and reliability of primary studies. A checklist, designed to address domain-specific issues, was used to evaluate the research quality. As shown in Table (2), these questions guided the selection of relevant studies for the Systematic Literature Review (SLR). The quality assessment criteria were crucial in identifying key studies that provided evidence on optimizing energy in IOT technology. Studies were analyzed based on these questions, with "Yes" earning 2 points, "No" earning 0 points, and "Partially" earning 1 point. After collecting 77 research studies, the QAC criteria were applied to filter those that addressed the research questions. Following this process, 21 studies were selected for review and mapping, representing 5% of the total studies, and were considered suitable for inclusion in the systematic literature review.

Data Extraction and Synthesis

During this phase, different folders were set up in EndNote to categorize publications from each database. Thus, search attributes were conducted in the chosen databases using the following filters:

- The author (s) details
- The topic area
- Year of publication
- Institution
- Type of document (Revision)
- The type of publication (Open Access)
- Language

Table 1: Inclusion and exclusion criteria

Inclusion criteria	Exclusion criteria
IC1 – Type of document: scientific research, book chapters	EC1 – Informative articles, news, papers, conference proceedings, specialized blogs, and book review
IC2 – Type of access: Open	EC2 – No open access
IC3 – Timing publication: 2017 - 2023	EC3 – Published before 2017
IC4 – Language: English	EC4 – Language other than English
IC5 - Keywords: “Battery optimization”, “Estimation method”, “State of Charge (SOC)”, “Battery Consumption Power”, and “Battery Management System for Internet of Things”	EC5 – Any reference that does not include keywords

Table 2: Quality assessment criteria

ID	Quality Assessment Criteria	Feedback Score
Q1	Optimization techniques	42
Q2	Scalability	21
Q3	Resource utilization	21
Q4	Robustness and reliability	42

Depending on the unique characteristics of each academic database, the search and filtering processes were adapted accordingly. Figure (4) illustrates the distribution of publications retrieved from the databases. Using the PRISMA flow chart, which is frequently used for presenting systematic reviews, specific information on the total number of publications included in the study was provided:

MQ1: How many studies have been published during the years 2017 -2023?
MQ2: What is the geographical distribution of publications in optimization energy in IOT?
MQ3: What are the main benefits of BMS in managing and controlling energy in IOT?

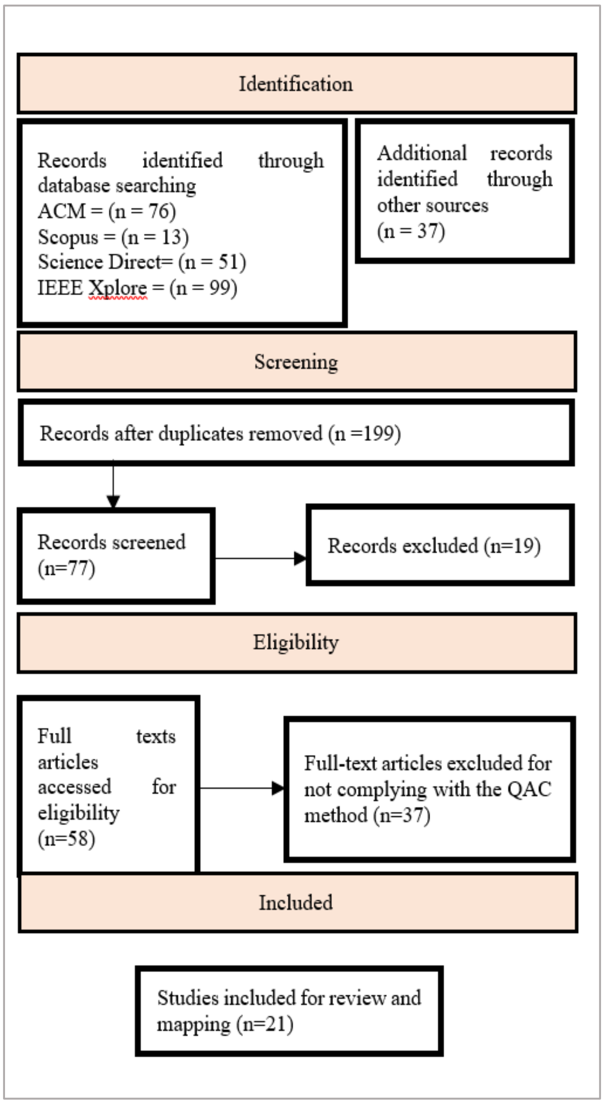

Fig. 4: PRISMA flowchart diagram

Results

Mapping Results

As a result, a total of 21 papers were carefully analyzed during the systematic literature review using predefined questions. Some articles were classified as two dimensions as they addressed two of the three research terms. Figure (5) demonstrates that the bulk of the papers linking the search criteria and available through open access are distributed by the following databases, listed from highest to lowest: ACM, Science Direct, IEEE Explore, and Scopus:

MQ1: How many studies have been published during the years 2017 -2023?
MQ2: What is the geographical distribution of publications in optimization energy in IOT?
MQ3: What are the main benefits of BMS in managing and controlling energy in IOT?

Battery Management Systems (BMS) are crucial parts of energy management and control in Internet of Things applications, particularly in battery-powered devices. The following are a few of the key advantages of BMS for IOT energy management and control.

Optimize Battery Performance

BMS continuously checks the condition and health of batteries to make sure they are operating within safe parameters. Battery management systems (BMS) can enhance battery performance, increasing longevity and efficiency, through the inclusion of algorithms for charging and discharging.

Prevention of Overcharging and Over-Discharging

BMS prevents overcharging, which can cause damage or pose a safety risk. Similarly, it prevents over-discharging, which can also cause damage to batteries. Battery management systems (BMS) regulate charging and discharging cycles to keep batteries operating within safe voltage and current limits.

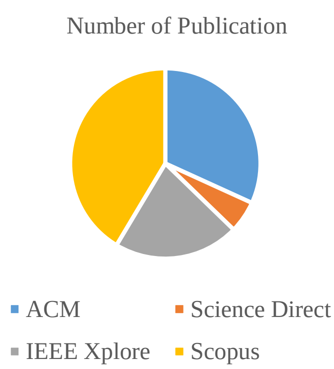

Fig. 5: Distribution of scientific production according to databases

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Figure (6) show publication numbers between 2017 and 2023. Four different type of databases publication has been reviewed which are ACM, Science Direct, IEEE Xplore and Scopus. Publication from Scopus database is the highest compared to others.

Meanwhile, Fig. (7) shows the comparison publications about optimization energy in IoT among North Amerika, Europe, and Asia. The result indicates total publication for North Amerika is 50, followed by Europe with 40 and Asia 30.

Improved Safety

BMS has safety measures to protect against any possible risks like thermal runaway or fire incidents, like temperature monitoring, short circuit protection, and cell balancing. These safety features ensure that batteries operate safely, particularly in vital Internet of Things applications.

Improved Reliability

BMS assists in determining possible issues or anomalies immediately by continuously monitoring battery features like voltage, current, and temperature.

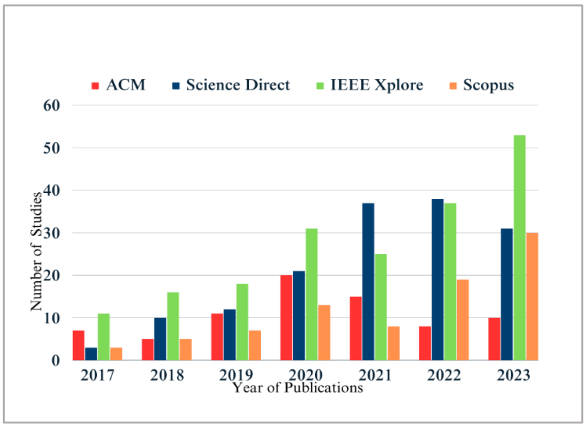

Fig. 6: Years of publications studies 2017-2023

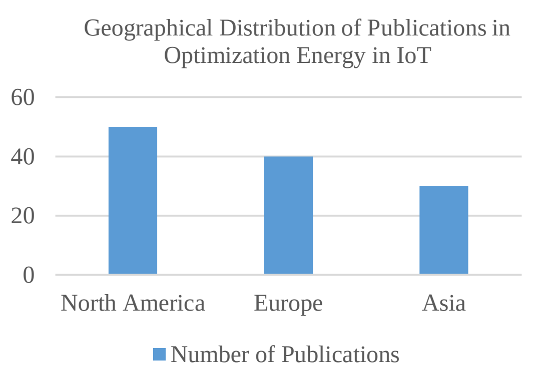

Fig. 7: Geographical distribution of publications

The dependability of battery-powered IOT devices is increased by this proactive monitoring, which makes preventative maintenance possible and minimizes the possibility of unexpected failures.

Optimized Energy Consumption

BMS controls the power transmission between batteries and linked devices to optimize energy consumption. BMS ensures efficient battery capacity usage, prolonging device uptime and cutting down on energy waste by effectively controlling charging and discharging processes.

Remote Monitoring and Control

BMS solutions offer remote monitoring and control capabilities, allowing users to obtain real-time battery data and adjust settings remotely. This functionality makes it possible to manage the battery and IOT devices proactively, makes troubleshooting easier, and even helps optimize energy usage from a distance.

Analytics and Insights Data

BMS gathers and examines information about battery life and consumption trends over time. Through the use of this data, users can anticipate maintenance requirements, learn more about the health of their batteries, and improve energy management techniques to reduce costs and increase efficiency.

Scalability and Flexibility

BMS solutions can be easily expanded to support various battery types, sizes, and configurations, which makes them compatible with a broad range of Internet of Things applications. BMS can be adapted to fulfill individual energy management requirements, regardless of the size of the sensors or industrial equipment.

Thus, Battery Management Systems (BMSs) are essential for managing and controlling energy in the Internet of Things (IOT) applications. They provide advantages including data analytics, scalability, safety, reliability, and optimized battery performance. These advantages are crucial for maintaining the efficient operation and durability of battery-operated Internet of Things devices across a range of sectors and uses.

Results of The Systematic Literature Review

RQ1: What is the purpose of optimization?

In the context of the Internet of Things (IOT), energy optimization is employed to manage and improve the usage of energy resources. The primary goals of optimization in IOT systems are to increase overall performance, ensure sustainability, and improve efficiency. By optimizing energy consumption, IOT systems can operate more effectively, with reduced power usage leading to extended device lifespans, lower operational costs, and minimal environmental impact. This is crucial for the scalability and long-term viability of IOT deployments, particularly in scenarios where devices must function autonomously over extended periods or in energy-constrained environments. IOT energy optimization has various important uses, including.

Energy Efficiency

Enhancing energy efficiency is one of the main goals of energy optimization in IOT technology. Through the optimization of energy consumption in IOT devices, energy consumption can be reduced resulting in longer battery life, lower energy costs, and improved energy efficiency within Internet of Things devices, networks, and systems.

Optimizing Battery Life

A lot of IOT devices run on batteries and are frequently set up in inaccessible locations. By optimizing battery life, energy efficiency ensures that Internet of Things devices can operate for longer periods without frequently requiring to be recharged or replaced with new batteries.

Improving Sustainability

Minimizing energy waste and encouraging sustainability is enhanced by the utilization of renewable energy sources and Internet of Things energy optimization approaches. Optimization energy helps reduce the environmental effect of IOT deployments and supports eco-friendly activities by consuming less energy.

Enhancing Performance

Reliability and enhanced performance of Internet of Things systems can also be attained by effective energy management. Optimization energy approaches can improve the overall functioning, stability, and responsiveness of Internet of Things devices and networks by ensuring that energy is used efficiently.

Reduce Cost

Optimizing energy usage in IOT can result in cost savings for organizations deploying IOT solutions. Optimization energy techniques can reduce the operating costs involved with powering and maintaining Internet of Things (IOT) deployments by extending device lifespans and reducing energy usage.

Hence, the primary objective of energy optimization in the Internet of Things is to develop smarter, cost-effective, and environmentally conscious IOT solutions that can satisfy the growing demands of connected devices and applications while reducing their adverse impact on the environment.

RQ2: What is the type of algorithm estimation method?

Battery capacity is a measure of the total amount of charge extracted from a fully charged battery before it reaches its optimal discharge rate. Thus, the amount of battery capacity is not a fixed value and varies throughout its lifespan due to the continuous aging process of the battery. Charging and discharge current, operating temperature, battery Depth of Discharge (DOD), number of charging and discharge cycles, and other variables all have an impact on how quickly batteries age. Unfortunately, there is not a clear definition of battery capacity either.

In the literature, various battery capacity definitions are provided. However, they are frequently ambiguous and inconsistent. This section proposes standardized battery capacity definitions, which are frequently cited in existing study literature Farmann *et al*. (2015):

- Nominal Capacity ($C_{Nominal}$)
  It is described as the capacity of the battery in the datasheet by the manufacturer for use under standard operating factors such as nominal discharge current, nominal temperature, and nominal capacity of the battery from the fully charged condition. In other words, the manufacturer's stated capacity is known as the nominal capacity
- Available Capacity ($C_{available}$)
  This represents the maximum capacity that can be drawn from a fully charged battery, taking its current age into account. This means that the new nominal capacity of a battery is equivalent to its usable power when a battery is operating under nominal conditions.
- Dynamic Capacity ($C_{dynamic}$)
  Dynamic capacity refers to the amount of charge sustained consistently over time. The energy stored in the battery changes as it varies between charging and discharging rates

Despite the complexities of battery degradation accurately estimating the battery capacity onboard remains a difficult task for the Battery Management System (BMS) prompting researchers to make substantial attempts to tackle this issue. This phase will provide a quick overview of the methods used to estimate battery capacity in the literature. The approaches are broadly classified as follows.

Direct Measurement Methods

Direct measurement methods are one of the simplest techniques to obtain battery capacity that builds charge during its cycle phase. These methods require the battery to be either fully charged or discharged under specific conditions. However, it is impractical to consistently meet the criteria of a battery's characteristics, especially since these evaluation techniques are limited to laboratory tests

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and cannot fully replicate real-world conditions.

A further issue is that the BESS cannot always be fully charged or discharged due to varying load conditions. Direct measurement techniques are ineffective when the battery is slightly charged or depleted, a scenario that frequently arises during practical use.

Analysis-Based Methods

In the case of indirect approaches, sensors can record voltage, current, and temperature which may then be utilized to determine the capacity. Researchers primarily offer five types of analysis-based methodologies in the study which include the Incremental Curve (IC), the Differential Thermal curve (DT), the Differential Voltage curve (DV), mechanical stress, and Electrochemical Impedance Spectroscopy (EIS). For instance, one of the analysis-based methods includes the IC curve analysis technique which is concerned with the variations of capacity with voltage, which is denoted as:

$$IC = \frac{dQ}{dV} \tag{1}$$

Equation (1) shows the dQ of the IC curve may be simply calculated by Coulomb counting the current while dV is denoted as the voltage of the current. Based on the studies, since noise in current and voltage readings is constantly present, a filter is frequently necessary to reduce the IC curve (Farmann *et al*., 2015) commonly Kalman Filter is one of the filtering methods that usually be used to enhance the extraction of the IC curve. Incremental Capacity Analysis (ICA) is commonly utilized in battery degradation mechanism studies because the characteristics of battery Incremental Capacity (IC) curves are directly connected to battery degradation and maximum usable capacity. However, the standard ICA approach for estimating battery capacity relies on a single charging circumstance (Farmann *et al*., 2015).

SOC-Based Methods

State of Charge-based methods is the famous literature among researchers to study the estimation of battery capacity. Recent studies often focus on estimating capacity along with other battery conditions, like State of Charge (SOC), in a process called joint estimation (Yu *et al*., 2019).

Capacity is a dynamic element, regarded as an advanced stage in the combined estimation of SOC and SOH, and then parametric filtering is conducted. Moreover, filters consist of two primary variables: Prediction and correction. Both conduct the state of estimation from the previous value and then correct based on the observances of measurement. The prediction and correction steps are iterative, continuously refining the state estimation.

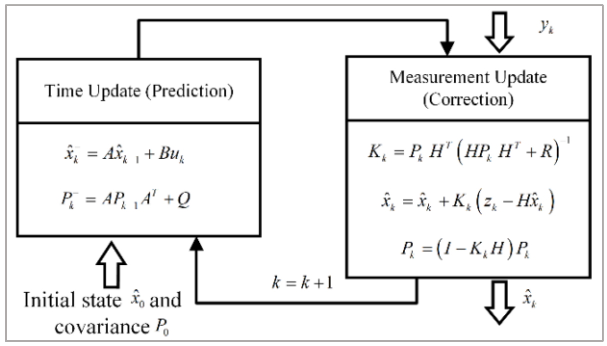

Fig. 8: Kalman filtering process

For instance, a schematic figure of the Kalman filter filtering approach is presented in Fig. (8) above (Xu *et al*., 2012), with the equations for a stochastic linear discrete system provided as essential for understanding the filter operation and performance are denoted as follows:

$$x_k = Ax_{k-1} + Bu_k + w_k \tag{2}$$

$$y_k = Hx_k + v_k \tag{3}$$

Equations (2-3) show where x denotes the state vector, A the state transfer matrix, u the state control vector, B the control variable matrix, y the measurement vector, H the transformation matrix from the state vector to the measurement vector, w, and v are both Gaussian noises and P the covariance matrix.

Various case studies were implemented using the Kalman filter which uses the SOC-based technique. As a result, for the SOC-based technique, the capacity identification estimator is completely independent of the SOC state estimator. To increase the accuracy of the outcome, several time scales are used.

The precise SOC is a vital requirement for the battery capacity estimation. However, accurately measuring SOC is challenging for lithium-ion batteries, which restricts the practical use of SOC-based approaches.

Data-Driven Methods

The data-driven method is distinguished by its dependence on a huge dataset to make decisions and is not dependent on the use of a specific battery model. For example, considering the explosive development of artificial intelligence and IOT, the daily performance data of the battery system can be effortlessly uploaded for edge computing estimates. With a sufficiently representative sample, a model can map data using a data-driven approach, eliminating the need for a predefined model.

Examples of existing data-driven methods include Neural Networks (NN), Support Vector Machines (SVM), Convolutional Neural Networks (CNN), and others. Hence, the accuracy of the data and an intensive training procedure are required for the deployment of data-driven approaches. The benefit lies in training the model to respond to the data, although this requires a large sample and training dataset to ensure precise estimation.

RQ3: What is the type of algorithm of SOC?

SOC acts as a vital indicator of a battery's current energy level in comparison to its total capacity. SOC provides a real-time estimate of how much charge remains in the battery, indicating to users the duration a battery will last before requiring a recharge. To accurately estimate SOC, various algorithms are employed, each with its strengths and limitations. The preference of the SOC algorithm is based on specifications that include required efficiency, computing intricacy, and application settings inside the Battery Management System (BMS).

In most cases, the State of Charge (SOC) is a percentage representation of the amount of energy supplied in a battery at a given point in time (Brush, 2019). The main equation of SOC is described as:

$$SOC(t) = \frac{Q(t)}{Q_n} \quad (4)$$

Equation (4) above defines the *SOC* of a battery which is described as the ratio of its current capacity ($Q(t)$) to the nominal capacity (Qn). The nominal capacity is to represent the maximum amount of charge that can be kept in the battery z (Chang, 2013).

The SOC is one of the most significant characteristics of batteries, however, describing it tends to involve a variety of issues. Since the SOC is a key metric that indicates battery performance, precise SOC estimation can help prevent over-discharge, extend battery life, and enable applications to implement efficient energy conservation strategies (Chang, 2013).

Existing SOC estimate approaches can be divided into five categories. The several mathematical estimating approaches are categorized based on methodology. The categorization of these SOC estimating methods varies throughout the literature. Nonetheless, certain literature allows classification into the following categories that comprise conventional technique, adaptive filter technique, machine learning technique, nonlinear observer, and hybrid technique. These approaches are listed below.

Conventional Method

Conventional methods are traditional methods of the standard techniques for estimating SOC including "ampere-hour counting", "the Open Circuit Voltage (OCV) method", "impedance and internal resistance measurements", "the electrochemical method" and "the model-based method" (Zhang *et al*., 2018).

Ampere-Hour Counting Method

Besides commonly known as coulomb counting, the ampere-hour method is utilized to estimate the amount of charge in a battery (Baccouche *et al*., 2016) useful for estimating the State of Charge (SOC) of lithium-ion batteries with high charging and discharging efficiency (Baccouche *et al*., 2016). It is used to determine how much charge is left in a battery by integrating the discharging or charging current as shown below (Zhang *et al*., 2018):

$$SOC(k) = SOC(0) - \frac{T}{C_n}\int_0^k (\eta \cdot \mathrm{I}(t) - S_d)dt \quad (5)$$

Equation (5) shows the ratio of a battery's remaining capacity to its nominal capacity is indicated where $SOC(0)$ is the initial SOC of the battery, $I(t)$ is denoted as the current time, T is the sampling period over the C_n is the nominal capacity of the battery, η is the coulombic efficiency, $I(t)$ is the current of time and S_d is the discharging-rate. According to the research, a self-discharge rate undergoes approximately 5% each month for a battery of η >0.994 at room temperature.

According to Zheng *et al*. (2018), despite its lower power computation cost, the ampere-hour counting method is commonly employed for battery SOC optimization. On the other hand, it also has the problem of not being very precise over lengthy periods. The ampere-hour counting method's error causes are an uncertain starting of the SOC, the ability diminishing, self-discharge proportion, and current detection faults. To increase the exactness of the technique, the initial capacity and the value of SOC of a battery, as well as the current detection deviation may rectified and modified frequently.

Open Circuit Voltage (OCV) Method

The OCV of a battery cell defines the potential difference between the positive and negative electrodes when no current flows and the electrode potentials are in a state of equilibrium. The SOC-OCV relationship is obtained in this manner by measuring OCV sequentially for different SOC values. For SOC estimation, the OCV method offers high accuracy and is easier to implement (Baccouche *et al*., 2016).

However, while there is a clear and established linear relationship, it varies amongst batteries and is dependent on the battery's capacity. Although the SOC-OCV relationship of lithium-ion batteries is mainly stable, it can differ depending on the surrounding temperature and the battery's life cycle. Hence, to determine an accurate SOC-OCV relationship, researchers may need to undertake large-scale investigations at various temperatures and battery cycle lifetimes (Baccouche *et al*., 2016).

Therefore, reliable OCV modeling is vital for controlling lithium-ion batteries. It is stated to determine the OCV value at corresponding SOC levels between two adjacent measuring points (Quanqing *et al*., 2021) where the OCV technique for estimate is based on fitting the OCV relaxation model parameters. Hence, the OCV approach is utilized to determine the SOC, which has minimal power use and high precision. However, its relevancy is inflexible because of the absence of specified requirements.

Impedance and Internal Resistance Methods

The impedance and internal resistance of the lithium-ion battery represent their inherent electricity under any current level, assuming that temperature, SOC, and SOH remain constant. However, measuring real-time Electrical Impedance Spectroscopy (EIS) is challenging since the sinusoidal Alternating Current (AC) may be needed, the SOC and impedance connection is unstable and it consumes high cost. (Baccouche *et al*., 2016) while measuring internal resistance, Direct Current (DC) as well as voltage and current readings over a short period of time are necessary.

Battery heat studies are primarily concerned with the irreversible heat generated by the internal resistance and the reversible heat produced by the electrochemical process. In general, reversible reaction heat is low and may be resisted at room temperature. As a result, the heat generated by the internal resistance is the primary source of the battery's heat (Chen *et al*., 2021). Hence, the thermal analysis of batteries and the design of thermal management systems depend on precise internal resistance modeling. Chen *et al*. (2021).

The higher the internal resistance, it increases the losses when charging and discharging, particularly at higher currents. It is challenging to determine the internal resistance for SOC estimation since it may differ gradually. Based on the research, SOC estimates based on impedance and internal resistance are not suitable for implementation in IOT technology.

Electrochemical Methods

Electrochemical Impedance Spectroscopy (EIS) is a very effective and extensively used non-invasive diagnostic technique for characterizing lithium-ion batteries (Barai *et al*., 2019). As a non-destructive technique, EIS can be utilized as a diagnostic or prognostic tool: For the characterization of second-life applications and quality assurance for state estimates, including SOC, SOH, and SOF for internal temperature monitoring. (Meddings *et al*., 2020).

Estimating the number of lithium-ion batteries and the average level in the positive or negative electrodes is essential for determining SOC using an electrochemical model based on partial differential equations. The SOC may be estimated simply from the quantity identification in the electrochemical model's negative or positive electrodes. On the other hand, partial differential equation solutions are usually too complicated for online applications (Baccouche *et al*., 2016).

In general, the electrochemical method can potentially deliver highly precise SOC estimation. However, this method is only suitable for offline development and functional research on lithium-ion batteries, which require obtaining the impedance spectrum, a process that is time-consuming. However, because of the intricacy of the electrochemical method and the hundreds of battery model parameters, this approach is very complex to use for online SOC estimation (Baccouche *et al*., 2016) and the chemical parameters of the battery are difficult to figure out. As a result, they are challenging to apply in real-time applications.

Model-Based Methods

The previous approaches are not adequate for online SOC estimation using traditional methods. Accurate online SOC values require the development of battery models. The electrochemical model and Equivalent Circuit Model (ECM) are the two most often utilized in battery models (Zhang *et al*., 2018).

ECMs primarily utilize resistances and RC circuits to model the power conduct of lithium-ion batteries. For an ECM to be effective, it must accurately simulate the actual battery voltage under varying current conditions. However, some characteristics of lithium-ion batteries cannot be adequately represented using circuit components. Therefore, pure mathematical models with persistence are used to significantly improve the precision of voltage simulations (Baccouche *et al*., 2016).

Model-based approaches focus on precisely estimating the SOC by simulating battery performance through complex mathematical equations that combine various components. These methods require the simulation of a battery’s electrical, chemical, or combined properties, relying on principles outlined in porous electrode theory (How *et al*., 2019).

Adaptive Filter Algorithm

The adaptive filter algorithm is an advanced technique in current control theory designed to enhance the estimation of the State of Charge (SOC) of batteries. This adaptability enhances the precision of SOC estimation by continuously refining the filter's variables to better match the battery’s actual performance. It provides more precise and reliable SOC estimates, which are crucial for effective battery management in various operational environments.

Machine Learning Algorithm

Machine learning algorithms have significantly advanced the estimation of State of Charge (SOC) in battery management systems. These algorithms leverage large datasets and sophisticated computational techniques to improve the precision and dependability of SOC estimates. Among the various machine learning methods, “Genetic Algorithms (GA)”, “Fuzzy Logic (FL)”, “Artificial Neural Networks (ANN)” and are commonly employed.

Non-Linear Observer

The SOC of lithium-ion batteries is determined with simple implementation studies to estimate the efficiency and precision using the "Proportional-Integral Observer (PIO)", "Non-linear Observer (NLO)" and "Sliding Mode Observer (SMO) approaches".

Hybrid Algorithm

The hybrid algorithm approach combines two additional algorithms. Hybrid approaches achieve globally optimal estimation performance by integrating the advantages of various SOC estimation techniques. According to the research, hybrid approaches create better estimates of SOC than individual techniques.

Estimating SOC, a key challenge in battery usage, indicates the remaining capacity and serves as a vital metric for control strategies (He *et al*., 2012).

Discussion

In this section, the research findings are discussed while also providing an extensive analysis. Based on this research, the specific difficulties encountered by BMS and their solutions were laid out as an outline for future study. Different approaches can be applied based on the circumstances to optimize BMS performance in IOT systems. The literature review discussed that the estimation method carried out by the researchers proved each of the algorithm that can be conducted to optimize the energy consumption of battery.

According to the previous overview, there have been several researches on battery capacity estimation. From the studies, we understand that certain techniques need special particular conditions. This study addresses current approaches for estimating battery capacity for Battery Management System (BMS) implementation which are grouped into four categories which are direct measurement methods, analysis-based methods, SOC-based methods, and data-driven methods.

Based on Table (3) presents the analysis of each algorithm that is used in estimating the battery capacity studies. The findings show that some techniques rely on their capacity characteristics to be estimated in tandem with the battery condition. For instance, from the analysis on measuring internal resistances of the capacity battery, it is vital as the main factor for each method to record the voltage, current, and temperature which may be utilized to determine the capacity.

Besides, the comprehensive discussion had been stated in other analyses that represent the comparative the state of charge estimation method. The findings show the characteristics that rely on the algorithms which include high charging and discharging efficiency, real-time adaptability, minimized interference, enhanced voltage monitoring, cell balancing, monitoring internal temperature, noise adaptive, efficient computing method, high precision and accuracy, and cost-effectiveness. The analysis of the studies is represented in the form of Table (4).

Thus, according to the outcomes of this discussion, the future framework for onboard capacity estimation will integrate data-driven methodologies with other advanced techniques. For example, the analysis-based method provides health insights for data-driven models and simplifies data processing, reducing the need for expert knowledge of lithium-ion battery degradation. In the BMS terminal, a SOC-based method can function alongside a data-driven approach while collaborating through a fusion mechanism.

Table 3: Comparative of capacity estimation method

Algorithms/Techniques	Characteristics						
	Measuring the Internal Resistance	Single Charging Circumstances	Real-Time Adaptability	Reduce Noise	Parametric Filtering	Limited for Laboratory Testing	Training Large Dataset
Direct measurement method	√	x	x	x	x	√	x
Analysis-based method	√	√	√	x	√	x	√
SOC-based method	√	x	√	√	√	x	√
Data-driven method	√	x	√	√	√	x	√

Table 4: Comparative of state of charge estimation method

Algorithms/Techniques		Characteristics									
		High Charging and Discharging Efficiency	Real-Time Adaptability	Minimize Interference	Enhance Voltage Monitoring	Cell Balancing	Monitoring Internal Temperature	Noise Adaptive	Efficient Computing Method	High Precision and Accuracy	Cost Effective
Conventional method	Ampere-hour counting method	x	x	x	√	√	√	x	√	x	√
	OCV method	x	x	x	√	√	x	x	x	√	√
	Impedance and internal resistance method	√	x	x	√	x	√	x	x	x	X
	Electrochemical method	x	x	x	√	√	√	x	x	√	x
	Model-based method	√	√	√	x	x	√	x	√	√	x
Adaptive filter algorithm		√	√	√	√	√	√	√	√	√	√
Machine learning algorithm		x	√	√	√	x	√	√	√	√	√
Non-linear algorithm		√	x	x	√	√	√	x	√	√	√
Hybrid algorithm		√	√	√	√	√	√	√	x	√	x

Additionally, this study also discussed deeply various SOC estimation family algorithms which are classified into five distinct types including conventional method, adaptive filter algorithm, machine learning algorithm, non-linear observer, and hybrid algorithm. Based on the research, the conventional methods of estimating SOC also can include ampere-hour counting, the Open Circuit Voltage (OCV) approach, the impedance and internal resistance method, the electrochemical method, and the model-based method.

Based on comparison observations, some approaches work well with a constant discharging current, while others are more effective with changing discharging current. However, comparing the performance of different methods is difficult due to the use of varying battery sizes and varying discharging conditions in existing implementations.

With the knowledge obtained from the literature review conducted as part of this research study, the estimation method will be used in the following phase of the studies. This method should have a reasonable level of computational complexity, be easy to implement, and guarantee good precision over a range of battery longevity and operating conditions.

Conclusion and Future Research

In conclusion, this systematic review paper has critically analyzed the current state of algorithms for battery optimization, with a particular focus on estimation methods and State of Charge (SOC) algorithms within Battery Management Systems (BMS). The review highlights that the primary objective of these algorithms is to minimize power consumption, which is increasingly vital given the growing global energy demand driven by population growth and the expanding deployment of Internet of Things (IOT) technology.

The findings indicate that data-driven methods and hybrid algorithms are particularly effective, offering superior performance in optimizing battery usage and extending battery lifespan. However, despite these advancements, there is a clear need for further refinement of these algorithms to enhance their accuracy and efficiency. The study underscores the critical role of BMS in ensuring the optimal use of battery power, which is essential for supporting the sustained growth of IoT applications and addressing the challenges of modern energy consumption.

Future research should focus on several key areas to advance the effectiveness of battery optimization algorithms in BMS. First, there is a need for the development of more sophisticated data-driven techniques that can better handle the complexities and variabilities in battery performance, particularly in diverse IOT environments. This could involve the integration of machine learning techniques with traditional estimation methods to create more adaptive and predictive models.

Additionally, further exploration into hybrid algorithms that combine the strengths of different approaches could result in greater durability and efficient approaches. Research should also explore real-time implementation and validation of these algorithms in practical IOT applications to assess their performance in dynamic, real-world conditions. Finally, considering the rapid evolution of IOT technology, future studies should investigate the scalability and adaptability of these algorithms to ensure they remain effective as IOT networks expand and evolve.

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Author’s Contributions

Nur Yasmin Salleh: Was primarily responsible for the conceptualization and methodology of the study. She conducted the formal analysis and contributed significantly to writing the original draft and creating visualizations for the paper.

Mohd Kamir Yusof: As the supervisor, provided overall guidance and evaluation during the research phase. He contributed valuable resources and was extensively involved in reading and revising the manuscript to verify its correctness and completeness.

Nur Farraliza Mansor: As the co-supervisor, focused on data curation and investigation, handling the software aspects of the study. She also participated in the review and editing process, ensuring the manuscript's quality.

Ethics

Final Set of Selected Primary Studies

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