energies

Review

Applications of Energy Storage Systems in Enhancing Energy Management and Access in Microgrids: A Review

Ziad M. Ali [1,*], Martin Calasan [2], Shady H. E. Abdel Aleem [3], Francisco Jurado [4] and Foad H. Gandoman [5]

[1] Electrical Engineering Department, College of Engineering, Prince Sattam Bin Abdulaziz University, Wadi Addawaser 11991, Saudi Arabia
[2] Faculty of Electrical Engineering, University of Montenegro, 81000 Podgorica, Montenegro; martinc@ucg.ac.me
[3] Department of Electric Power and Machines Engineering, Institute of Aviation Engineering and Technology, Giza 25152, Egypt; engyshady@ieee.org
[4] Department of Electrical Engineering, University of Jaen, 23700 Linares, Spain; fjurado@ujaen.es
[5] Reliability & Safety Technical Center (RSTER), 1930 Zaventem, Belgium; foad.h.gandoman@rster.org
* Correspondence: dr.ziad.elhalwany@aswu.edu.eg

Abstract: As the world's population continues to grow and the demand for energy increases, there is an urgent need for sustainable and efficient energy systems. Renewable energy sources, such as wind and solar power, have the potential to play a significant role in meeting this demand, but their intermittency can make integration into existing energy systems a challenge. Moreover, the development of sustainable energy systems has become even more critical in recent years, due to a confluence of events, including the decline in fuel prices, geopolitical conflicts, and the recent COVID-19 pandemic. The decrease in fuel prices has led to a decline in investment in renewable energy and has slowed the transition to sustainable energy systems. Additionally, geopolitical conflicts and pandemics have highlighted the need for resilient and self-sufficient energy systems that can operate independently of external factors. Also, energy storage technologies play a critical role in achieving this goal by providing reliable backup power and enabling microgrids to operate independently of the larger power grid. As such, developing efficient and effective energy storage technologies is essential for creating sustainable energy systems that can meet the demands of modern society while mitigating the impact of external factors. In this regard, this work provides an overview of microgrids' latest energy storage technologies, including their applications, types, integration strategies, optimization algorithms, software, and uncertainty analysis. Energy storage technologies have a wide range of applications in microgrids, including providing backup power and balancing the supply and demand of energy. Different energy storage techniques have been discussed, including batteries, flywheels, supercapacitors, pumped hydro energy storage, and others. Moreover, integration strategies of energy storage in microgrids, models, assessment indices, and optimization algorithms used in the design of energy storage systems are presented in detail. The capabilities of software used in energy storage sizing are explored. Further, uncertainty analysis in modeling energy storage devices is presented and discussed. This state-of-the-art technology has been prepared to demonstrate the effectiveness of energy storage technologies in microgrids, providing valuable insights for future developments in the field.

Keywords: assessment indices; batteries; energy access; energy storage; energy management; microgrids; optimization algorithms; power sharing; software; uncertainty analysis

Citation: Ali, Z.M.; Calasan, M.; Aleem, S.H.E.A.; Jurado, F.; Gandoman, F.H. Applications of Energy Storage Systems in Enhancing Energy Management and Access in Microgrids: A Review. *Energies* **2023**, *16*, 5930. https://doi.org/10.3390/en16165930

Academic Editors: Marco Marengo, Massimiliano Renzi and Antonio Gagliano

Received: 21 March 2023
Revised: 2 August 2023
Accepted: 8 August 2023
Published: 10 August 2023

1. Introduction

At present, microgrids (MGs) and nanogrids (NGs) are becoming increasingly important in current power systems, due to several aspects, such as resilience, renewable energy integration, energy efficiency, cost savings, and energy access [1,2]. MGs and NGs are designed to operate independently or in parallel with the main power grid, providing a more resilient and reliable power source. This is particularly important in areas prone to power outages, natural disasters, or wars, as MGs can provide backup power and help maintain critical services. Also, they can integrate renewable energy sources (RESs) such as solar, hydropower, hydrogen, and wind power, reducing the reliance on fossil fuels and lowering greenhouse gas emissions [3]. They can be designed to optimize energy efficiency, using energy storage systems, smart grid technologies, and energy management systems (EMSs) to reduce energy waste and improve overall system performance. Moreover, MGs and NGs can reduce the cost of electricity for consumers by providing a more localized and efficient power source. They can also reduce the need for expensive infrastructure investments by utilities, such as transmission lines and substations. They can provide electricity access for communities not currently connected to the main power grid, such as rural areas or developing countries. Overall, MGs and NGs provide a more flexible, efficient, and resilient power system that can better meet the needs of consumers and communities. As such, they will become increasingly important in power systems as the demand for renewable energy, energy efficiency, and resilience grows.

Electrically speaking, the MG describes a small-scale power network that comprises a cluster of load centers, energy storage systems (ESSs), and distributed generators (DGs), whether RESs, micro-turbines, or diesel generators, operating together with an EMS, control units, and protection components. The purpose of MGs is to break up the massive traditional utility network into smaller, more manageable grids [4]. These smaller electrical networks can manage their DGs, load demands, storage systems, and protective devices. If each MG operates accurately and efficiently, then the utility grid as a whole can be correctly operated [5].

From a scale and complexity point of view, MGs, NGs, and picogrids (PGs) are all small-scale power systems designed to operate independently or in parallel with the main power grid. While they share some similarities, there are also some key differences between them. MGs are the largest of the three, and typically serve communities or small towns. MGs often incorporate advanced control systems and EMSs to optimize performance. NGs are smaller than MGs, and typically serve individual buildings or small clusters. They may consist of a single RES, such as a solar panel or a wind turbine, along with an ESS, and may be connected to the main grid or operate independently. NGs often incorporate smart grid technologies to optimize energy use and minimize waste. PGs are the smallest of the three, and typically serve individual homes or small businesses. They may consist of a single RES, such as a solar panel or a wind turbine, along with a small ESS. PGs are typically designed to operate independently of the main grid, providing a localized and reliable power source.

In summary, MGs, NGs, and PGs provide localized and reliable power sources but differ in scale and complexity. MGs are the largest and most complex, while NGs and PGs are smaller and more focused on individual buildings or homes.

Scopus and Web of Science (WoS) databases are used for identifying relevant papers related to ESSs and MGs from 2018 to early 2023. Only articles published in English are considered. The number of publications per year is depicted in Figure 1, and the top five journals in the research area of the application of ESS in MGs are presented in Figure 2. The keywords of the publications focusing on the application of ESS in MGs and their distribution are depicted in Figure 3 to show the primary research focus of the examined articles, simplifying comprehension of the areas of strength. Moreover, Figure 3 provides directions for future investigations. The size of the spheres corresponds to the prevalence of keywords. In other words, larger clouds and patterns indicate a higher frequency of appearance [6]. Moreover, Figure 4 illustrates the distribution of publications concerning the country. It is observed that China and India had the highest number of publications in this area of research. These figures clearly demonstrate the soundness of ESSs in MG applications in the last five years.

ESSs are widely used in MGs for several purposes, as shown in Figure 5 [3,4]. ESSs are commonly used to shift the electric energy time and reduce operation costs by storing electrical energy during low-cost and excess power periods and injecting power during peak hours. ESSs help reduce the MG total operating cost, considering the time of charging and discharging and the fluctuating price of kWhs on the markets [7]. In MGs, the consumption is stochastic and unpredictable, which may affect the system's stability. Some storage systems have a quick response time, and can be used to adapt to load changes and securely maintain MGs [8]. ESSs are also suitable for improving system reliability by avoiding unintentional interrupts and speeding up MG restoration time. Furthermore, they can be used to balance generation and load demands. ESSs help MGs avoid cascading failure by ensuring *N*-1 and *N*-2 security [9]. ESS can be used as a spinning reserve support for MGs, to cover energy shortages during unexpected and abnormal situations by storing extra power during off-peak periods and assisting the MG during uncounted interruptions [10]. Generally, low-inertia MGs are prone to frequency and voltage fluctuations, particularly in the presence of RESs. Quick-response ESSs are commonly preferred to mitigate this issue [11]. Many research studies recommend using ESSs to improve power quality [12–14], especially if RES is widely installed. They also play a vital role in increasing renewables' hosting capacity (HC) [15,16].

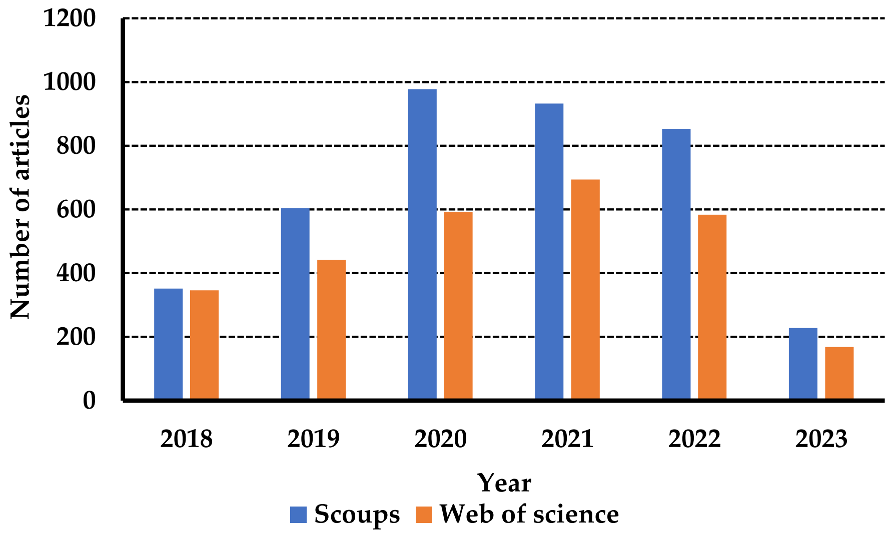


Figure 1. Distribution of the investigated articles per year.

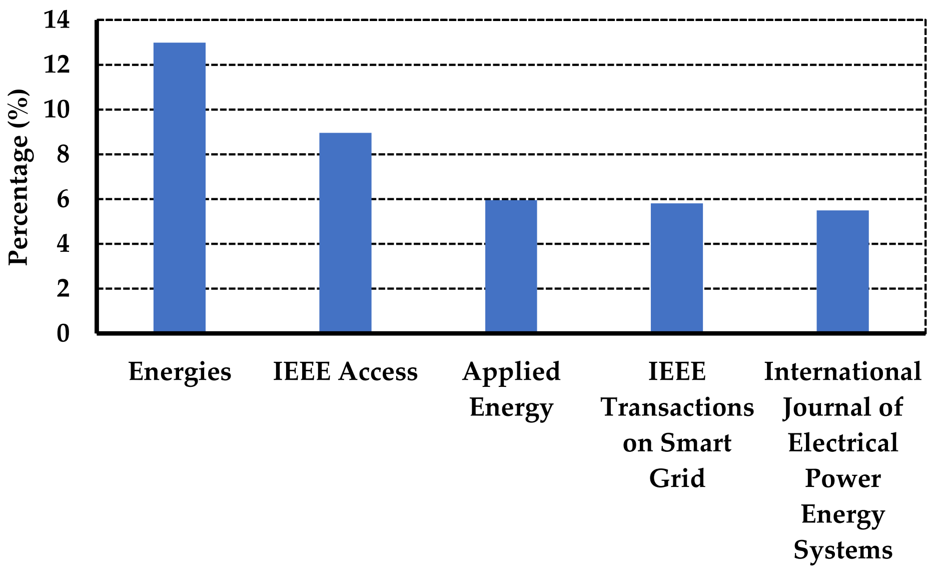


Figure 2. Top five journals in the research area of the applications of ESS in MGs.

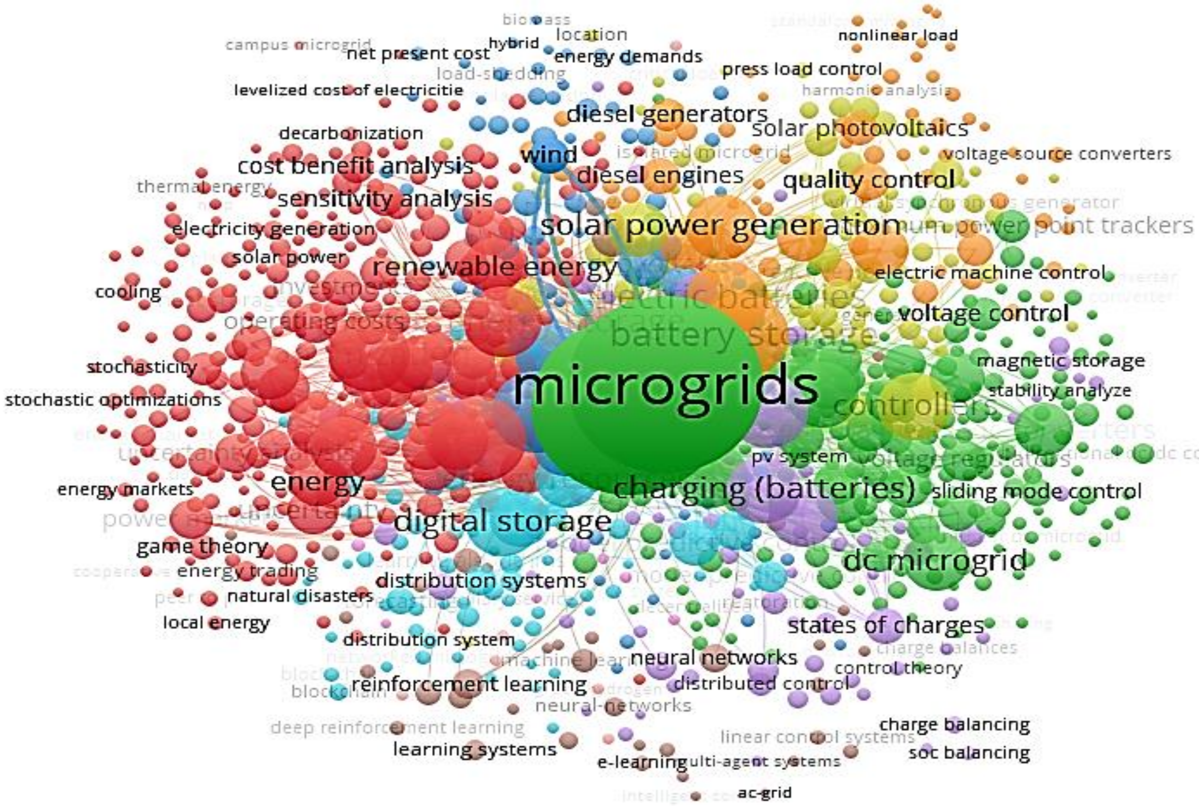


Figure 3. Co-occurrence analysis map of the articles focusing on the applications of ESS in MGs.

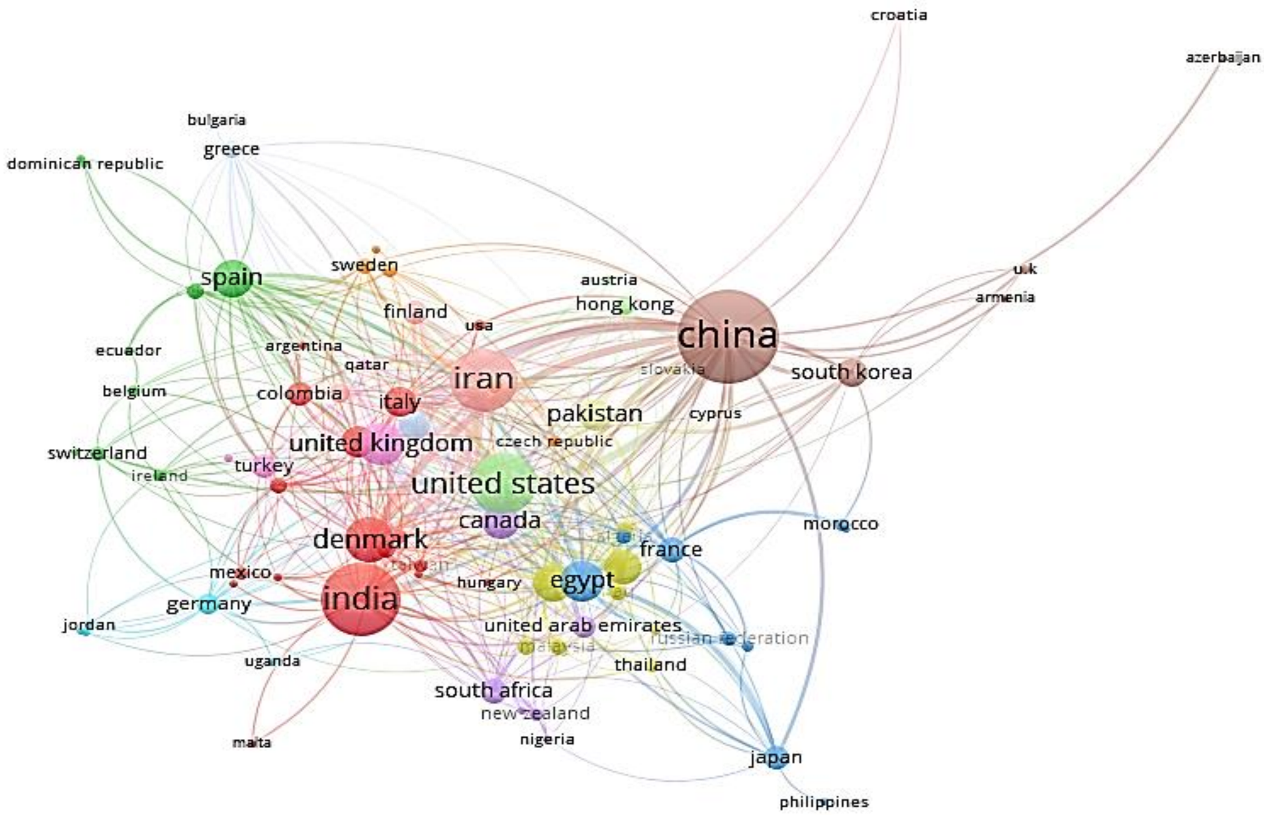


Figure 4. Distribution of articles concerning countries in the period between 2018 and early 2023.

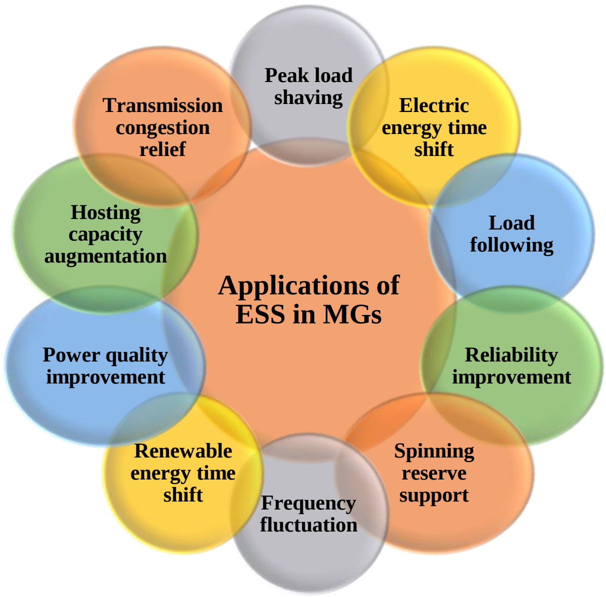


Figure 5. Applications of ESSs in MGs.

The output of RES is stochastic, and continuously varies during the day. For example, photovoltaic (PV) system output energy varies with changes in solar radiation and ambient temperature. The output energy of a wind turbine is affected by wind speed. The use of ESS is critical, particularly for isolated MGs, to firm RES capacity and provide a constant power supply in MGs [17]. Electric consumption steadily increases, which may cause congestion on the transmission lines. ESS can be installed near heavy loads to reduce power flow through power lines [18].

Moreover, due to the stochastic or intermittent nature of RESs, integrating RES into MGs may deteriorate the system's reliability and threaten the MG's stability. In order to achieve the optimal operation of an ESS-integrated MG, an EMS and an accurate forecasting algorithm must be integrated into the MG central controller to keep the MG secure and reduce reliance on the primary grid [19]. The EMS is the brain of MGs, and should meet both the long-term and short-term requirements. Many energy management optimization strategies have been presented in the literature [20]. They depend mainly on properly scheduling alternative energy resources or storage to preserve stability and optimally dispatching the generated power to maximize economic profits [21].

In this regard, this work provides an overview of MGs' latest energy storage technologies, including their applications, types, integration strategies, optimization algorithms, software, and uncertainty analysis. Energy storage technologies have a wide range of applications in microgrids, including providing backup power and balancing the supply and demand of energy. Different energy storage techniques have been discussed, including batteries, flywheels, supercapacitors, pumped hydro energy storage, and others. Moreover, integration strategies of energy storage in MGs, models, assessment indices, and optimization algorithms used in the design of energy storage systems are presented in detail. The capabilities of software used in energy storage sizing are explored. Further, uncertainty analysis in modeling energy storage devices is presented and discussed. Finally, this state-of-the-art technology has been prepared to demonstrate the effectiveness of energy storage technologies in microgrids, providing valuable insights for future developments in the field.

Moreover, the existing literature review papers on the application of ESS in MGs are also investigated in the period between 2018 and early 2023. Table 1 presents the existing literature reviews on the application of ESS in MGs and their main findings. A comparison between existing literature reviews on ESS application in MGs and the current paper is presented in Table 2, which highlights the novelty of this manuscript in terms of ESS technologies, energy management/control, sizing approaches, ESS software, economic indices, and bibliometric analysis.

Table 1. Existing literature reviews on the application of ESS in MGs and their main findings.

Refs.	Author	Year	Location of the Main Author	Main Findings
[22]	Faisal et al.	2018	Malaysia	ESS technologies, structures, configurations, classifications, characteristics, energy conversion, and evaluation processes were discussed. This review emphasized key factors, issues, challenges, and potential recommendations for developing ESS for future MG applications.
[23]	Hajiaghasi et al.	2018	Iran	A comprehensive review of the application of the hybrid ESS system in MG was presented. An economic analysis and design methodology were conducted to discuss the hybrid ESS from the perspectives of investors and distribution system engineers.
[24]	Arani et al.	2019	Iran	An introduction to MG architecture and its challenges was presented. Further, essential types of ESSs and a brief description of their characteristics were reviewed. Different ESS operations, their control methods, and future trends were also discussed.
[25]	Hannan et al.	2020	Malaysia	This work discussed the traits of optimal ESS sizing methods and algorithms and the scenarios between ESS and decarbonization in MG applications to find ways to address their flaws. This review focused on ESS sizing to maximize storage capacity, lower usage, keep storage costs as low as possible, find the best storage place, and reduce carbon emissions for decarbonization.
[26]	Nikam et al.	2020	India	A brief review of the state-of-the-art operation and control strategies of distributed energy resources, ESS, and electric vehicles in the MG 3 was presented.
[27]	Chaudhary et al.	2021	Norway	A review of the different ESSs widely used in MGs was introduced. The working operations and characteristics of ESSs were discussed. An overview of the controls of energy management systems for microgrids with distributed energy storage systems was included in this review.
[28]	Georgious et al.	2021	Egypt	The most common ESS classifications were presented, summarized, and compared, according to their characteristics and environmental impacts.
[29]	Hu et al.	2021	Australia	The paper comprehensively reviewed predictive model control in MGs, including converter-level and grid-level control strategies.
[30]	Saeed et al.	2021	China	The paper discussed various technical aspects of MGs and economic and market considerations for commercialization. Different MG control schemes, technical issues related to MG integration with utility grids, and feasible solutions were also presented.
[31]	Lin et al.	2022	New Zealand	A critical analysis and comparison of the control methods of the hybrid ESS in an MG were presented. A novel droop-coordinated control method in a case study was presented to verify the feasibility of the simplification and multi-function of the controller.
[32]	Reza et al.	2022	Malaysia	This bibliometric study was conducted over the last few decades, based on the year of publication, interrelation of co-occurrence keywords, articles type, country of origin, journal, and the publisher that published the 120 top-cited articles.
[19]	Thirunavukkarasu et al.	2022	Australia	A review of the different optimization methods applied in the literature to solve energy management problems in MGs was presented.
[33]	Mohammadi et al.	2022	Canada	The paper discussed robust control techniques for MGs, including AC, DC, and hybrid microgrids, with different topologies and interconnection types to conventional power systems, based on recently published research studies.

Table 2. Comparison between existing literature reviews on ESS application in MGs and current paper.

Refs.	Author	Discussed Items					
		ESS Technologies	Energy Management/Control	Sizing Approaches	Software	Economic Indices	Bibliometric Analysis
[22]	Faisal et al.	✓	✓	✓	×	×	×
[23]	Hajiaghasi et al.	✓	✓	✓	×	×	×
[24]	Arani et al.	✓	✓	×	×	×	×
[25]	Hannan et al.	✓	×	✓	×	×	×
[26]	Nikam et al.	×	✓	×	×	×	×
[27]	Chaudhary et al.	✓	✓	✓	×	×	×
[28]	Georgious et al.	✓	×	×	×	×	×
[29]	Hu et al.	×	✓	×	×	×	×
[30]	Saeed et al.	×	✓	×	×	×	×
[31]	Lin et al.	×	✓	×	×	×	×
[32]	Reza et al.	×	×	×	×	×	✓
[19]	Thirunavukkarasu et al.	×	✓	×	×	×	✓
[33]	Mohammadi et al.	×	✓	×	×	×	×
Current paper		✓	✓	✓	✓	✓	✓

✓ denotes included, and × denotes not included.

The rest of this article is organized as follows: Section 2 explores the different types of ESSs used in MGs and energy hubs. Section 3 presents integration strategies and models of ESSs in MGs. Section 4 presents the energy management strategies for MGs with ESS. Section 5 presents software used in modeling ESSs in MGs, economic assessment indices, and uncertainty analysis methods. Finally, Section 6 is dedicated to presenting conclusions and future directions of ESS in MGs.

2. Types of Energy Storage Systems Used in Microgrids and Energy Hubs

Generally, ESS used in MGs can be classified into three categories: energy store type, nominal power, energy ratings, and applications, shown in Figure 6. ESS can store energy chemically, as in hydrogen-based energy storage systems (HBS); mechanically, as in pumped hydro storage systems (PHS), compressed air energy storage systems (CAES), and flywheel energy storage systems (FWES); electrically, as in supercapacitor energy storage systems (SCES) and super-magnetic energy storage systems (SMES); and electro-chemically, as in lead acid batteries (LA), lithium-ion batteries (Li-ion), sodium sulfur batteries (NaS), zinc-bromine batteries (ZnBr), nickel-cadmium batteries (Ni-Cd) and vanadium redox batteries (VR) [27].

The ESSs, considering their nominal power and energy, can be classified into long-, medium-, and short-term ESSs. PHS and above-ground and underground UCAES and ACAES are long-term types. Medium-term types are VR, ZnBr, Li-ion, LA, NaS, Ni-Cd, and HES. Short-term technologies comprise FWES, SMES, and SCES [34].

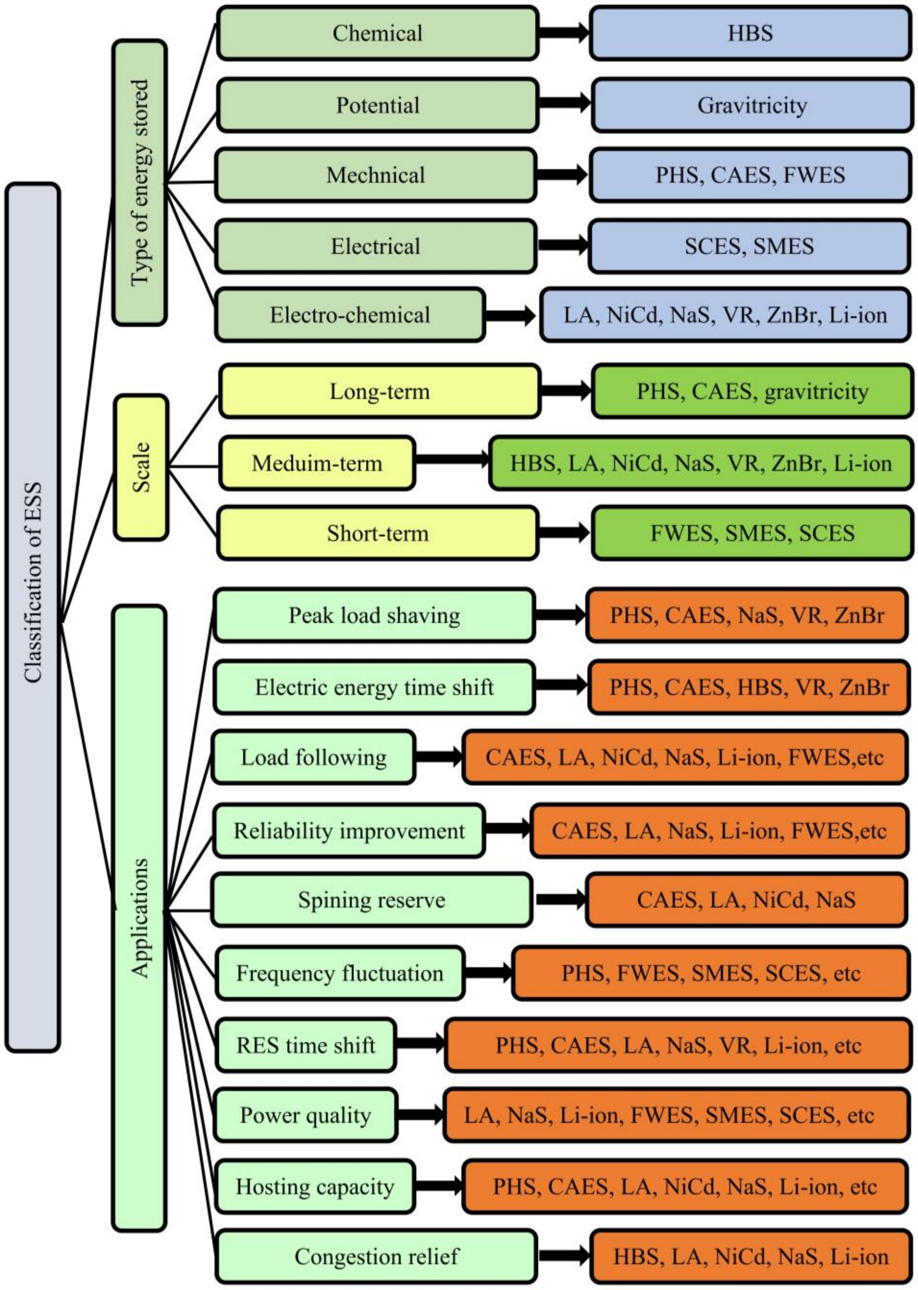


Figure 6. Classifications of ESSs according to energy store type, nominal power and energy ratings, and applications.

ESSs have different technical characteristics, such as energy density, power density, response time, discharging time, efficiency, and lifetime. Therefore, each type has its suitable applications, according to the characteristics of each type, as described in Figure 3. The following subsections briefly describe many ESSs commonly integrated into MGs. The main features of each type are introduced, along with the applications for which they are used.

2.1. Pumped Hydro Storage System

The PHS is a type of hydroelectric ESS. It is composed of two water reservoirs at different levels, where the electric energy is generated when water flows from the upper reservoir to the lower one and passes through the turbine. During off-peak load and low-cost energy hours, the energy is stored by storing the water in the upper reservoir, using a pump. PHS functions similarly to a battery, in that it can store and then release energy as required. The PHS is characterized by a long lifespan of about 40–60 years. Its rated power exceeds 50 MW based on the reservoir's location and capacity [34]. The PHS efficiency varies between 75% and 85%, and its discharge time relies mainly on the reservoir's capacity. PHS discharge time may exceed 24 h. However, the PHS has a slow response time of several hours.

MGs use PHS to shift electric energy and RES timing, shave peak load, improve hosting capacity, and mitigate frequency fluctuations. Adeyanju et al. [35] proposed a dedicated pumped-hydro storage-based MG planning and operation for distribution network support, where the MG was oriented to service rather than operation. A unique short-term operation capacity index, power purchase agreement, and levelized energy cost were used to manage the MG without affecting the distribution network. The results demonstrated that while deviation tracking of PHS can minimize specialized MG operation costs, it may make the MG overly conservative and limit its profitability. Dedicated MGs reduced distribution network pollutant emissions and power losses in all situations. However, dedicated MG storage facilities may need to be well-planned to make the distribution network safer, especially considering the network's tendency to lose power during high wind and solar power profiles. A PHS non-strategic and strategic involvement was examined by Alharbi et al. [36] in day-ahead energy and performance-based regulation (PBR), including regulating capacity and mileage markets. The PHS was modeled in hydraulic short-circuit mode with specific operational limitations and combined with an energy-cum-PBR market-clearing model. Because of its flexibility in regulation-up capacity and mileage provisions, strategic PHSs made more significant profit than conventional PHSs. The PHS energy market offer/bid approach was more conservative than in the regulated markets, to secure the selection of its bids and maintain its reservoir water volume in all stochastic scenarios of demand, RES generation, and rival offers.

In Su et al. [37], optimal Taiwan power system scheduling was developed to coordinate highly penetrated RESs and PHS under the needed spinning reserve. Simulations showed that Taiwan's PHS units could mitigate the duck-shaped net load curve in future Taiwan power system generator scheduling, even in the worst case. A wind-solar-thermal-hydro-coupled multi-source standalone MG considering demand response and PHS was presented by Zhao et al. [38]. For peak load shaving, load partitioning was suggested to obtain time-of-use in demand response. The simulation results showed that the multi-source coordination increased the operation's profit and promoted wind and solar power accommodation. Rezaee et al. [39] suggested a strategy to determine the optimal location of battery swap stations in microgrids with PHS, PV, wind, and geothermal units. The results found that the optimal location of the battery swap station depended on its size and maximum charging power but not on PHS capacity or maximum charging or discharging power.

While PHS has some advantages over other forms of energy storage, it also has several disadvantages, including:

- High upfront costs: One of the main disadvantages of PHS is the high upfront cost of building and installing the necessary infrastructure. This includes the cost of constructing the reservoirs, powerhouses, and transmission lines needed to transport the electricity to where it is needed.
- Limited availability of suitable sites: Another disadvantage of PHS is that it requires a suitable site with two water reservoirs at different elevations, which can be difficult to find in some areas. This means that PHS may not be a feasible option for all regions.
- Environmental impacts: The construction of PHS facilities can have significant environmental impacts, including flooding large areas of land to create the lower reservoir and the potential for habitat destruction and water pollution. Additionally, the large amounts of concrete and steel required for construction can lead to significant carbon emissions.
- Water availability: PHS requires large amounts of water to operate, and in areas where water resources are scarce or subject to droughts, this may not be a sustainable option.

Additionally, the water used for PHS may need to be treated to prevent contamination, which can add to the cost and complexity of the system.

- Energy loss: While PHS is a relatively efficient way to store energy, energy losses are still associated with pumping water uphill and generating electricity. This means that some energy stored in the system is lost as heat or friction, reducing the system's overall efficiency.
- Limited scalability: While PHS can be an effective way to store energy on a large scale, it may not be practical for smaller applications due to the high upfront costs and the need for suitable sites. This means that PHS may not be suitable for all energy storage needs.

2.2. Compressed Air Storage System

CAES is equivalent mainly to PHS in terms of its applications. However, instead of pumping water from a lower to an upper reservoir during periods of excess power, ambient air or another gas is compressed and stored under pressure in a CAES underground cavern or above-ground container. During peak load hours, the pressurized air is heated and expanded in an expansion turbine, driving a generator for power production. The CAES's capacity reaches 600 MWh, and its rated power can reach 400 MW. The CAES has a lower discharge time compared to PHS. It is only 4 h long. It has a faster response time than the PHS, of about 1–10 min. The CAES has a lifespan of up to 40 years, and its efficiency reaches 90% [34].

MGs use CAES to shift electric energy time, shave peak load, mitigate load variation issues, enhance the MG's reliability, apply spinning reserves, mitigate frequency fluctuation issues, and improve the hosting capacity. Jalili et al. [40] developed an energy hub model to optimize day-ahead microgrid operation with many energy carrier infrastructures. The proposed strategy also managed the combined cooling, heat, power units, wind turbines, PV stations, and ESS. The adopted ESS included an ice storage conditioner and a thermal energy storage system. A solar-powered CAES was examined for its effects on energy hub performance, efficiency, and environmental costs. ESSs reduced operation costs and emissions in day-ahead energy management when deployed on a typical energy hub. A cost-effective two-stage planning and scheduling strategy for microgrids with CAES and preventive maintenance was proposed by Gao et al. [41]. A two-objective planning model was derived in the first stage based on power loss and voltage deviation, to find the best MG location and size. In the second stage, a stochastic scheduling model was developed to balance distributed generation outputs, CAES charging and discharging power, microgrid power exchange costs, and DG preventive maintenance costs. The IEEE testing system demonstrated that CAES and preventive maintenance could decrease the operation cost of MGs by boosting wind power penetration and increasing the MG's self-sufficiency by decreasing its reliance on the main grid.

A techno-economic analysis of adiabatic CAES was conducted by Li et al. [42]. An MW-scale adiabatic CAES plant and microgrid were dynamically modeled to analyze dynamic system performance during emergency backup power. An economic benefit estimation model was also created to analyze the economic benefits of adiabatic CAES operation with different microgrid designs, power supply reliabilities, and diesel costs. The study found that decreasing mechanical inertia can reduce power recovery time by 8 min and increase air pressure ramping rate by 1 min when an MW-scale adiabatic CAES system is utilized for emergency backup. Further, the adiabatic CAES can often restore power to critical loads in several minutes, and hence it cannot replace an uninterruptible power supply. Maintaining power continuity requires a hybrid system with adiabatic CAES and fast-response electrical energy storage devices like flywheels. In a microgrid with low power supply reliability, high diesel cost, and abundant RESs, adiabatic CAES can provide emergency backup power at a lower cost than diesel generators. Wen et al. [28] developed a new energy hub technique to optimize a microgrid's performance with diverse energy carriers for each day. The target was decreasing running costs and considering environmental requirements. The impacts of solar-powered CAES on energy hub performance were studied and analyzed. The results proved that energy storage is crucial in decreasing operating expenses. The ESS can reduce the power demand during peak hours and mitigate RES stochastic fluctuations.

Latha et al. [43] suggested using CAES for MGs to meet demand under varying load situations by regulating grid frequency via an airflow controller. The simulations verified CAES's role in balancing the mismatch between power generated and consumed. Hamedi et al. [44] evaluated the performance of a multi-carrier microgrid with high-efficiency technologies like CAES and power-to-gas systems. A multi-objective model was formulated to reduce operating costs and greenhouse gases. CAES's simple-cycle mode added flexibility to the charging and discharging modes, and further reduced peaks with demand response. The results showed that the mix of CAES and P2G systems mitigated wind power curtailment and decreased cost and pollution.

Finally, although CAES has some advantages over other forms of energy storage, it also has several technical disadvantages, including:

- Energy loss: One of CAES's main technical disadvantages is its lower round-trip efficiency than other energy storage systems. This means some energy stored in the compressed air is lost during storage and retrieval, reducing the system's overall efficiency.
- Limited operating times: another technical disadvantage of CAES is that it is typically only capable of operating for a few hours at a time, which makes it less suitable for applications that require longer-term energy storage.
- Geographical limitations: CAES requires suitable underground reservoirs for the compressed air, which can be challenging to find in some areas. Additionally, the reservoirs must be located near the power generation facility to minimize energy losses during transmission.
- Equipment wear and tear: Compressing and decompressing air can cause wear and tear on the equipment used in the CAES system. This can lead to maintenance issues and the need for replacement parts, which can add to the cost and complexity of the system.
- Environmental impacts: The construction and operation of CAES facilities can have environmental impacts, including the potential for air and water pollution. Additionally, the noise and vibration associated with air compression and decompression can negatively impact local wildlife and communities.
- Cost: The cost of building and operating a CAES system can be high, especially compared to other energy storage systems. This can make CAES less attractive economically, especially in regions with relatively low electricity prices.

2.3. Hydrogen-Based Storage System

In the HBS, power is generated by releasing energy in the chemical bonds of atoms and molecules via electron transfer reactions. HBS has the lowest efficiency compared to the other ESS technologies. Its efficiency is not more than 66% and may reach 20%. The HBS has limited applications compared to the other medium-term ESSs. Generally, it is used for electrical energy shifting and transmission congestion relief. In addition, it is suitable for applications with a life not exceeding 15 years. A techno-economic feasibility study was conducted by Cruz-Soto et al. [45] to implement a hydrogen-based power-to-gas-to-power in a rural Baja California, Mexico MG. This novel alternative used an electrolyzer to produce green hydrogen from excess renewable energy in winter, store it, and inject it into the grid as electricity using a fuel cell in the high-energy-demand season. This study showed that using a mix of hydrogen and fuel cells to replace diesel generators can reduce CO_2 emissions by 27%, but the fuel cell cost must be half-reduced to be cost-competitive. The hydrogen storage system was a viable medium-to-long-term option for decarbonizing distributed energy generation. A model-based parametric analysis was implemented by Monforti et al. [46] to determine the optimal size of a hybrid of battery and HBS in a real hybrid renewable microgrid in Huelva, Spain. Four storage configurations—battery-only, H_2-only, hybrid battery priority, and hybrid H_2 priority—were assessed under different energy management strategies. The system performance was measured using many index parameters, like loss of load, overproduction, round-trip ESS storage efficiency, and total storage cost, depending on ESS sizing characteristics. The results indicated that a hybridized ESS capacity was advantageous from an energy security and efficiency standpoint, but represented a high additional overall cost, particularly for the HBS, which presented higher expenses. Increasing the capacity of HBS to absorb surplus energy was more beneficial than batteries.

K/bidi et al. [47] presented a multi-stage power and energy management strategy for microgrids with PV units, a battery ESS, a fuel cell, and an electrolyzer. The power management system used distributed explicit model predictive control, while the energy management system used a mixed-integer quadratic programming optimization approach. Unlike previous works, the integration of power and energy management systems was proposed, and their interplay was studied to increase overall system efficiency. This was a significant step forward for advancing hydrogen technologies and hybrid installations that utilize intermittent power sources. Shi et al. [48] proposed a planning and optimization model for microgrid clusters with hydrogen storage systems. The suggested strategy was implemented in three stages. In the first stage, a two-layer optimization model was used for capacity planning and daily operating optimization of energy storage schemes in diverse circumstances. The second stage compared clustered microgrids and shared energy storage to assess the total benefits of all scenarios, whereas in the third stage, the benefits of the microgrid cluster members were reasonably distributed. The results showed that power outages could be avoided, microgrids could depend less on the super grid, peak regulation capacity could be increased, more renewable energy could be used, and there could be financial benefits if microgrids and HBS are well planned together. A hierarchical self-regulation control for an MG with HBS was suggested by Yang et al. [49]. It is divided into supervisory and local layers. Based on the operation cost function, the supervisory layer economically controls the battery and HBS output power, whereas the lower layer is concerned with improving the system stability by applying global power support-based virtual inertia control. The results validated the superiority of the suggested strategy compared to the case when droop control only was applied.

Hydrogen-based energy storage has some advantages over other forms of energy storage, but it also has several disadvantages, including:

- High cost: One of the main disadvantages of hydrogen-based energy storage is the high cost of producing, storing, and transporting hydrogen. This is due to the energy-intensive nature of the electrolysis process in addition to the cost of building and maintaining the necessary infrastructure for storage and transportation.
- Efficiency losses: Another disadvantage of hydrogen-based energy storage is the efficiency losses associated with converting electricity to hydrogen and back to electricity. This can result in a lower round-trip efficiency than other energy storage systems, making it less cost-effective in some applications.
- Safety concerns: Hydrogen is highly flammable, and can be explosive under certain conditions, presenting safety risks during production, storage, and transportation. This can add to the cost and complexity of the system, as additional safety measures must be taken to prevent accidents.
- Limited infrastructure availability: Some existing infrastructure for transporting and storing hydrogen is not as widely available or established as other energy storage systems, such as pumped hydro or lithium-ion batteries. This can make it difficult and costly to implement hydrogen-based energy storage in some regions.
- Environmental impacts: The production of hydrogen through electrolysis typically requires a significant amount of energy, which can lead to greenhouse gas emissions if the electricity is generated from fossil fuels. The transport and storage of hydrogen can also have environmental impacts, such as the potential for leaks or spills that can contaminate water and soil.

- Scalability: while hydrogen-based energy storage can be adequate on a small-to-medium scale, it may not be as scalable as other energy storage systems, due to the limitations of the electrolysis process and the need for large-scale infrastructure for storage and transportation.

2.4. Lead Acid Storage System

In the LA batteries, Pb is used as the anode, PbO_2 as the cathode, and sulfuric acid as the electrolyte. When a battery is discharged, a chemical reaction causes ions to move from the anode to the cathode in an external circuit. When batteries are charged, voltage is applied between the electrodes, causing ions to flow in the opposite direction from the discharge. LA is characterized by a fast response time of less than 1 s and a short discharge time that does not exceed 4 h. LA's efficiency reaches 80%. Generally, it is implemented in MGs for regulating the grid's frequency, improving networks' reliability, mitigating the stochastic behavior of loads, and handling congestion.

In Sharma et al. [50], a techno-economic analysis of a building's integrated PV system and LA storage system in a South Norwegian house was carried out, with a suitable energy tariff for decreasing the annualized energy cost. The financial and technical results revealed that such systems with ESS could perform much better than their counterparts, from a technical and economic point of view. Santos-Pereira et al. [51] analyzed an MG's operational requirements when coupled with LA and Li-ion batteries. The study was carried out for an MG in Ilha Grande in Brazil, and it took into account battery life cycles, logistics, maintenance, and the initial investment. The results found that the maximum DOD limit of LA batteries affected the size of the storage system, which tended to be much higher than the Li-ion batteries for the same project. Moreover, the LA batteries' equalization process and low charge and discharge curve rates depended too much on an auxiliary energy source. LA batteries have certain advantages, but their disadvantages, such as limited lifespan (typically three to five years), high regular maintenance (regular maintenance, such as topping up with distilled water, cleaning of terminals, and regular checking of electrolyte levels), heavy weight, low energy density that limits their usefulness in applications that require high power output, environmental concerns from toxic materials such as lead, sulfuric acid, and cadmium, limited charging efficiency, and temperature sensitivity that necessitates the presence of additional cooling or heating systems to maintain their performance, make them less attractive compared to newer battery technologies like Li-ion.

2.5. Lithium-Ion Battery Batteries

In Li-ion batteries, the cathode is made from lithium metal oxide, and the anode is made from a graphite carbon cell, while the electrolyte can be prepared using an organic solvent with dissolved Li salt. Li-ion is featured with the highest efficiency, up to 97%, compared to the long- and medium-term ESSs. It has a fast response time of about less than 1 s and a low discharge period of about an hour. The Li-ion battery has a life expectancy of fewer than 15 years.

Li-ion batteries are preferred for load following, reliability enhancement, frequency regulation, and congestion relief applications. A new methodology for calculating the optimal size of the Li-ion battery integrated into an MG was suggested by Fallahifar et al. [52]. The Li-ion battery degradation function was formulated, and integrated into the size- model. The formulated problem was mixed-integer linear programming to minimize the overall system costs. Simulations with different cycles and depths of discharge were carried out. The results demonstrated the efficiency of the proposed method. In Wei et al. [53], five sets of accelerated aging were extracted from the working profile of an MG with EVs and PV stations. Many experimental studies were carried out to study the effect of various capacities of ESS on Li-ion degradation. A reduced-order semi-empirical model was developed, and its accuracy was demonstrated. The Li-ion battery degradation was estimated with relative errors of less than 1.6%, and the computational time for 500 cycles was less than 5 s. The relative errors were further reduced with an artificial neural network correction.

In González et al. [54], a monitoring system was proposed to visualize the proper operation of a Li-ion battery in the MG. The Internet of Things (IoT) technology was used, and the operator could monitor the lithium-ion system in real time for data such as current, voltage, temperature, and state of charge (SOC). The proposed system was superior to previous works in terms of operation in the long term, medium-scale power and capacity alerts for a safe range of critical magnitudes, real-time operating conditions, and compatibility management. Habib et al. [55] proposed a protection scheme for MGs with Li-ion batteries when communication is established. Further, a control algorithm was designed for the Li-ion ac/dc with the capability of operating in a single mode, to eliminate the need for control command signals to alter the controller between the different modes. During the islanded mode, the Li-ion battery helped the system ride through the communication failure by contributing to the fault current and assisting the circuit breaker to trip.

Esparcia et al. [41] conducted a techno-economic analysis to compare the long-duration Li-ion batteries, FWESS, and LA batteries for isolated MGs. The results showed that FWESS offered a relatively high probability of yielding a lower levelized cost of storage and levelized cost of electricity than Li-ion batteries. A higher probability could be attained if the cost of FESS components is reduced or diesel prices increase.

While lithium-ion batteries have several advantages over LA batteries, they also have a few disadvantages, including:

- Cost: Li-ion batteries are generally expensive. The high cost is due to the manufacturing complexity and the use of expensive materials such as cobalt and nickel.
- Capacity loss: Li-ion batteries lose capacity over time and with use. The rate of capacity loss depends on factors such as temperature, charging and discharging cycles, and the depth of discharge.
- Performance degradation: Li-ion batteries can experience performance degradation over time. The battery's ability to hold a charge and deliver power can decrease, reducing battery life.
- Limited temperature range: Li-ion batteries have a limited operating temperature range. Extreme temperatures can cause the battery to degrade faster, reducing its performance and lifespan.
- Environmental concerns: Li-ion batteries contain toxic materials such as cobalt and nickel, which can harm the environment if not disposed of properly.
- Safety: Li-ion batteries are susceptible to thermal runaway, which can cause them to overheat and catch fire.

2.6. Vanadium Redox Flow Batteries

Generally, in a redox flow battery (RFB), electricity is made by a redox chemical reaction between electrolytes in two tanks that are separated by an ion-selective membrane. The electrolytes can be switched in these batteries, which means they can be used as cathodes or anodes. The size of the tanks and the materials used as electrolytes directly affect the size of the batteries. Vanadium is a prevalent and well-known example of this technology. VR batteries have an efficiency of 65 to 85% and a response time of up to 10 min. They have a short life expectancy of fewer than ten years. The discharging time of VR is a few seconds for small-scale applications, and can extend to ten hours for medium-scale applications.

VR batteries are preferred for an electric time shift, peak load shaving, load following, reliability enhancement, power quality improvement, frequency regulation, and congestion relief applications. In Mohiti et al. [56], a novel EMS for isolated MGs was proposed. The objective was to optimally schedule the energy and reserve of VR batteries in coordination with DGs. The hierarchical control structure decreased the total operation cost and preserved the MG's dynamic and static frequency securities. Furthermore, the non-linear characteristics of VR batteries were considered in the formulated model and were properly linearized by an efficient linearization approach. The results showed that the optimal coordination of VR batteries reduced the operating cost by more than 11.67%. Huang et al. [57] offered insights into enhancing the performance of VR batteries, and provided a systematic analysis of VR battery problems in MGs. The analysis was carried out in terms of modeling the VR battery, optimizing the structure's design, optimizing the flow field and flow, designing the stack, treating the heat, and figuring out how the temperatures are distributed.

In Sarkar et al. [58], a unique integration of PV sources, wind turbines, biomass, and VR batteries incorporated into a hybrid MG was modeled and employed. The capacity determination of RESs was carried out through HOMER software. In comparison, the peak load shaving was performed through PSCAD simulation. An intelligent scheduler and controller were also designed, to ensure zero loss of power supply probability. The simulation used real-world data from RESs, VR batteries, and consumption profiles. In Jefimowski et al. [59], a new approach to optimizing the parameters of VR batteries and EMS for the transportation microgrid was developed by considering the payback period as the optimization criterion. The VR batteries in the transportation MG were used for regenerative and renewable energy and power-shaving applications. A sensitivity analysis revealed that incorrect sizing of VR batteries has little impact on the payback period. However, the deviations from the EMS parameters had a non-negligible effect on the payback period.

In Chen et al. [60], VR batteries were vital in mitigating voltage fluctuations and achieving optimum economic dispatch in the DC MGs. To this end, a distributed cooperative control system was designed and incorporated with droop-based primary controllers to ensure the accuracy of the power shared. The designed control scheme guaranteed information synchronization by exchanging DG data over a low-bandwidth communication network. The simulations showed the proposed controller method's efficacy in maintaining MG stability.

VR batteries have certain advantages, but disadvantages, such as low energy density, complex design (involving many components such as pumps, tanks, and membranes) leading to higher manufacturing costs and lower reliability, limited power density (cannot deliver high power outputs quickly), low efficiency, temperature sensitivity, high maintenance (replacement of electrolyte solutions, cleaning of membranes, and checking of pumps and tanks), and limited lifespan (typically 10–15 years), make them less attractive compared to other battery technologies like Li-ion batteries.

2.7. Supercapacitor Energy Storage System

SCESs have the advantage of having a fast response time that does not exceed 1 s, and their efficiencies may reach 97%. However, they have a low energy density and a high self-discharge loss of about 20–40%. Their life span is approximately 10–35 years [61–63]. SCESs are commonly used for power quality improvement and frequency regulation. A passive fractional-order sliding-mode control of a SCES in MG was developed by Yang et al. [64]. A storage function was established to study the SCES's physical characteristics. The efficiency of the suggested controller was tested in terms of its capability to supply active and reactive power, its behavior under power grid faults, and its robustness in the face of increasing system uncertainties. Serban et al. [48] developed an improved control approach to synchronize and transfer autonomous MGs to the grid. The proposed strategy relied mainly on the SCES inverter coordinating the MG in both islanded and grid-tied operational modes. The target was to achieve a seamless transfer between the two modes. The results demonstrated the proposed SCES inverter's ability to ensure seamless transfer of the MG in both modes with no change in the control requirements of the other inverters integrated into the MG.

Chang et al. [49] presented an active damping approach relying on an SCES to overcome the instability of DC MG, due to the constant power loads. The simulations demonstrated that the proposed method is effective for DC-MGs, in which ESS is essential, multiple flexible elements are present, and different operation modes are available. Jami et al. [65]

proposed the SCES as a fast-responding ESS, to overcome the low-inertia issues in DC MGs. The SCES was connected to the grid via a bidirectional converter, and an inner control loop with a virtual capacitor and a virtual conductance-based control strategy was implemented to simulate inertia and damping. The effectiveness of the proposed control structure was demonstrated through numerical simulations. In de Carvalho et al. [66], a fuzzy-based control strategy was applied to smooth out the power fluctuations of a wind generation unit and manage the state of charge of SCES during faults in the MGs. The efficacy of the suggested approach was examined and compared with a traditional technique.

However, like any technology, SCESs also have some disadvantages, including:

- Low energy density: SCESs have a low energy density, limiting their usefulness in applications that require high-energy storage.
- Voltage limitations: SCESs have a voltage limitation, which means they cannot be used as a direct replacement for batteries in applications that require a specific voltage range.
- High self-discharge rate: SCESs have a high self-discharge rate, which means they lose charge quickly when not in use. (This makes them unsuitable for applications that require long-term energy storage.)
- Cost: SCESs are more expensive than other energy storage devices, such as batteries. The high cost is due to the manufacturing complexity and the use of expensive materials such as carbon and electrolytes.
- Limited temperature range: SCESs have a limited operating temperature range. Extreme temperatures can cause the capacitor to degrade faster, reducing its performance and lifespan.

2.8. Flywheel Energy Storage System

FWES stores electric energy in the form of kinetic energy from a rotor mass spinning at high speed via an integrated motor generator. The amount of energy that can be stored is proportional to the object's moment of inertia times the square of its angular velocity. The same motor-generator produces electricity during discharge by drawing down the kinetic energy. In general, FESS features a lifespan of about 15–20 years, a fast response time of less than 1 s, and the ability to inject high power quickly. The discharge time of FWES ranges from milliseconds to 15 min. Hence, FWES is preferred in many applications in future MGs, particularly those with integrated RESs.

FWESs are commonly used for load-following applications, reliability enhancement, power quality improvement, and frequency regulation. A new structure of FWES in MGs was presented by Saleh et al. [67]. The FWES, the fuel cells, and the PV were connected through the same inverter to the same bus, unlike conventional topologies where the FWES is connected through a separate inverter. Fuel cells enable the FWES to function as an uninterruptible power supply unit for extended periods. The suggested topology reduced the overall system cost, increased PV penetration level, and decreased power losses, compared to the traditional topology. The results proved the capability of FESS to support the MG with reactive power and maintain the MG's stability. Kikusato et al. [68] developed a frequency control strategy based on FWES for low-inertia MGs. It utilizes the fast reaction time characteristic of FWES to maintain the MG frequency as stable. The performance of the suggested control system was evaluated under several frequency events, and the results demonstrated the capability of the FWESS to provide a smooth frequency profile. In Mahdavi et al. [69], an enhanced control approach was proposed for FWES to preserve the frequency stability of MGs.

Unlike traditional techniques, the suggested controller was applied to the grid-side converter to boost the FWES's ramp rate and decrease the frequency deviation due to load changes. The proposed control system was a three-layer controller, and consisted of a DC-link voltage control layer, a speed control layer, and a field-oriented control layer. The linear model of the system was derived, and the small-signal analysis was conducted to design the parameters of the proportional integral controllers optimally. The experimental results verified the superiority of the control system developed, compared to the conventional method.

Some of the main disadvantages of FWESs include:

- Limited energy storage capacity: FWESs have a limited capacity compared to other storage technologies, such as batteries (making them unsuitable for long-term energy storage applications).
- High cost: FWESs are more expensive than other storage technologies, such as batteries. The high cost is due to the manufacturing complexity and the use of expensive materials such as carbon fiber.
- Noise and vibration: FWESs produce noise and vibration during operation, which can be a concern in certain applications.
- Limited lifespan: FWESs have a limited lifespan due to wear and tear on the moving components. They require regular maintenance and replacement, adding to their overall cost.
- Temperature sensitivity: FWESs are sensitive to temperature changes. They perform poorly in extreme temperatures, and require additional cooling or heating systems to maintain their performance.
- Safety concerns: FWESs can be dangerous if not properly contained. The high-speed rotating mass can cause injury or damage if it comes loose from its housing.

2.9. Superconducting Magnetic Energy Storage

SMESs are characterized by high efficiency of up to 97%, a fast response time of fewer than five milliseconds, and a life expectancy of about 15–20 years. They have a high self-discharge loss of about 10–15%. Their discharge time ranges from milliseconds to 8 s.

SMESs are commonly used for power quality improvement and frequency regulation. Jin et al. [70] proposed an SMES based on an active shunt filter to mitigate harmonics, power fluctuations, and unbalanced currents in MGs with PV sources. The shunt filter's AC side was connected to the point of common coupling, while its DC link was interfaced with a DC-to-DC converter and an ES superconducting coil. A hysteresis-based SVPWM-based multi-objective control strategy was applied to suppress power fluctuations and mitigate harmonics. In addition, a fuzzy logic control approach for the DC-to-DC converter was employed to preserve the DC-link voltage while decreasing the SMES depth of discharge. Simulation results showed that the suggested strategy reduced harmonics and kept the DC-link voltage stable. In Salama et al. [71], SMES was used to mitigate the intermittent behavior of wind generation sources. A fuzzy logic controller was adopted to realize active power sharing, while the SMES was responsible for regulating voltage fluctuations. The results proved the effectiveness of the suggested control strategy in mitigating the frequency fluctuations and the capability of the SMES controller to maintain the voltage stability.

In Kotb et al. [72], a comparative analysis was carried out to evaluate the performance of DC MGs with batteries and SMES. A fuzzy logic control strategy for the battery and SMES was implemented to ensure the MG's stability and enhance power quality under extreme climatic and loading changes. The developed FLC was in charge of smoothing the load power and mitigating DC-bus fluctuations. The proposed controller was examined under severe climatic conditions, such as wind gusts, rapid shadow, and sudden balanced and unbalanced loading events. The findings demonstrated the efficacy of the suggested methods in enriching MG stability. Moreover, the superiority of SMES over batteries was proved in terms of response time, peak overshoot and undershoot, load voltage profile, and load power smoothness. Alkhafaji et al. [73] focused on using SMES to enhance batteries' lifespan, maintain system reliability, and balance RES-generated power and consumption, especially in the presence of PV sources. The charge and discharge modes of the SMES were controlled using fuzzy logic. Simulations verified the robustness and effectiveness of the strategy applied. In Zhang et al. [74], the SMES was used to suppress sizeable transient power fluctuations in a DC MG. To this end, a voltage-based segmented control approach was developed. The voltage deviation caused by power distribution can be tolerated by

SMES. Meanwhile, the dynamic recovery capability of the DC voltage is improving. The proposed control method has the advantage that it is independent of other components in DC MGs, and does not rely on communication.

While SMESs have certain advantages, their disadvantages, such as limited energy storage capacity, high cost, cryogenic cooling to maintain the superconductivity of the coils that adds to the complexity and cost of the system, temperature sensitivity, safety concerns (they can be dangerous if not properly maintained, and cryogenic cooling systems can cause injury or damage if not handled properly), and limited lifespan (due to wear and tear on the superconducting coils), make them less attractive, compared to other storage technologies such as batteries or flywheels, especially for applications that require long-term energy storage.

2.10. Hybrid Energy Storage Systems

Hybrid ESSs (HESSs) have evolved to obtain the needed performance by combining two or more ESSs with different characteristics. Individually, ESSs are incapable of performing the required task. They have a limited lifespan, a high price, a low energy and power density, and a poor dynamic response [75]. Various HESS configurations have been presented in the literature, each considering storage type, interface, control technique, and service. For example, four hybrid storage systems were suggested by Elnozahy et al. [76]. A techno-economic strategy was carried out to evaluate the hybrids of batteries and SCES, batteries and FWES, batteries and PHS, and batteries and fuel cells, regarding their cost and the amount of greenhouse gas emitted from the system. A probabilistic approach based on the ANN was implemented to deal with the system uncertainties. The hybrid algorithm of PSO and GOA was developed to solve the proposed techno-economic model. A sensitivity analysis was performed to demonstrate the variable parameters that majorly influence investment costs and GHG emissions. The calculated solution revealed that the hybrid system of SCES and battery appeared to be a suitable option for current MGs, with improvements in emissions and a levelized cost of energy. A novel multi-level hybrid ESS topology composed of Li-ion and LA batteries was suggested by Jing et al. [77].

Furthermore, a power management approach was developed to eliminate the charge and discharge stress on the battery. The results showed that the suggested multi-level hybrid system effectively mitigated stress on batteries without causing a significant reduction in battery health. The financial analysis revealed no significant increase in overall system costs. Akram et al. [78] presented an optimization model to optimally determine the capacity of the MG components, like RESs, the hybrid system of batteries, and the SCES system. The objective of the proposed model was to minimize the cost, improve reliability, and reduce greenhouse gas emissions. A comparison analysis was performed, based on overall cost, reliability requirements, and greenhouse gas emissions. The results showed that the SCES prolonged the battery lifespan, and the MG with the hybrid storage system increased the system reliability, improved the environmental requirements, and had a lower cost. Oriti et al. [79] developed a power flow control method for a remote military MG that comprised a hybrid storage system of batteries and SCESs. The target of integrating SCESs with batteries was to increase the battery life by redirecting the higher-frequency current to the SCESs. The proposed control strategy ensures that the SCESs are not overcharged and that the SCES does not support the MG when its SOC falls below a certain threshold. The simulations and experimental results demonstrated the efficiency of the proposed control strategy for the hybrid storage system.

Coban et al. [80] investigated an isolated MG frequency and power balance by integrating the hybrid battery and PHS storage system. The objective was to ensure energy security by stabilizing the intermittent generation of RES. The results revealed that the MG exhibited a more consistent and smooth dynamic performance using the hybrid storage system than in the case where the storage system was not used. In Barelli et al. [81], the impacts of the hybrid of batteries and FWES on the performance of an MG coupled to a PV-based generation station were investigated. The energy performances of the different

MG configurations were also presented and analyzed. The gathered results showed a significant improvement in the battery, compared to the non-hybrid configurations.

HESSs have some advantages over single technology systems, but they also have several disadvantages, including [82]:

- Complexity: One of the main disadvantages of HESSs is their complexity. Integrating multiple storage technologies requires sophisticated control systems and advanced monitoring capabilities, to ensure the system works efficiently and effectively. This can make HESSs more expensive and difficult to operate and maintain.
- Cost: HESSs can be more expensive than single technology systems, due to the need for additional components, such as control systems, monitoring equipment, and power electronics. This can make them less cost-effective in some applications.
- Efficiency losses: HESSs can suffer from efficiency losses, due to the need to convert energy from one storage technology to another. This can result in lower overall round-trip efficiencies than single technology systems, making them less cost-effective in some applications.
- Scalability: while HESSs can be effective on a small-to-medium scale, they may not be as scalable as some single technology systems, due to the complexity of the system and the need for sophisticated control and monitoring equipment.
- Maintenance and repair: HESSs can be more complex to maintain and repair than single technology systems, due to the integration of multiple components. This can result in more extended downtime and higher maintenance costs.
- Environmental impacts: the manufacture and disposal of the components used in hybrid energy storage systems can have environmental impacts, including the potential for releasing toxic materials and greenhouse gas emissions.

To sum up, the optimal choice of energy storage technology or hybrid system will depend on the specific needs and requirements of the application, as well as the economic, safety, and environmental factors of the region.

3. ESSs in Microgrids: Integration Strategies and Models

This section will explore the integration strategies of ESSs into MGs, and their design models.

3.1. Integration Strategies

As shown in Figure 7, ESSs are generally integrated into MGs through four configurations: distributed, aggregated, isolated, and grid-tied. In the distributed configuration, ESSs are placed in different locations in the MG, while in the aggregated configuration, all ESSs are placed in the same location. In the isolated configuration, ESSs are disconnected from the grid, whereas in the grid-tied configuration, the main grid is available, which promotes all the system inertia.

For instance, in Hemeida et al. [83], a hybrid MG comprised of a PV system, a wind turbine, an ESS, and a diesel generator was introduced to meet load demands in Bernice, Egypt, a remote area on the Red Sea. Different configurations for the MG, such as a PV-battery configuration, wind-battery configuration, PV-wind-battery configuration, PV-battery-diesel configuration, wind-battery-diesel configuration, and PV-wind-battery-diesel configuration, were also suggested and analyzed. The goal of the design process was to optimize the cost of electricity, the renewable factor (RF), and the power supply's loss probability.

Hemeida et al. [84] introduced an optimal design approach for a remote MG in Makadi Bay, Red Sea, Hurghada, Egypt, consisting of an aggregated ESS, a PV generation source, and a wind turbine. The load demand data, solar radiation, temperature, and wind speed were recorded for a year, and used to find the optimal configuration of the system. The results demonstrated that constructing a hybrid MG comprising a wind generation source, PV, and ESS is cheaper than building each individually. Jalilpoor et al. [68] described an approach for determining the optimal size and management of distributed ESSs integrated into shipboard power systems. The system comprised four conventional generation units, two wind turbines, and two ESS units. The objective was to minimize the power generated from fuel oil-based generation units, the greenhouse gas emissions, and the cost. In Al-Ghussain et al. [85], a techno-economic analysis of an MG consisting of a wind turbine and a PV system was performed using four configurations—no ESS, PHS only, HBS only, and a hybrid PHS and HBS. The results revealed that integrating PHS and HBS with the PV and wind energy sources increased the RES fraction.

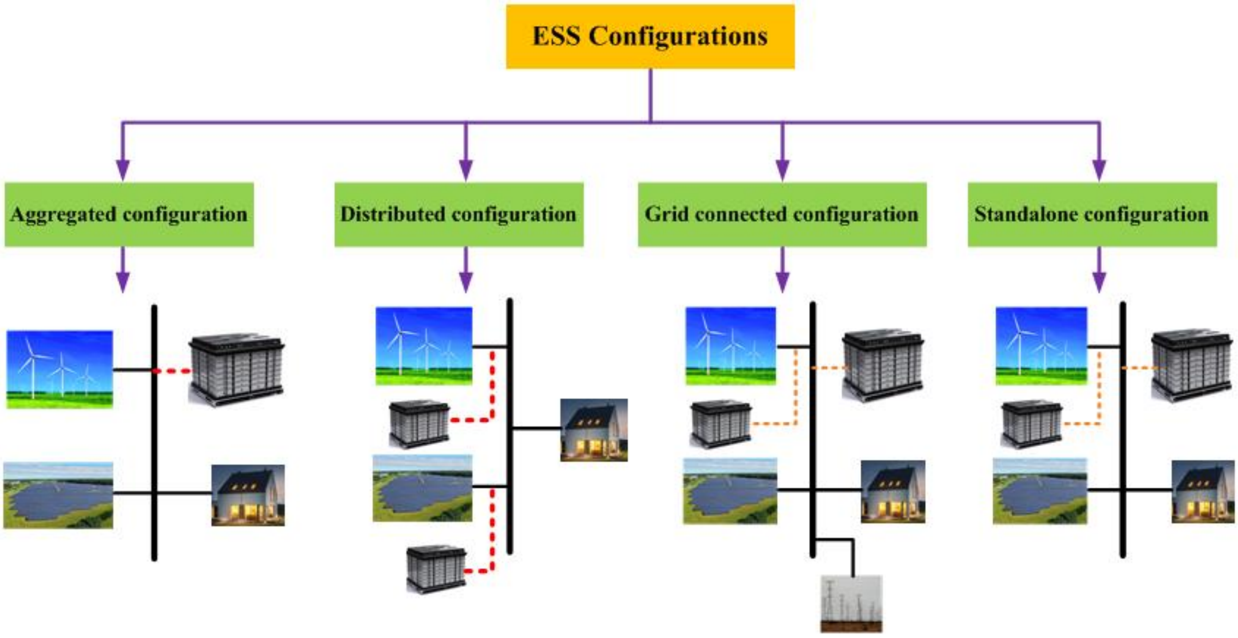


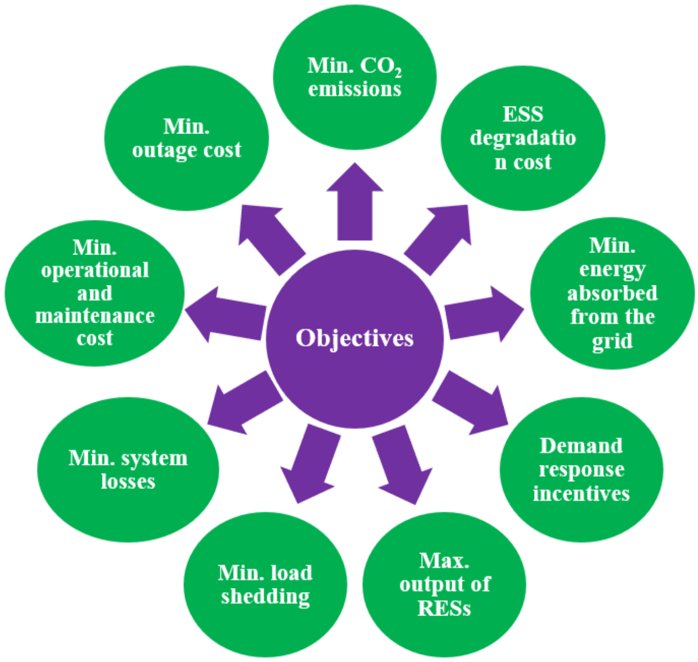
Figure 7. Configurations of ESSs in MGs.

A grid-tied MG consisting of a PV unit, an ESS, and electrical loads was suggested by Xie et al. [86] to verify the effectiveness of a proposed optimal sizing approach for a two-layer battery, taking into account the dispatch of a virtual ESS in a smart MG with a high PV penetration level. Sharma et al. [87] presented quasi-oppositional swine influenza model-based optimization with quarantine to reduce the total operation cost and optimize the size of a grid-tied MG, consisting of an aggregated Li-ion battery system, a wind turbine, a PV unit, a fuel cell, and a micro-turbine. In Sharma et al. [88], twelve suggested configurations of an MG with and without a grid-tied system for the rural community in India were studied in terms of the levelized cost of energy and total net present cost. Various generation sources were used, like a PV source, a wind turbine source, a hydropower source, and the main utility grid. The simulations showed that the hybrid configuration of a PV-wind-hydro-based utility grid-tied network was economically the best. Further, Yang et al. [89] investigated the fluctuation reduction problem of a grid-connected MG with a wind turbine and a battery ESS. The objective was to decrease the fluctuation of grid power by dynamically charging or discharging the battery ESS.

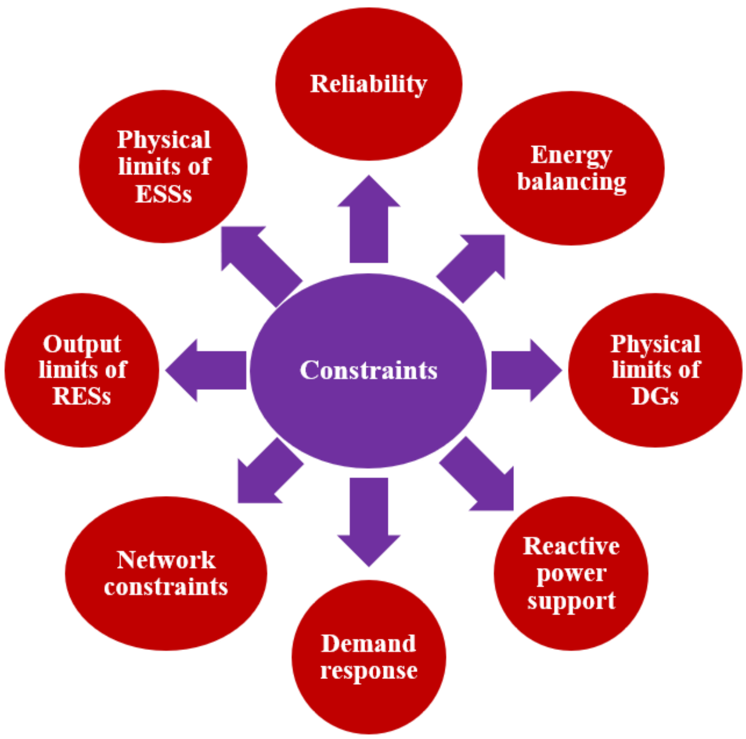
3.2. Integration Models

The key mathematical challenge in incorporating ESS into an MG is determining the optimal ESS size to prevent MG instability and collapse. The installation of ESS at a random or non-optimal size can result in increased costs, system losses, and increased ESS capacity. The MG sizing problem is commonly formulated as an optimization problem with single or multi objectives, and is subjected to a set of linear/non-linear constraints, as shown in Figure 8. Chen et al. [90] presented, for example, a method for the optimal allocation and economic assessment of ESS in MGs, based on net present value. It aimed to maximize the difference between the MG operating costs without ESS (C_{NS}^{op}) and with ESS (C_{S}^{op}). Bahramirad et al. [91] provided a methodology for finding the appropriate size of an

ESS in an MG when reliability criteria were considered. A larger ESS necessitates greater investment costs but reduces microgrid operational expenses. The problem's goal was to reduce both the ESS investment cost and the MG operation cost. The power balancing constraints and ESS charging (P^{ch}) and discharging (P^{dch}) rating power and capacity (E^{ESS}) constraints were considered. The reliability constraint was designed so that the expected load lost (ELL) did not exceed the maximum allowable limit (ELL^{max}).



(**a**)

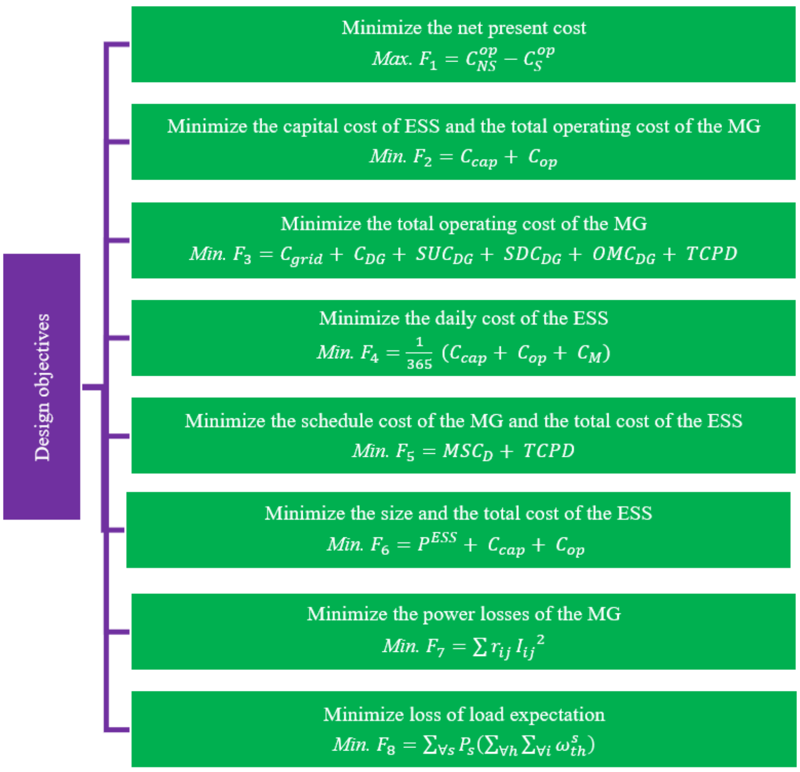


(**b**)

Figure 8. Energy management models (**a**) Objectives; (**b**) Constraints.

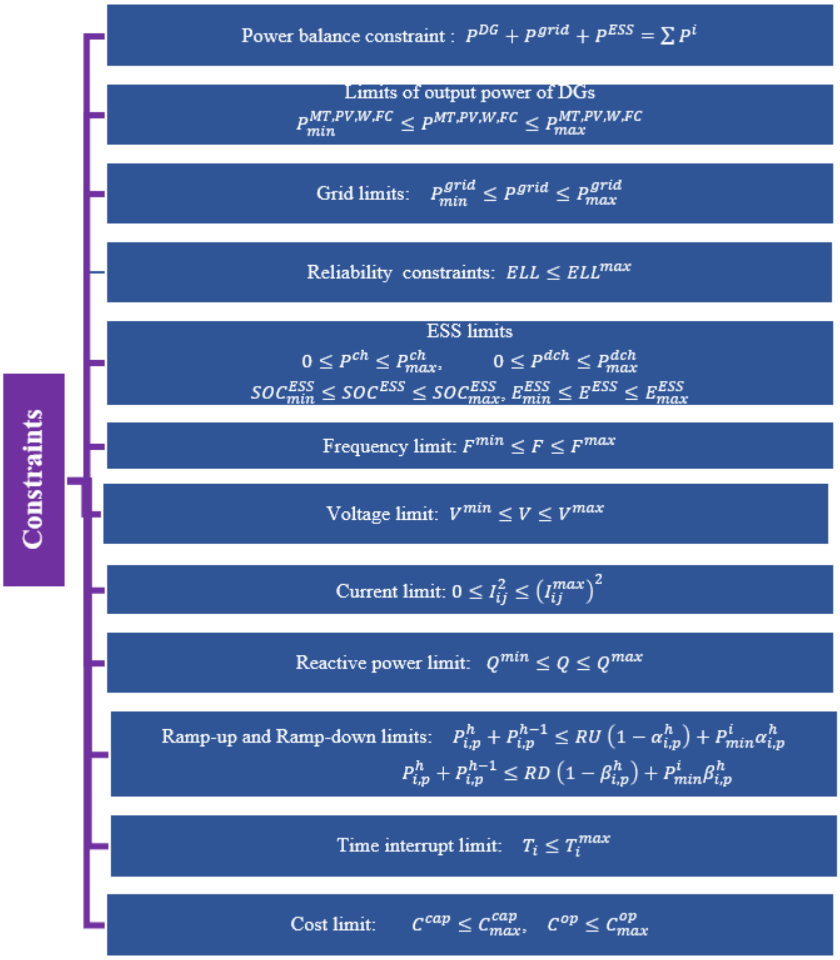
Sharma et al. [92] suggested that an ESS sizing model decreases the MG operating cost. The study considered the output power limits of DGs like wind turbines, PV systems, micro-turbines, and fuel cells. Furthermore, ESS limitations were modeled, and power grid constraints were used to limit grid sharing. In Xie et al. [93], the size of the ESS was determined based on the daily cost of the ESS. Besides the power generation limits, ESS constraints, and the power balance equation, the loss of power supply probability constraints were also considered. The value of losses in the MG was the main point in determining the required ESS capacity [94]. The current and voltage limitation equations were considered, to maintain the system's thermal and voltage stability. Furthermore, the reactive power capability constraints were taken into account. In Liu et al. [95], the size of ESS was calculated so that the lifecycle cost of the MG was decreased. The time interrupt limit was considered. The load interrupt time should not exceed a specific period. Nojavan et al. [96] aimed to reduce the MG operating costs, besides minimizing the expected load loss. The minimum downtime and uptime of DGs were considered in the proposed model.

Furthermore, MGs use either an MG central controller to manage a decentralized layout or a centralized EMS to ensure that all devices operate optimally. Although an EMS is necessary for the operation of the MG, its deployment necessitates the resolution of control, communication, and timing problems. The EMS models are usually formulated as mixed-integer, linear, or non-linear optimization problems [97]. As shown in Figure 9a, the EMS commonly aims to minimize CO_2 emissions, outage costs, ESS degradation costs, energy absorbed from the grid, operating and maintenance costs, system losses, and load shedding. In addition, the EMS aims to maximize the use of RES and control demand response programs. The EMS constraints can be categorized into reliability constraints, energy balancing constraints, physical limits of ESSs and DGs, reactive power support constraints, network constraints, RES constraints, and demand response constraints, as depicted in Figure 9b.



(**a**)

Figure 9. *Cont.*



(**b**)

Figure 9. Sizing models (**a**) Objectives; (**b**) Constraints.

4. Energy Management Strategies for MGs with ESS

This work also presents a comprehensive overview of the many optimization algorithms applied in the literature for the EMS of MGs. As shown in Figure 10, there are four main types of EMS optimization strategies for MGs: strategies based on artificial intelligence (AI); strategies based on mathematical algorithms; strategies based on meta-heuristics; and hybrid and other algorithm-based EMS strategies.

4.1. Artificial Intelligence EMS-Based Methods

Artificial neural networks (ANN), fuzzy logic systems (FLS), and ANFIS are widely adopted for MG energy management. A detailed overview of the most recent AI-based techniques used in the literature is presented in this work.

A strategy for intelligent multi-MG EM based on deep neural networks and model-free reinforcement learning techniques was proposed by Du et al. [98]. The objective was to reduce the demand-side peak-to-average ratio and maximize energy sales profits. The deep NN was developed to protect consumer privacy by simulating the operation of several MGs under dynamic retail pricing signals, without requiring local generation or consumption data. A model-free Monte Carlo reinforcement learning method was also used to improve its pricing strategy, to maximize profits and minimize the demand-side peak-to-average ratio. A non-intrusive load monitoring-based EMS for residential MGs was presented by Çimen et al. [99]. Initially, smart meter data were analyzed using a multi-task deep NN-based technique, and consumer appliance data were collected. The operational and consumption status of the appliance were recorded. Using these data, the energy consumption behaviors of end-users were then evaluated. Simulations revealed that the proposed EMS achieved a higher operation cost/customer satisfaction than the conventional method.

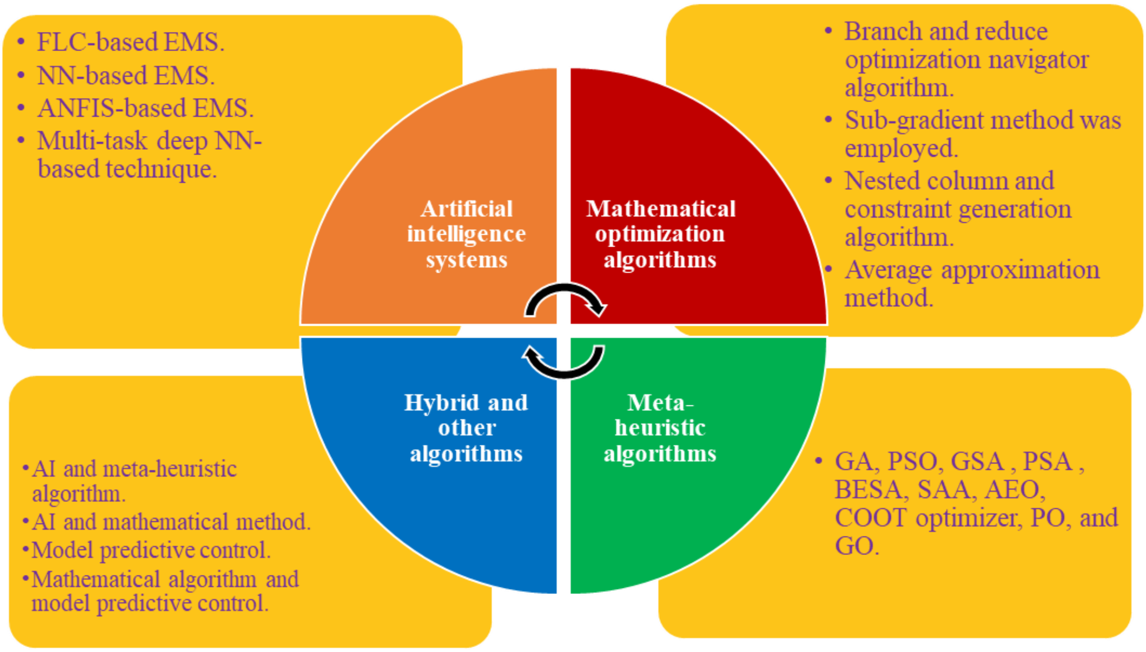


Figure 10. Classification of commonly used types of algorithms in energy management.

Kang et al. [100] suggested an energy management system based on artificial NNs (ANN) for regulating power in the hybrid AC and DC distribution networks. The suggested ANN-based EMS determined the optimal operating mode by gathering data on distributed generation power, load demand, and the battery's SOC. Experiments were carried out to validate the proposed EMS operating algorithm by building a small-scale MG and monitoring system in a laboratory unit that connected the ESS, solar power production system, wind power generation system, and interlinking converter. Experiments were undertaken to determine if the ANN-based EMS can work reliably in the suggested mode by altering the amount of generated power, the amount of load power, and the SOC of the ESS. Abdolrasol et al. [101] employed an ANN to manage multiple MGs. An ANN-based backtracking search algorithm and an ANN-based binary PSO were adopted as two scheduling control approaches. The efficacy of both algorithms was proven in limiting fuel consumption, decreasing CO_2 emissions, and boosting system efficiency in the direction of grid decarbonization. Wu et al. [102] applied a microgrid EMS and proposed a demand-side response function-based distributed energy, real-time management model. A deep adaptive dynamic programming optimization strategy was also presented. The MG operators' and users' interactions in real time were realized. It was demonstrated that the proposed model satisfies the application conditions and represents a particular application of bounded rationality approaching complete rationality in the electricity market. In addition, it was demonstrated that the optimal solution is included in the model's collection of satisfactory solutions. Sumarmad et al. [103] suggested an optimized FLS energy management system for an isolated MG comprising a PV unit, a wind turbine, batteries, a fuel cell, and a diesel generator, which supplied a typical household load. A low-complexity FLS with only 25 base rules controlled the system. The entire system was mathematically represented, and the optimization problem was handled using an artificial bee colony, yielding improved control and energy conservation efficiency outcomes. Dong et al. [104] provided an adaptive, optimal FLS-based EMS for real-time energy dispatch. Using a novel offline metaheuristic optimization technique, the solution was found by an ideal fuzzy inference system, based on the forecasted data during a given period. Real-time energy dispatch was performed, based on the optimal fuzzy logic rules to meet various operational goals, such as minimal power fluctuations and operating costs. The proposed technique was thoroughly tested through simulation tests, and compared to two conventional approaches. The results revealed that the proposed energy EMS offered improved performance compared to other approaches. Alahmadi et al. [105] created an intelligent EMS for a smart DC-MG by combining FLS and fractional-order proportional-integral-derivative controller approaches. The tested MG comprised a battery bank, a wind farm, and PV panels. The Matlab/Simulink simulations were conducted to compare the performance of the proposed strategy with alternative non-linear controls. In Leonori et al. [106], an approach for synthesizing EMS based on ANFIS was developed. In addition, three distinct clustering algorithms were tested for the ANFIS rule synthesis, both with and without the classifier support being taken into account. The problem was formulated as a mixed-integer linear programming problem, and the conducted simulations showed the efficacy of the approach suggested.

4.2. Mathematical EMS-Based Methods

Mathematical optimization algorithms are widely used to solve simple and linear energy management optimization problems. Mathematical algorithms lose their robustness for non-convex and complex schemes, and the optimal global solution is not guaranteed. Further, applying linearization and decomposition approaches is essential to simplifying the problem.

Zhu et al. [90] developed a novel energy management method to remedy the shortcomings of the conventional two-stage robust method that focuses mainly on the worst-case scenario. Contrary to other methods, the suggested model was formulated to consider the ESS charging and discharging states in the re-dispatch stage, rather than the pre-dispatch stage, to improve the ESS operational flexibility for energy management. The developed two-stage robust optimization model was a mixed integer programming model with recourse, and the nested column and constraint generation algorithm was employed to solve it. Results proved the superiority of the suggested model in decreasing operational costs and minimizing the negative impacts on the main grid. In Rahim et al. [107], a robust real-time EMS was suggested. Convex optimization created the objective function to maximize profits, including the generation cost, load utilities, and transactional cost. A sub-gradient method was employed to solve it, and Lagrangian dual decomposition was adopted to decompose the problem into sub-problems. The numerical results verified the proposed problem's convexity and the proposed methodology's superiority in solving the problem with less computational time.

Mosa et al. [92] applied the branch and reduced optimization navigator algorithm to solve the suggested EM optimization problem. The objective function considered the generation cost, including the no-load cost, loss behavior within DGs, DG start/stop cost, and power losses. The problem was a non-convex, mixed integer, non-linear problem. The results demonstrated the efficiency of the adopted solving methodology in obtaining high-quality solutions. Apache Spark was used by Marino et al. [108] to improve the performance of the EM model for MGs in many buildings and to effectively utilize the output power of wind turbines. The problem was designed as a chance constraint two-stage optimization model, and the sample average approximation method was applied to solve the proposed model.

4.3. Metaheuristic EMS-Based Methods

The genetic algorithm (GA), particle swarm optimization (PSO), COOT optimizer, slap swarm algorithm (SSA), porcellio scaber algorithm (PSA), and grasshopper optimization algorithm (GOA) are commonly used to solve the energy management optimization problem. For example, Torkan et al. [109] adopted a multi-objective genetic algorithm to solve energy management's technical and economic problems. The demand response programs, reactive consumptions, and uncertainties were considered in the proposed stochastic model. The results demonstrated that participation in demand response programs and reactive loads reduced the costs of generation, reservation, and startup, and decreased pollution. HassanzadehFard et al. [110] presented a method for minimizing the operational costs of a hybrid MG composed of PV panels, wind turbines, electrolyzers, HSS, reformers, and FCs. Two distinct approaches were adopted for generating hydrogen, to guarantee the efficacy of the suggested methodology. The PSO was applied to optimally determine the system size and manage the MG operation. The model was formulated to consider the total net present value of the system expenditures incurred over the project lifetime. A PSO-based EMS was established by Wang et al. [111] to study the different battery degradation models' impacts on the MG operation. Five degradation models were explored and mathematically integrated into the objective function of the proposed EMS. This work highlighted the simplified degradation models' considerable and non-negligible impact on microgrid energy management, and suggested abandoning single-factor-based models.

The PSO was also adopted by Tooryan et al. [112], to solve the MG energy management problem. The EM's objective function was to minimize the overall system cost, reduce environmental emissions, and increase the penetration level of RES. An MG energy management strategy was established by Li et al. [113], based on a three-layer multi-agent system model for MGs in China. The objective was to decrease the total cost and realize a secure and stable economic operation for MG. An improved PSO was implemented to solve the problem. The adaptive weight and chaotic series were combined with the PSO, to balance global search and local search capabilities. An energy management scheme for the optimum operation of an MG incorporating DGs, ESSs, and EVs was proposed by Li et al. [114]. The objective was to minimize the overall system cost, including the expenses of load supply, EV charging needs, and power losses. A mix of gravitational and pattern search algorithms was employed to solve the proposed problem. The simulation validated the superiority of the hybrid algorithm over conventional approaches. In addition, the results demonstrated that the generation costs were significantly lower than those of conventional optimization methods.

Ferahtia et al. [115] suggested an effective EMS for the economic operation of a microgrid in both isolated and grid-connected operational modes. The goal was to optimize the operation of the microgrid, based on the energy pricing, the operating cost of the power sources, and the anticipated load power. In addition, the EMS had to maintain the MG power quality and stability. The proposed solution strategy was based on the PESA. Compared with PSO, SSA, AEO, COOT optimizer, and PO, the PESA proved its superiority regarding the quality of the solution obtained and its robustness. A new parallel hybrid GA-PSO algorithm was developed by Mellouk et al. [116] to solve the problem of MG sizing and energy management of an MG. The objective was to satisfy typical load demand while minimizing operating costs, maximizing the integration of RES, and avoiding power losses and overload. The results demonstrated that the proposed algorithm outperformed conventional optimization methods regarding solution quality and convergence time.

A rule-based EMS was proposed by Bukar et al. [117], and the GOA was used for optimizing the long-term capacity of a grid-independent MG comprising a wind turbine, a PV, an ESS, and a diesel generator. Comparing the GOA, PSO, and cuckoo search algorithms indicated that the proposed technique was superior in its convergence when compared with the best solutions. An efficient energy management strategy was proposed by Keshta et al. [118] to optimally determine the operation schedule of two isolated interconnected MGs during the day. The modified version of the basic PSA was developed to solve the suggested problem. The results proved that the developed global PSA outperformed many other meta-heuristics in determining the optimal economic dispatch of multiple MGs with different energy sources.

4.4. Hybrid EMS-Based Methods

Many studies in the literature have recently resorted to combining several energy management strategies, and have demonstrated the superiority of hybrid schemes compared to individual ones. The hybrid algorithms can be classified into AI and meta-heuristics-based EMS, AI and mathematically-based EMS, and mathematical algorithms and model predictive control-based EMS.

Using advanced machine learning, Yuan et al. [104] proposed an EMS for hybrid AC/DC MGs. The suggested strategy was composed of two parts, forecasting and scheduling. One class support vector was used for the forecast, while a heuristic method was applied for optimal energy scheduling. An optimization algorithm inspired by improved whale optimization (WO) was used for the scheduling proposal and for adjusting the forecasting model's parameters. Results proved the effectiveness of the proposed algorithm.

Moreover, the simulations showed that the proposed framework reduced total operation costs, improved the voltage profile, and minimized power losses. A new methodology was proposed by Rocha et al. [119] to solve the energy management planning problem in smart homes and achieve a balance between energy cost and user comfort. Three different AI techniques were combined to formulate the demand-side management problem, and then the modified version of the elitist non-dominated sorting genetic algorithm II was derived to solve the energy management optimization problem. The suggested strategy considered electricity price fluctuations, the importance of each intelligent home equipment, operating cycles, and an ESS. The methodology also applied the support vector regression approach to predict the distributed generation power and the K-means clustering technique to evaluate the user comfort levels.

Samuel et al. [120] proposed an EMS that turns an infinite number of MGs into a coherent system without affecting the perspectives and goals of each MG. The suggested model was formulated to consider the exponential growth of coalition in the energy cost problem. The energy cost allocation problem was solved using a column generation algorithm. Further, a deep convolutional neural network was adopted to estimate the daily operating cost of the MGs. The model comprised ESSs, demand loads, real-time electricity prices, and renewables. An optimal scheduling policy was also proposed to optimize the MMG daily operating cost. The proposed methodology significantly reduced the MG operation cost, compared to the model predictive control, the greedy policy, and the approximate dynamic programming-based approaches. In Leonori et al. [121], different strategies for synthesizing a fuzzy inference system-based EMS were investigated, using a hierarchical GA to reduce the complexity of the EMS rule-based system and boost the profits of the energy exchange with the grid. The results revealed that the hierarchical optimization framework reduced the number of rules needed by more than half.

Arkhangelski et al. [108] presented a developed predictive control-based EMS for urban MGs using the day-ahead optimal power flow strategy. The ancillary flexibility services of DGs were considered in the model. Furthermore, forecasting-based intelligent deep learning data and mixed-integer non-linear programming optimization methods were employed. The findings demonstrated that considering the DGs' ancillary flexibility services increased economic benefits. Elkazaz et al. [122] presented a novel EMS for minimizing an MG operating cost and maximizing the RES self-consumption during the day, by optimally defining the setting for a central ESS. The proposed EMS was formulated through a two-layer structure where a convex optimization technique was applied to solve the upper-level optimization problem and to set the power reference values that the MG should use to dispatch the main grid. While in the lower control layer, the settings of the ESS were determined, and then it was ensured that the MG accurately supplied the grid with the reference values obtained in the upper layer. To meet its objectives, the lower control layer employed a rolling horizon predictive controller and model predictive controllers. A hybrid approach for short-term demand forecasting was proposed by Tayab et al. [123]. It depended mainly on combining the wavelet packet transform and Harris hawks optimization-based feed-forward NN. The Harris hawks optimization was employed to train the feed-forward NN. The results demonstrated that more reduction was realized for the average mean absolute percentage error using the proposed strategy, compared to the PSO-based ANN, PSO-based least-squares support vector machine, and back-propagation-based NN.

5. Software Used for Modeling ESS in MGs, Economic Assessment Indices, and Uncertainty Analysis Methods

5.1. Software Used for Modeling ESS

Several software packages are dedicated to modeling and optimizing energy storage systems in power systems, each with unique features and applications. The choice of software relies on the project's specific needs and requirements and the expertise level. Also, the software's maturity should be considered, as it can affect the reliability and quality of the results. Some of the most popular software packages include:

- Hybrid Optimization of Multiple Energy Resources (HOMER) [124,125]: This software models and optimizes the economics and performance of MGs and distributed energy systems. HOMER is explicitly designed for optimizing and modeling microgrids and distributed energy systems. It is relatively easy to use and has a user-friendly interface. It also has an immense renewable energy and storage technology database, making it an excellent system design-and-optimization tool. HOMER is commercial software, but offers a free version with limited capabilities. The cost of the full version (HOMER Pro) varies depending on the number of users, but it can be relatively affordable for small-scale projects. The software has been around for over a decade and has a proven track record of success in the industry, and it is considered mature software [126].
- Open Distribution System Simulator (OpenDSS) [127,128]: This open-source software analyzes and simulates power distribution systems, including integrating ESSs. It has advanced capabilities for modeling and analyzing energy storage systems, and can handle large and complex systems. However, it has a steeper learning curve than HOMER and requires more technical expertise. The software has been around for several decades and is widely used in the industry.
- Grid Laboratory for Distribution Systems (GridLab-D) [129,130]: This open-source software simulates and analyzes power distribution systems, including integrating energy storage systems and distributed energy resources. It is well-suited for research and development projects. However, it is also relatively complex and requires high technical expertise. Like OpenDSS, GridLab-D has been around for several decades and is widely used in the industry.
- Power Engineering eXpert Optimization System(PLEXOS) [131,132]: A commercial software, which is used for power system planning, operations, and market analysis, and has a module for modeling storage systems, including electrochemical batteries, thermal storage, and pumped-hydro storage. It is widely used in the industry and can model different types of storage systems and their interactions with power systems. However, it may require some level of expertise to use. PLEXOS is commercial software with a cost that varies depending on the modules and options needed. It is generally considered expensive but widely used in the industry, and has a proven track record of success.
- MATLAB/Simulink r2016a and r2021a [133,134]: A commercial software, which is widely used in the power systems industry for modeling and simulation. It offers a variety of toolboxes and libraries that can be used to model and optimize energy storage systems. However, MATLAB is a general-purpose programming language that could commonly be used in energy storage modeling.
- Energy Storage Valuation Tool (ESVT) [135,136]: A free and open-source software developed by the Pacific Northwest National Laboratory (PNNL) and Sandia National Laboratories, which is used to evaluate the economic feasibility of energy storage projects. It allows users to estimate the costs and benefits of energy storage systems and calculate the levelized cost of energy (LCOE) and others.
- StorageVET [135,136]: A commercial software package specifically designed for energy storage optimization in power systems. It allows users to model the performance of energy storage systems and optimize their design for different applications, such as peak shaving, load shifting, and frequency regulation.

- DNV GL Synergi Electric [137,138]: A commercial software, which is commonly used for power system analysis and planning, including energy storage modeling. It allows users to simulate the performance of energy storage systems in distribution and transmission networks and optimize their design for different applications, such as peak shaving, load balancing, and voltage support.
- Distributed Energy Resources Customer Adoption Model (DER-CAM) [139,140]: A free and open-source software developed by the National Renewable Energy Laboratory (NREL). This software tool is used to model the integration of distributed energy resources, including energy storage systems, in power systems. It allows users to simulate the performance of different combinations of energy storage and renewable energy technologies and optimize their design for different applications and business models.
- EnergyPLAN [141]: A free and open-source software tool developed by Aalborg University for energy system modeling and optimization. It allows users to simulate the performance of different energy storage and renewable energy technologies and optimize their design for different applications, such as heat and electricity generation, transportation, and industry.
- Hybrid Simulation (HYSIM) [142]: A free and open-source software tool developed by NREL. It allows users to simulate the performance of different combinations of renewable energy and energy storage technologies and optimize their design for different applications, such as grid-connected or off-grid systems.

5.2. Economic Assessment Indices for ESS Projects in MGs

Deploying ESS projects in MGs must be justified economically and technically. Economic and technical indices are crucial for evaluating the ESS benefits in MGs. Economic indices enable us to compare the cost-effectiveness of energy storage technologies, sizing, and locations. Economic indices (besides the technical ones) can help MG planners and operators make informed decisions about ESSs. The most common economic indices are shown in Figure 11, and are explained below.

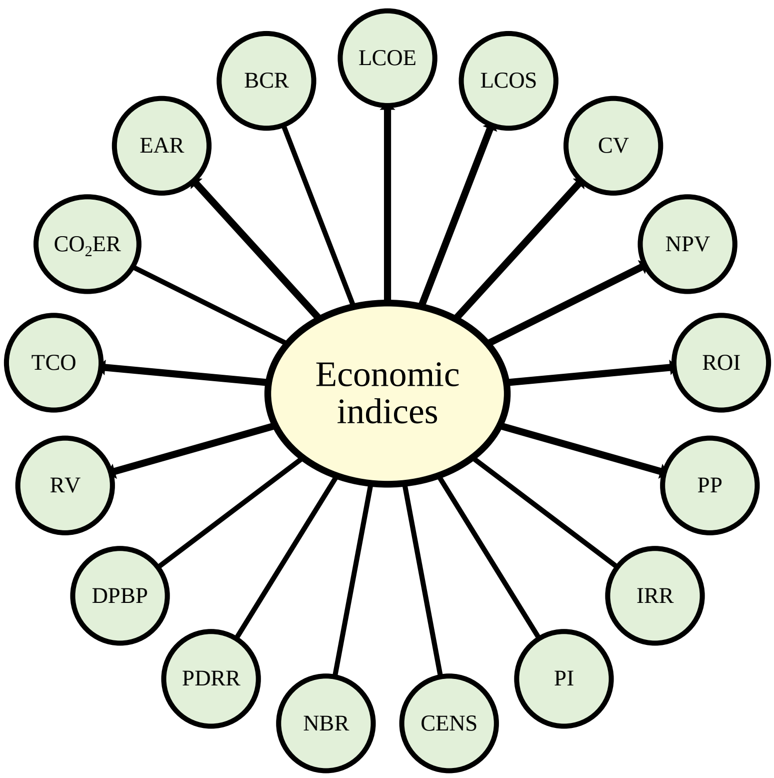


Figure 11. Economic assessment indices for ESS in MGs.

1. Levelized cost of energy (LCOE) [143]: The LCOE is a commonly used economic index that represents the cost of generating a unit of electricity over the lifetime of an energy storage system. It considers the initial capital, operating, and maintenance costs over the system's lifespan. A lower LCOE indicates a more cost-effective energy storage system.
2. Levelized cost of storage (LCOS) [144,145]: LCOS is the total cost of the energy storage system over its lifetime, divided by the total amount of energy it stores. A lower LCOS indicates a more cost-effective storage system.
3. Net present value (NPV) [146]: The NPV represents the present value of the expected cash flows generated by an energy storage system over its lifetime, considering the initial investment and operating costs. A positive NPV indicates that the project is economically viable.
4. Return on investment (ROI) [147]: The ROI represents the return percentage on the initial investment in an energy storage system. It is calculated by dividing the net profit by the initial investment.
5. Payback period (PP) [148,149]: the payback period represents the energy storage system's time to generate enough revenue for the initial investment.
6. Internal rate of return (IRR) [150,151]: The IRR represents the discount rate that makes the net present value of the cash flows generated by the energy storage system equal to zero. A higher IRR indicates a more profitable investment.
7. Profitability index (PI) [152]: PI is the ratio of the present value of future cash flows to the initial investment. A PI higher than one indicates a profitable investment.
8. Benefit–cost ratio (BCR) [153]: The BCR represents the energy storage system's expected benefits ratio compared with the discounted cost value. A BCR greater than 1 indicates that the benefits outweigh the costs.
9. Energy arbitrage revenue (EAR) [154]: The EAR represents the profit generated by buying low-cost electricity from the grid during off-peak periods, storing it in the energy storage system, and selling it back to the grid during peak periods when prices are high. Any revenue stream could further improve the profitability of the energy storage system.
10. Cost of energy not served (CENS) [155]: CENS is the cost of unserved energy to the microgrid. It represents the economic value of the energy that is not available when needed. A lower CENS indicates a more reliable ESS.
11. Net benefit ratio (NBR) [156]: NBR is the ratio of the net present value of the benefits to the net present value of the costs. A ratio greater than one indicates a beneficial investment.
12. Peak demand reduction ratio (PDRR) [157]: PDRR is the ratio of the reduction in peak demand achieved through energy storage to the total peak demand of the microgrid. A higher PDRR indicates a more effective ESS.
13. CO_2 emissions reduction (CO_2ER) [158]: the reduction in CO_2 emissions achieved by implementing energy storage can be calculated and used as an index to evaluate the environmental benefits of energy storage.
14. Total cost of ownership (TCO) [159]: This index measures the total cost of owning and operating the ESSs over their lifetime. It includes the initial investment cost, maintenance and operating costs, and the cost of replacing the system at the end of its life. A lower TCO indicates a more financially attractive investment.
15. Resiliency value (RV) [160]: RV is the value of an energy storage system in improving the resiliency of a microgrid. ESSs can provide backup power during outages or other disruptions, thereby reducing the economic impact of such events.
16. Discounted payback period (DPBP) [161]: DPBP is the time it takes for the total discounted cash inflows from an investment to equal the initial investment. This metric accounts for the time value of money and is, therefore, more accurate than the traditional payback period.

17. Capacity value (CV) [162]: CV is the value of an energy storage system in meeting peak demand requirements. ESSs can provide additional capacity during periods of high demand, thereby reducing the need for expensive peaker plants.

5.3. Methods of Uncertainty Analysis of ESS in MGs

Several ways exist to model uncertainty in energy storage sizing and location in an MG [163]. One common approach is stochastic optimization, which involves modeling uncertain variables as probability distributions and optimizing the system under different scenarios [164]. In this method, random values for the uncertain variables are generated in each scenario, and an optimization problem is solved to obtain the objective function value. The process is repeated for many scenarios to estimate the objective function's expected value and standard deviation. Monte Carlo simulation involves randomly sampling values for uncertain variables and running simulations to obtain estimates of system performance metrics [165]. First, probability distributions for the uncertain variables are defined to implement this approach. Second, random samples are generated from these distributions to be used as inputs to the optimization problem. Then, this process is repeated for many samples, in which each sample's objective function value is calculated. These values estimate system performance metrics, such as the objective function's expected value and standard deviation. Scenario analysis involves identifying a small number of plausible scenarios and analyzing the system performance under each scenario. To implement this approach, we first identify scenarios representing different possible values for the uncertain variables. We then solve the MG optimization problem for each scenario, and calculate the objective function value.

There are several other ways to model uncertainty in energy storage, including sensitivity analysis, which involves varying the values of the uncertain variables over a range of values and observing the effect on the objective function. This can help identify which variables have the most significant impact on the objective function, and inform decisions about which variables to prioritize in the design process. Robust optimization involves formulating the optimization problem to ensure the system performance is guaranteed to meet some performance criteria, even under worst-case scenarios. This can be useful when the uncertain variables' probability distributions are unknown or difficult to estimate. Bayesian optimization involves using Bayesian inference to estimate the probability distributions of the uncertain variables, based on observed data. This can be useful when there is prior knowledge about the probability distributions of the uncertain variables or when data can be collected from the system over time. Each method has advantages and disadvantages, and the choice of method will depend on the specific problem being addressed and the available data and resources. The reader can refer to [163] for more details about the uncertainty analysis techniques of ESSs in MGs.

6. Conclusions and Future Directions of ESS in MGs

The area of energy storage in MGs is rapidly evolving, and there are several exciting future directions in this field, such as the research directions explored in Figure 12 and discussed below.

- Advanced control and optimization strategies: Researchers are developing advanced control and optimization strategies that can improve the performance and efficiency of energy storage systems in MGs. These strategies may involve machine learning, artificial intelligence, or other advanced techniques.
- Hybrid energy storage systems [166]: Hybrid energy storage systems that combine multiple storage technologies, such as batteries, capacitors, and supercapacitors, are being investigated to overcome the limitations of individual storage technologies and provide better overall performance.
- Grid integration and management: as MGs become more common, there is a growing need for effective grid integration and management strategies to ensure the MG's reliable and efficient operation and interactions with the main grid.

- New storage technologies: researchers are exploring new energy storage technologies, such as flow batteries, thermal storage, and hydrogen storage, which may provide better performance and efficiency than existing technologies.
- Smart grid integration: with the increasing adoption of smart grid technologies, researchers are exploring new ways to integrate energy storage systems into smart grids, to improve the efficiency and reliability of power delivery.
- Cybersecurity: as MGs become more connected and automated, there is a growing need to ensure the cybersecurity of energy storage systems to prevent hacking or other malicious attacks.
- Life cycle analysis: researchers are conducting life cycle analyses of MG energy storage systems to understand their environmental impact better and identify improvement opportunities.
- Standardization: with the proliferation of different energy storage technologies and MG configurations, standardization is needed to ensure interoperability and compatibility between different systems.

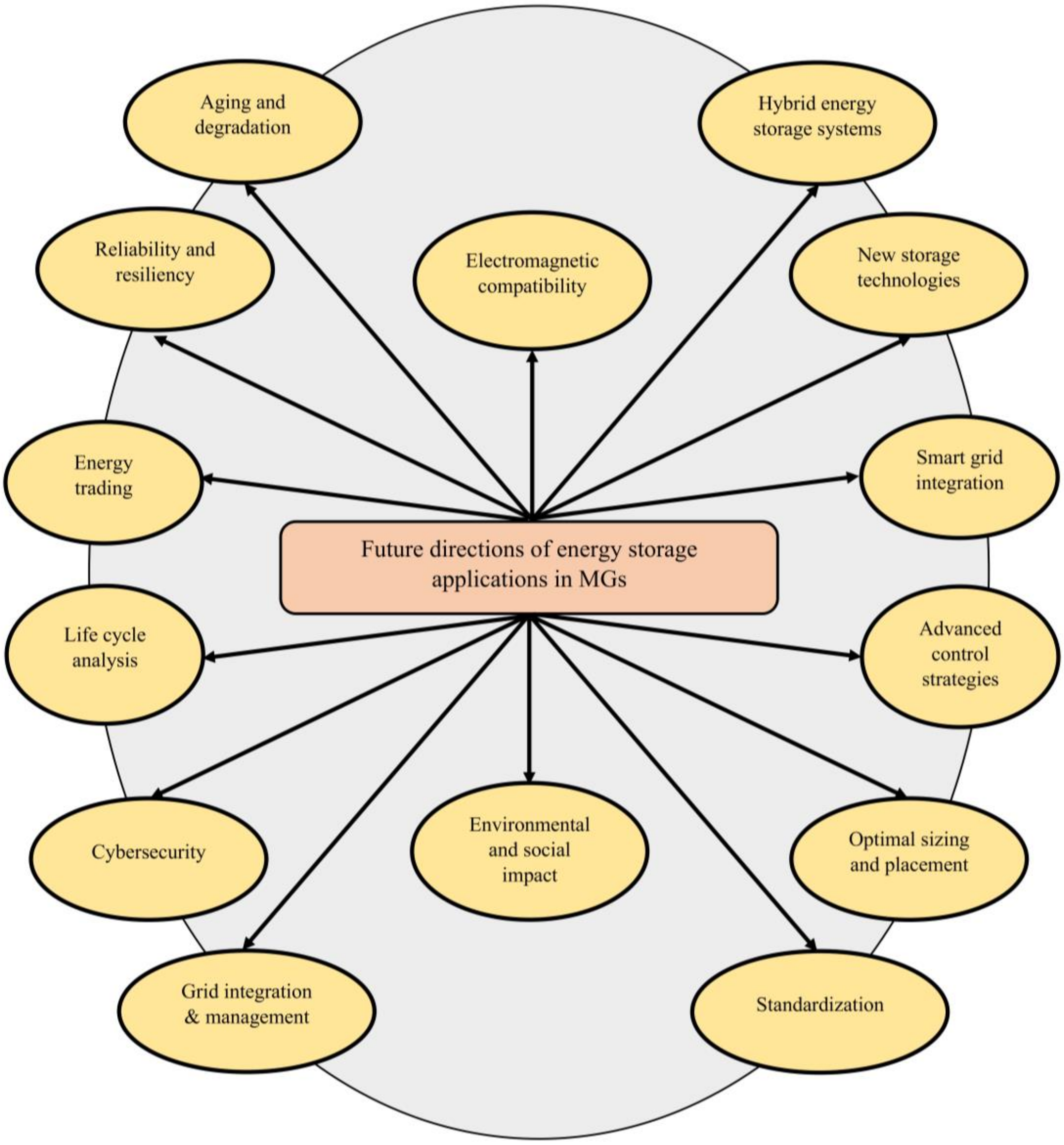


Figure 12. Expected future directions of ESS in MGs.

- Energy trading: researchers are exploring the potential for energy trading between microgrids and the main grid and between different MGs, to optimize energy use and reduce costs.
- Reliability and resiliency [166]: researchers are exploring ways to improve the reliability and resiliency of energy storage systems in MGs, including redundant storage systems and advanced control strategies.
- Optimal sizing and placement: as the demand for energy storage systems in MGs grows, there is a need for effective methods for sizing and placing these systems, to optimize their performance and cost-effectiveness.
- Aging and degradation: As energy storage systems age, their performance and capacity can degrade, reducing efficiency and reliability. Researchers are exploring ways to model and predict the aging and degradation of energy storage systems in MGs, to optimize their maintenance and replacement.
- Environmental and social impact: researchers are studying the environmental and social impact of energy storage systems in MGs, including land use, resource consumption, and social equity, to identify ways to minimize negative impacts and promote sustainability.
- Electromagnetic compatibility: with the proliferation of electronic devices and wireless communications in microgrids, there is a growing need to ensure the electromagnetic compatibility of energy storage systems to prevent interference and ensure reliable operation.

Last but not least, as the field progresses, it is expected to see continued innovation and improvement in energy storage technologies and their applications in MG systems.

Author Contributions: Conceptualization, Z.M.A. and S.H.E.A.A.; methodology S.H.E.A.A. and M.C.; validation, F.H.G., F.J. and M.C.; formal analysis, Z.M.A. and S.H.E.A.A.; investigation, Z.M.A.; resources, M.C. and Z.M.A.; data curation, M.C. and S.H.E.A.A.; writing—original draft preparation, M.C. and Z.M.A.; writing—review and editing, S.H.E.A.A., F.H.G. and F.J.; visualization, Z.M.A., M.C. and S.H.E.A.A.; project administration, Z.M.A. and S.H.E.A.A. All authors have read and agreed to the published version of the manuscript.

Funding: This study was sponsored by Prince Sattam bin Abdulaziz University via project number 2023/RV/015.

Data Availability Statement: Not applicable.

Acknowledgments: The authors acknowledge the Prince Sattam bin Abdulaziz University for funding this project.

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

Glossary

Abbreviations

ACAES	Above-ground compressed air energy storage systems
ANN	Artificial neural networks
BCR	Benefit–cost ratio
CAES	Compressed air energy storage systems
CENS	Cost of energy not served
CO_2ER	CO_2 emissions reduction
CV	Capacity value
DR	Demand response
DG	Distributed generator
DER-CAM	Distributed Energy Resources Customer Adoption Model
DPBP	Discounted payback period
EAR	Energy arbitrage revenue
ESS	Energy storage system
ESVT	Energy Storage Valuation Tool
EMS	Energy management system

GA	Genetic algorithm
GOA	Grasshopper optimization algorithm
FLS	Fuzzy logic systems
GridLab-D	Grid Laboratory for Distribution Systems
HC	Hosting capacity
FWES	Flywheel energy storage
HBS	Hydrogen-based energy storage
HOMER	Hybrid Optimization of Multiple Energy Resources
HT	Heuristic technique
HYSIM	Hybrid Simulation
IRR	Internal rate of return
LA	Lead-acid batteries
LCOE	Levelized cost of energy
LCOS	Levelized cost of storage
Li-ion	Lithium-ion
LOLE	Loss of load expectation
MG	Microgrid
NBR	Net benefit ratio
NG	Nanogrid
NPV	Net present value
NaS	Sodium-sulfur
Ni-Cd	Nickel-cadmium batteries
OpenDSS	Open Distribution System Simulator
PDRR	Peak demand reduction ratio
PG	Picogrid
PHS	Pumped hydroelectric storage
PI	Profitability index
PLEXOS	Power Engineering eXpert Optimization System
PP	Payback period
PSO	Particle swarm optimization
PV	Photovoltaic
PSA	Porcellio scaber algorithm
SCs	Supercapacitors
SOC	State of charge
SMES	Superconducting magnetic energy storage
SSA	Slap swarm algorithm
RF	Renewable factor
RESs	Renewable energy sources
ROI	Return on investment
RV	Resiliency value
TCO	Total cost of ownership
UCAES	Under-ground compressed air energy storage systems
VR	Vanadium redox
WO	Whale optimization
Wos	Web of Science
ZnBr	Zinc-bromine
Nomenclature	
C_{NS}^{op}	MG operating cost without ESS
C_{S}^{op}	MG operating cost with ESS
C_{grid}	Grid cost
C_{grid}	Cost of DGs
C_{cap}, C_{op}, C_{M}	Capital, operating, and maintenance costs, respectively
E^{ESS}	Capacity of ESS in kWh
$s = 1, 2, \ldots M$	Number of hours
I_{ij}	Current flows between node i and node j
MSC	The mean daily schedule cost
P_s	Probability of scenarios

V_i	Voltage at node i
r_{ij}	Resistance of cable connection between node i and the node j
$s = 1, 2, \ldots M$	Number of scenarios
ω_{th}^{s}	Binary factor for load curtailment
SUC_{DG}, SDC_{DG}, OMC_{DG}	Startup cost, shutdown cost, and operating and maintenance cost of DGs
$TCPD$	Total cost per day of ESS

References

1. Lu, D.; Hu, D.; Yi, F.; Li, J.; Yang, Q. Optimal selection range of FCV power battery capacity considering the synergistic decay of dual power source lifespan. *Int. J. Hydrogen Energy* **2023**, *48*, 13578–13590. [CrossRef]
2. Zhou, J.; Feng, C.; Su, Q.; Jiang, S.; Fan, Z.; Ruan, J.; Sun, S.; Hu, L. The Multi-Objective Optimization of Powertrain Design and Energy Management Strategy for Fuel Cell–Battery Electric Vehicle. *Sustainability* **2022**, *14*, 6320.
3. Eshra, N.M.; Zobaa, A.F.; Abdel Aleem, S.H.E. Assessment of mini and micro hydropower potential in Egypt: Multi-criteria analysis. *Energy Rep.* **2021**, *7*, 81–94. [CrossRef]
4. Ustun, T.S.; Ozansoy, C.; Zayegh, A. Recent developments in microgrids and example cases around the world—A review. *Renew. Sustain. Energy Rev.* **2011**, *15*, 4030–4041. [CrossRef]
5. Ahmed, M.; Meegahapola, L.; Vahidnia, A.; Datta, M. Stability and Control Aspects of Microgrid Architectures-A Comprehensive Review. *IEEE Access* **2020**, *8*, 144730–144766. [CrossRef]
6. Balali, A.; Yunusa-Kaltungo, A.; Edwards, R. A systematic review of passive energy consumption optimisation strategy selection for buildings through multiple criteria decision-making techniques. *Renew. Sustain. Energy Rev.* **2023**, *171*, 113013. [CrossRef]
7. Rohit, A.K.; Rangnekar, S. An overview of energy storage and its importance in Indian renewable energy sector: Part II—energy storage applications, benefits and market potential. *J. Energy Storage* **2017**, *13*, 447–456. [CrossRef]
8. Muzhikyan, A.; Farid, A.M.; Youcef-Toumi, K. Relative merits of load following reserves & energy storage market integration towards power system imbalances. *Int. J. Electr. Power Energy Syst.* **2016**, *74*, 222–229. [CrossRef]
9. Sciences, H. *Energy Storage at Different Voltage Levels Energy Storage at Different Voltage Levels*; Institution of Engineering and Technology: London, UK, 2016; Volume 4, ISBN 2013206534.
10. Banshwar, A.; Sharma, N.K.; Sood, Y.R.; Shrivastava, R. Market-based participation of energy storage scheme to support renewable energy sources for the procurement of energy and spinning reserve. *Renew. Energy* **2019**, *135*, 326–344. [CrossRef]
11. Arrigo, F.; Bompard, E.; Merlo, M.; Milano, F. Assessment of primary frequency control through battery energy storage systems. *Int. J. Electr. Power Energy Syst.* **2020**, *115*, 105428. [CrossRef]
12. Elbasuony, G.S.; Abdel Aleem, S.H.E.; Ibrahim, A.M.; Sharaf, A.M. A unified index for power quality evaluation in distributed generation systems. In *Energy*; Elsevier: Amsterdam, The Netherlands, 2018; Volume 149, pp. 607–622.
13. Omar, A.I.; Abdel Aleem, S.H.E.; El-Zahab, E.E.A.; Algablawy, M.; Ali, Z.M. An improved approach for robust control of dynamic voltage restorer and power quality enhancement using grasshopper optimization algorithm. *ISA Trans.* **2019**, *95*, 110–129. [CrossRef]
14. Das, C.K.; Bass, O.; Mahmoud, T.S.; Kothapalli, G.; Mousavi, N.; Habibi, D.; Masoum, M.A.S. Optimal allocation of distributed energy storage systems to improve performance and power quality of distribution networks. *Appl. Energy* **2019**, *252*, 113468. [CrossRef]
15. Diaaeldin, I.M.; Abdel Aleem, S.H.E.; El-Rafei, A.; Abdelaziz, A.Y.; Zobaa, A.F. Enhancement of hosting capacity with soft open points and distribution system reconfiguration: Multi-objective bilevel stochastic optimization. *Energies* **2020**, *13*, 5446. [CrossRef]
16. Rawa, M.; Abusorrah, A.; Al-Turki, Y.; Mekhilef, S.; Mostafa, M.H.; Ali, Z.M.; Aleem, S.H.E.A. Optimal allocation and economic analysis of battery energy storage systems: Self-consumption rate and hosting capacity enhancement for microgrids with high renewable penetration. *Sustainability* **2020**, *12*, 10144. [CrossRef]
17. Conlon, T.; Waite, M.; Modi, V. Assessing new transmission and energy storage in achieving increasing renewable generation targets in a regional grid. *Appl. Energy* **2019**, *250*, 1085–1098.
18. Rawa, M.; AlKubaisy, Z.M.; Alghamdi, S.; Refaat, M.M.; Ali, Z.M.; Aleem, S.H.E.A. A techno-economic planning model for integrated generation and transmission expansion in modern power systems with renewables and energy storage using hybrid Runge Kutta-gradient-based optimization algorithm. *Energy Rep.* **2022**, *8*, 6457–6479. [CrossRef]
19. Thirunavukkarasu, G.S.; Seyedmahmoudian, M.; Jamei, E.; Horan, B.; Mekhilef, S.; Stojcevski, A. Role of optimization techniques in microgrid energy management systems—A review. *Energy Strateg. Rev.* **2022**, *43*, 100899. [CrossRef]
20. Leonori, S.; Martino, A.; Frattale Mascioli, F.M.; Rizzi, A. Microgrid Energy Management Systems Design by Computational Intelligence Techniques. *Appl. Energy* **2020**, *277*, 115524. [CrossRef]
21. McIlvenna, A.; Herron, A.; Hambrick, J.; Ollis, B.; Ostrowski, J. Reducing the computational burden of a microgrid energy management system. *Comput. Ind. Eng.* **2020**, *143*, 106384. [CrossRef]
22. Faisal, M.; Hannan, M.A.; Ker, P.J.; Hussain, A.; Mansor, M.B.; Blaabjerg, F. Review of energy storage system technologies in microgrid applications: Issues and challenges. *IEEE Access* **2018**, *6*, 35143–35164. [CrossRef]
23. Hajiaghasi, S.; Salemnia, A.; Hamzeh, M. Hybrid energy storage system for microgrids applications: A review. *J. Energy Storage* **2019**, *21*, 543–570.

24. Arani, A.A.K.; Gharehpetian, G.B.; Abedi, M. Review on energy storage systems control methods in microgrids. *Int. J. Electr. Power Energy Syst.* **2019**, *107*, 745–757.
25. Hannan, M.A.; Faisal, M.; Jern, P.; Begum, R.A.; Dong, Z.Y.; Zhang, C. Review of optimal methods and algorithms for sizing energy storage systems to achieve decarbonization in microgrid applications. *Renew. Sustain. Energy Rev.* **2020**, *131*, 110022. [CrossRef]
26. Nikam, V. A review on control strategies for microgrids with distributed energy resources, energy storage systems, and electric vehicles. *Int. Trans. Electr. Energy Syst.* **2021**, *31*, e12607. [CrossRef]
27. Chaudhary, G.; Lamb, J.J.; Burheim, O.S.; Austbø, B. Review of energy storage and energy management system control strategies in microgrids. *Energies* **2021**, *14*, 4929. [CrossRef]
28. Georgious, R.; Refaat, R.; Garcia, J. Review on Energy Storage Systems in Microgrids. *Electronics* **2021**, *10*, 2134. [CrossRef]
29. Hu, J.; Shan, Y.; Guerrero, J.M.; Ioinovici, A.; Chan, K.W.; Rodriguez, J. Model predictive control of microgrids—An overview. *Renew. Sustain. Energy Rev.* **2021**, *136*, 110422. [CrossRef]
30. Saeed, M.H.; Fangzong, W.; Kalwar, B.A.; Iqbal, S. A Review on Microgrids' Challenges Perspectives. *IEEE Access* **2021**, *9*, 166502–166517. [CrossRef]
31. Lin, X.; Zamora, R. Controls of hybrid energy storage systems in microgrids: Critical review, case study and future trends. *J. Energy Storage* **2022**, *47*, 103884.
32. Reza, M.S.; Rahman, N.; Wali, S.B. Optimal Algorithms for Energy Storage Systems in Microgrid Applications: An Analytical Evaluation Towards Future Directions. *IEEE Access* **2022**, *10*, 10105–10123.
33. Mohammadi, F.; Mohammadi-Ivatloo, B.; Gharehpetian, G.B.; Ali, M.H.; Wei, W.; Erdinc, O.; Shirkhani, M. Robust Control Strategies for Microgrids: A Review. *IEEE Syst. J.* **2022**, *16*, 2401–2412. [CrossRef]
34. Mostafa, M.H.; Abdel Aleem, S.H.E.; Ali, S.G.; Ali, Z.M.; Abdelaziz, A.Y. Techno-economic assessment of energy storage systems using annualized life cycle cost of storage (LCCOS) and levelized cost of energy (LCOE) metrics. *J. Energy Storage* **2020**, *29*, 101345. [CrossRef]
35. Adeyanju, O.M.; Siano, P.; Canha, L.N. Dedicated Microgrid Planning and Operation Approach for Distribution Network Support with Pumped-Hydro Storage. *IEEE Trans. Ind. Inform.* **2022**, *19*, 8229–8241. [CrossRef]
36. Alharbi, H.; Bhattacharya, K. Participation of Pumped Hydro Storage in Energy and Performance-Based Regulation Markets. *IEEE Trans. Power Syst.* **2020**, *35*, 4307–4323. [CrossRef]
37. Su, H.Y.; Liu, J.H.; Chu, C.C.; Lee, S.H.; Hong, Y.Y.; Lin, Y.J. Roles of Pumped Hydro Storages in Optimal Scheduling of Future Taiwan Power System with Highly Penetrated Renewable Energy Resources. In Proceedings of the 2020 IEEE Industry Applications Society Annual Meeting, Detroit, MI, USA, 10–16 October 2020; Volume 57, pp. 1973–1986. [CrossRef]
38. Zhao, Y.; Chen, J. A quantitative risk-averse model for optimal management of multi-source standalone microgrid with demand response and pumped hydro storage. *Energies* **2021**, *14*, 2692. [CrossRef]
39. Rezaee Jordehi, A.; Javadi, M.S.; Catalão, J.P.S. Optimal placement of battery swap stations in microgrids with micro pumped hydro storage systems, photovoltaic, wind and geothermal distributed generators. *Int. J. Electr. Power Energy Syst.* **2021**, *125*, 106483. [CrossRef]
40. Jalili, M.; Sedighizadeh, M.; Fini, A.S. Stochastic optimal operation of a microgrid based on energy hub including a solar-powered compressed air energy storage system and an ice storage conditioner. *J. Energy Storage* **2021**, *33*, 102089. [CrossRef]
41. Gao, J.; Chen, J.J.; Qi, B.X.; Zhao, Y.L.; Peng, K.; Zhang, X.H. A cost-effective two-stage optimization model for microgrid planning and scheduling with compressed air energy storage and preventive maintenance. *Int. J. Electr. Power Energy Syst.* **2021**, *125*, 106547. [CrossRef]
42. Li, Y.; Miao, S.; Luo, X.; Yin, B.; Han, J.; Wang, J. Dynamic modelling and techno-economic analysis of adiabatic compressed air energy storage for emergency back-up power in supporting microgrid. *Appl. Energy* **2020**, *261*, 114448. [CrossRef]
43. Latha, R.; Palanivel, S.; Kanakaraj, J. Frequency control of microgrid based on compressed air energy storage system. *Distrib. Gener. Altern. Energy J.* **2012**, *27*, 8–19. [CrossRef]
44. Hamedi, K.; Sadeghi, S.; Esfandi, S.; Azimian, M.; Golmohamadi, H. Eco-emission analysis of multi-carrier microgrid integrated with compressed air and power-to-gas energy storage technologies. *Sustainability* **2021**, *13*, 4681. [CrossRef]
45. de la Cruz-Soto, J.; Azkona-Bedia, I.; Velazquez-Limon, N.; Romero-Castanon, T. A techno-economic study for a hydrogen storage system in a microgrid located in baja California, Mexico. Levelized cost of energy for power to gas to power scenarios. *Int. J. Hydrogen Energy* **2022**, *47*, 30050–30061. [CrossRef]
46. Monforti Ferrario, A.; Bartolini, A.; Segura Manzano, F.; Vivas, F.J.; Comodi, G.; McPhail, S.J.; Andujar, J.M. A model-based parametric and optimal sizing of a battery/hydrogen storage of a real hybrid microgrid supplying a residential load: Towards island operation. *Adv. Appl. Energy* **2021**, *3*, 100048. [CrossRef]
47. K/bidi, F.; Damour, C.; Grondin, D.; Hilairet, M.; Benne, M. Multistage power and energy management strategy for hybrid microgrid with photovoltaic production and hydrogen storage. *Appl. Energy* **2022**, *323*, 119549. [CrossRef]
48. Shi, M.; Huang, Y.; Lin, H. Research on power to hydrogen optimization and profit distribution of microgrid cluster considering shared hydrogen storage. *Energy* **2023**, *264*, 126113. [CrossRef]
49. Yang, H.; Li, Q.I.; Zhao, S.; Chen, W.; Liu, H. A Hierarchical Self-Regulation Control for Economic Operation of AC / DC Hybrid Microgrid With Hydrogen Energy Storage System. *IEEE Access* **2019**, *7*, 89330–89341. [CrossRef]

50. Sharma, P.; Kolhe, M.; Sharma, A. Economic performance assessment of building integrated photovoltaic system with battery energy storage under grid constraints. *Renew. Energy* **2020**, *145*, 1901–1909. [CrossRef]
51. Santos-Pereira, K.; Pereira, J.D.F.; Veras, L.S.; Cosme, D.L.S.; Oliveira, D.Q.; Saavedra, O.R. The requirements and constraints of storage technology in isolated microgrids: A comparative analysis of lithium-ion vs. lead-acid batteries. *Energy Syst.* **2021**. [CrossRef]
52. Fallahifar, R.; Kalantar, M. Optimal planning of lithium ion battery energy storage for microgrid applications: Considering capacity degradation. *J. Energy Storage* **2023**, *57*, 106103. [CrossRef]
53. Wei, Y.; Wang, S.; Han, X.; Lu, L.; Li, W.; Zhang, F.; Ouyang, M. Toward more realistic microgrid optimization: Experiment and high-efficient model of Li-ion battery degradation under dynamic conditions. *eTransportation* **2022**, *14*, 100200. [CrossRef]
54. González, I.; Calderón, A.J.; Folgado, F.J. IoT real time system for monitoring lithium-ion battery long-term operation in microgrids. *J. Energy Storage* **2022**, *51*, 104596. [CrossRef]
55. Habib, H.F.; Esfahani, M.M.; Mohammed, O.A. Investigation of protection strategy for microgrid system using lithium-ion battery during islanding. *IEEE Trans. Ind. Appl.* **2019**, *55*, 3411–3420. [CrossRef]
56. Mohiti, M.; Mazidi, M.; Rezaei, N.; Khooban, M.H. Role of vanadium redox flow batteries in the energy management system of isolated microgrids. *J. Energy Storage* **2021**, *40*, 102673. [CrossRef]
57. Huang, Z.; Mu, A. Research and analysis of performance improvement of vanadium redox flow battery in microgrid: A technology review. *Int. J. Energy Res.* **2021**, *45*, 14170–14193. [CrossRef]
58. Sarkar, T.; Bhattacharjee, A.; Samanta, H.; Bhattacharya, K.; Saha, H. Optimal design and implementation of solar PV-wind-biogas-VRFB storage integrated smart hybrid microgrid for ensuring zero loss of power supply probability. *Energy Convers. Manag.* **2019**, *191*, 102–118. [CrossRef]
59. Jefimowski, W.; Szeląg, A.; Steczek, M.; Nikitenko, A. Vanadium redox flow battery parameters optimization in a transportation microgrid: A case study. *Energy* **2020**, *195*, 116943. [CrossRef]
60. Chen, S.; Gong, Q.; Lu, X.; Lai, J. Distributed cooperative control for economic dispatch and SOC balance in DC microgrids with vanadium redox batteries. *Sustain. Energy Grids Netw.* **2021**, *28*, 100534. [CrossRef]
61. Ali, Z.M.; Calasan, M.; Aleem, S.H.E.A.; Hasanien, H.M. On the Exact Analytical Formulas of Leakage Current-Based Supercapacitor Model Operating in Industrial Applications. *Energies* **2023**, *16*, 1903. [CrossRef]
62. Rawa, M.; Alghamdi, S.; Milyani, A.H.; Hariri, F.; Alghamdi, B.; Ajour, M.; Ćalasan, M.; Ali, Z.M.; Hasanien, H.M.; Popovic, B.; et al. Thermal model of supercapacitors operating in constant power applications: New mathematical expressions for precise calculation of temperature change. *J. Energy Storage* **2022**, *49*, 104121. [CrossRef]
63. Ćalasan, M.; Zobaa, A.F.; Hasanien, H.M.; Abdel Aleem, S.H.E.; Ali, Z.M. Towards accurate calculation of supercapacitor electrical variables in constant power applications using new analytical closed-form expressions. *J. Energy Storage* **2021**, *42*, 102998. [CrossRef]
64. Yang, B.; Wang, J.; Sang, Y.; Yu, L.; Shu, H.; Li, S.; He, T.; Yang, L.; Zhang, X.; Yu, T. Applications of supercapacitor energy storage systems in microgrid with distributed generators via passive fractional-order sliding-mode control. *Energy* **2019**, *187*, 115905. [CrossRef]
65. Jami, M.; Shafiee, Q.; Gholami, M.; Bevrani, H. Control of a super-capacitor energy storage system to mimic inertia and transient response improvement of a direct current micro-grid. *J. Energy Storage* **2020**, *32*, 101788. [CrossRef]
66. de Carvalho, W.C.; Bataglioli, R.P.; Fernandes, R.A.S.; Coury, D.V. Fuzzy-based approach for power smoothing of a full-converter wind turbine generator using a supercapacitor energy storage. *Electr. Power Syst. Res.* **2020**, *184*, 106287. [CrossRef]
67. Saleh, A.; Awad, A.; Ghanem, W. Modeling, Control, and Simulation of a New Topology of Flywheel Energy Storage Systems in Microgrids. *IEEE Access* **2019**, *7*, 160363–160376. [CrossRef]
68. Kikusato, H.; Ustun, T.S.; Suzuki, M.; Sugahara, S.; Hashimoto, J.; Otani, K.; Ikeda, N.; Komuro, I.; Yokoi, H.; Takahashi, K. Flywheel energy storage system based microgrid controller design and PHIL testing. *Energy Rep.* **2022**, *8*, 470–475. [CrossRef]
69. Mahdavi, M.S.; Gharehpetian, G.B.; Moghaddam, H.A. Enhanced Frequency Control Method for Microgrid-Connected Flywheel Energy Storage System. *IEEE Syst. J.* **2020**, *15*, 4503–4513. [CrossRef]
70. Jin, J.X.; Wang, J.; Yang, R.H.; Zhang, T.L.; Mu, S.; Fan, Y.J.; Xing, Y.Q. A superconducting magnetic energy storage with dual functions of active filtering and power fluctuation suppression for photovoltaic microgrid. *J. Energy Storage* **2021**, *38*, 102508. [CrossRef]
71. Salama, H.S.; Aly, M.M.; Abdel-Akher, M.; Vokony, I. Frequency and voltage control of microgrid with high WECS penetration during wind gusts using superconducting magnetic energy storage. *Electr. Eng.* **2019**, *101*, 771–786.
72. Kotb, K.M.; Elmorshedy, M.F.; Salama, H.S.; Dán, A. Enriching the stability of solar/wind DC microgrids using battery and superconducting magnetic energy storage based fuzzy logic control. *J. Energy Storage* **2022**, *45*, 103751. [CrossRef]
73. Alkhafaji, A.S.; Trabelsi, H. Uses of Superconducting Magnetic Energy Storage Systems in Microgrids under Unbalanced Inductive Loads and Partial Shading Conditions. *Energies* **2022**, *15*, 8597. [CrossRef]
74. Zhang, T.L.; Zhou, Q.; Mu, S.; Li, H.; Li, Y.J.; Wang, J. Voltage-Based Segmented Control of Superconducting Magnetic Energy Storage for Transient Power Fluctuation Suppression in Island DC Microgrid. *IEEE Trans. Appl. Supercond.* **2021**, *31*, 1–5.
75. Ćalasan, M.; Abdel Aleem, S.H.E.; Hasanien, H.M.; Alaas, Z.M.; Ali, Z.M. An innovative approach for mathematical modeling and parameter estimation of PEM fuel cells based on iterative Lambert W function. *Energy* **2023**, *264*, 126165. [CrossRef]

76. Elnozahy, A.; Ramadan, H.S.; Abo-Elyousr, F.K. Efficient metaheuristic Utopia-based multi-objective solutions of optimal battery-mix storage for microgrids. *J. Clean. Prod.* **2021**, *303*, 127038. [CrossRef]
77. Jing, W.; Lai, C.H.; Wong, W.S.H.; Wong, M.L.D. Dynamic power allocation of battery-supercapacitor hybrid energy storage for standalone PV microgrid applications. *Sustain. Energy Technol. Assess.* **2017**, *22*, 55–64. [CrossRef]
78. Akram, U.; Khalid, M.; Shafiq, S. An innovative hybrid wind-solar and battery-supercapacitor microgrid system—Development and optimization. *IEEE Access* **2017**, *5*, 25897–25912. [CrossRef]
79. Oriti, G.; Anglani, N.; Julian, A.L. Hybrid Energy Storage Control in a Remote Military Microgrid with Improved Supercapacitor Utilization and Sensitivity Analysis. *IEEE Trans. Ind. Appl.* **2019**, *55*, 5099–5108. [CrossRef]
80. Coban, H.H.; Rehman, A.; Mousa, M. Load Frequency Control of Microgrid System by Battery and Pumped-Hydro Energy Storage. *Water* **2022**, *14*, 1818. [CrossRef]
81. Barelli, L.; Bidini, G.; Bonucci, F.; Castellini, L.; Fratini, A.; Gallorini, F.; Zuccari, A. Flywheel hybridization to improve battery life in energy storage systems coupled to RES plants. *Energy* **2019**, *173*, 937–950. [CrossRef]
82. Refaat, M.M.; Aleem, S.H.E.A.; Atia, Y.; Zahab, E.E.D.A.; Sayed, M.M. A New Decision-Making Strategy for Techno-Economic Assessment of Generation and Transmission Expansion Planning for Modern Power Systems. *Systems* **2023**, *11*, 23. [CrossRef]
83. Hemeida, A.M.; Omer, A.S.; Bahaa-Eldin, A.M.; Alkhalaf, S.; Ahmed, M.; Senjyu, T.; El-Saady, G. Multi-objective multi-verse optimization of renewable energy sources-based micro-grid system: Real case. *Ain Shams Eng. J.* **2022**, *13*, 101543. [CrossRef]
84. Hemeida, A.M.; El-Ahmar, M.H.; El-Sayed, A.M.; Hasanien, H.M.; Alkhalaf, S.; Esmail, M.F.C.; Senjyu, T. Optimum design of hybrid wind/PV energy system for remote area. *Ain Shams Eng. J.* **2020**, *11*, 11–23. [CrossRef]
85. Al-Ghussain, L.; Samu, R.; Taylan, O.; Fahrioglu, M. Sizing renewable energy systems with energy storage systems in microgrids for maximum cost-efficient utilization of renewable energy resources. *Sustain. Cities Soc.* **2020**, *55*, 102059. [CrossRef]
86. Xie, C.; Wang, D.; Lai, C.S.; Wu, R.; Wu, X.; Lai, L.L. Optimal sizing of battery energy storage system in smart microgrid considering virtual energy storage system and high photovoltaic penetration. *J. Clean. Prod.* **2021**, *281*, 125308. [CrossRef]
87. Sharma, S.; Bhattacharjee, S.; Bhattacharya, A. Operation cost minimization of a Micro-Grid using Quasi-Oppositional Swine Influenza Model Based Optimization with Quarantine. *Ain Shams Eng. J.* **2018**, *9*, 45–63. [CrossRef]
88. Sharma, S.; Sood, Y.R.; Sharma, N.K.; Bajaj, M.; Zawbaa, H.M.; Turky, R.A.; Kamel, S. Modeling and sensitivity analysis of grid-connected hybrid green microgrid system. *Ain Shams Eng. J.* **2022**, *13*, 101679. [CrossRef]
89. Yang, Z.; Xia, L.; Guan, X. Fluctuation Reduction of Wind Power and Sizing of Battery Energy Storage Systems in Microgrids. *IEEE Trans. Autom. Sci. Eng.* **2020**, *17*, 1195–1207. [CrossRef]
90. Chen, C.; Duan, S.; Cai, T.; Liu, B.; Hu, G. Optimal allocation and economic analysis of energy storage system in microgrids. *IEEE Trans. Power Electron.* **2011**, *26*, 2762–2773. [CrossRef]
91. Bahramirad, S.; Reder, W.; Khodaei, A. Reliability-constrained optimal sizing of energy storage system in a microgrid. *IEEE Trans. Smart Grid* **2012**, *3*, 2056–2062. [CrossRef]
92. Sharma, S.; Bhattacharjee, S.; Bhattacharya, A. Grey wolf optimisation for optimal sizing of battery energy storage device to minimise operation cost of microgrid. *IET Gener. Transm. Distrib.* **2016**, *10*, 625–637. [CrossRef]
93. Xie, X.; Wang, H.; Tian, S.; Liu, Y. Optimal Capacity Configuration of Hybrid Energy Storage for an Isolated Microgrid Based on QPSO Algorithm. In Proceedings of the 2015 5th International Conference on Electric Utility Deregulation and Restructuring and Power Technologies (DRPT), Changsha, China, 26–29 November 2015; pp. 2094–2099. [CrossRef]
94. Liu, S.; Liu, F.; Ding, T.; Bie, Z. Optimal Allocation of Reactive Power Compensators and Energy Storages in Microgrids Considering Uncertainty of Photovoltaics. *Energy Procedia* **2016**, *103*, 165–170. [CrossRef]
95. Liu, Z.; Chen, Y.; Zhuo, R.; Jia, H. Energy storage capacity optimization for autonomy microgrid considering CHP and EV scheduling. *Appl. Energy* **2018**, *210*, 1113–1125. [CrossRef]
96. Nojavan, S.; Majidi, M.; Esfetanaj, N.N. An efficient cost-reliability optimization model for optimal siting and sizing of energy storage system in a microgrid in the presence of responsible load management. *Energy* **2017**, *139*, 89–97. [CrossRef]
97. Zobaa, A.; Abdel Aleem, S.; Abdelaziz, A. Preface. In *Classical and Recent Aspects of Power System Optimization*; Zobaa, A.F., Abdel Aleem, S.H.E., Abdelaziz, A.Y., Eds.; Elsevier: Amsterdam, The Netherlands, 2018; pp. xxi–xxvii. ISBN 978-0-12-812441-3.
98. Du, Y.; Li, F. Intelligent Multi-Microgrid Energy Management Based on Deep Neural Network and Model-Free Reinforcement Learning. *IEEE Trans. Smart Grid* **2020**, *11*, 1066–1076. [CrossRef]
99. Çimen, H.; Çetinkaya, N.; Vasquez, J.C.; Guerrero, J.M. A Microgrid Energy Management System Based on Non-Intrusive Load Monitoring via Multitask Learning. *IEEE Trans. Smart Grid* **2021**, *12*, 977–987. [CrossRef]
100. Kang, K.M.; Choi, B.Y.; Lee, H.; An, C.G.; Kim, T.G.; Lee, Y.S.; Kim, M.; Yi, J.; Won, C.Y. Energy management method of hybrid ac/dc microgrid using artificial neural network. *Electronic* **2021**, *10*, 1939. [CrossRef]
101. Abdolrasol, M.G.M.; Hannan, M.A.; Suhail Hussain, S.M.; Ustun, T.S.; Sarker, M.R.; Ker, P.J. Energy management scheduling for microgrids in the virtual power plant system using artificial neural networks. *Energies* **2021**, *14*, 6507. [CrossRef]
102. Wu, N.; Wang, H.; Yin, L.; Yuan, X.; Leng, X. Application Conditions of Bounded Rationality and a Microgrid Energy Management Control Strategy Combining Real-time Power Price and Demand-side Response. *IEEE Access* **2020**, *8*, 227327–227339. [CrossRef]
103. Al Sumarmad, K.A.; Sulaiman, N.; Wahab, N.I.A.; Hizam, H. Microgrid Energy Management System Based on Fuzzy Logic and Monitoring Platform for Data Analysis. *Energies* **2022**, *15*, 4125. [CrossRef]
104. Dong, W.; Yang, Q.; Fang, X.; Ruan, W. Adaptive optimal fuzzy logic based energy management in multi-energy microgrid considering operational uncertainties. *Appl. Soft Comput.* **2021**, *98*, 106882. [CrossRef]

105. Al Alahmadi, A.A.; Belkhier, Y.; Ullah, N.; Abeida, H.; Soliman, M.S.; Khraisat, Y.S.H.; Alharbi, Y.M. Hybrid wind/PV/battery energy management-based intelligent non-integer control for smart DC-microgrid of smart university. *IEEE Access* **2021**, *9*, 98948–98961. [CrossRef]
106. Leonori, S.; Martino, A.; Mascioli, F.M.F.; Rizzi, A. ANFIS Microgrid Energy Management System Synthesis by Hyperplane Clustering Supported by Neurofuzzy Min-Max Classifier. *IEEE Trans. Emerg. Top. Comput. Intell.* **2019**, *3*, 193–204. [CrossRef]
107. Rahim, S.; Javaid, N.; Khan, R.D.; Nawaz, N.; Iqbal, M. A convex optimization based decentralized real-time energy management model with the optimal integration of microgrid in smart grid. *J. Clean. Prod.* **2019**, *236*, 117688. [CrossRef]
108. Marino, C.A.; Marufuzzaman, M. A microgrid energy management system based on chance-constrained stochastic optimization and big data analytics. *Comput. Ind. Eng.* **2020**, *143*, 106392. [CrossRef]
109. Torkan, R.; Ilinca, A.; Ghorbanzadeh, M. A genetic algorithm optimization approach for smart energy management of microgrids. *Renew. Energy* **2022**, *197*, 852–863. [CrossRef]
110. HassanzadehFard, H.; Tooryan, F.; Collins, E.R.; Jin, S.; Ramezani, B. Design and optimum energy management of a hybrid renewable energy system based on efficient various hydrogen production. *Int. J. Hydrogen Energy* **2020**, *45*, 30113–30128. [CrossRef]
111. Wang, S.; Guo, D.; Han, X.; Lu, L.; Sun, K.; Li, W.; Sauer, D.U.; Ouyang, M. Impact of battery degradation models on energy management of a grid-connected DC microgrid. *Energy* **2020**, *207*, 118228. [CrossRef]
112. Tooryan, F.; HassanzadehFard, H.; Collins, E.R.; Jin, S.; Ramezani, B. Optimization and energy management of distributed energy resources for a hybrid residential microgrid. *J. Energy Storage* **2020**, *30*, 101556. [CrossRef]
113. Li, C.; Jia, X.; Zhou, Y.; Li, X. A microgrids energy management model based on multi-agent system using adaptive weight and chaotic search particle swarm optimization considering demand response. *J. Clean. Prod.* **2020**, *262*, 121247. [CrossRef]
114. Li, N.; Su, Z.; Jerbi, H.; Abbassi, R.; Latifi, M.; Furukawa, N. Energy management and optimized operation of renewable sources and electric vehicles based on microgrid using hybrid gravitational search and pattern search algorithm. *Sustain. Cities Soc.* **2021**, *75*, 103279. [CrossRef]
115. Ferahtia, S.; Rezk, H.; Abdelkareem, M.A.; Olabi, A.G. Optimal techno-economic energy management strategy for building's microgrids based bald eagle search optimization algorithm. *Appl. Energy* **2022**, *306*, 118069. [CrossRef]
116. Mellouk, L.; Ghazi, M.; Aaroud, A.; Boulmalf, M.; Benhaddou, D.; Zine-Dine, K. Design and energy management optimization for hybrid renewable energy system- case study: Laayoune region. *Renew. Energy* **2019**, *139*, 621–634. [CrossRef]
117. Bukar, A.L.; Tan, C.W.; Yiew, L.K.; Ayop, R.; Tan, W.S. A rule-based energy management scheme for long-term optimal capacity planning of grid-independent microgrid optimized by multi-objective grasshopper optimization algorithm. *Energy Convers. Manag.* **2020**, *221*, 113161. [CrossRef] [PubMed]
118. Keshta, H.E.; Malik, O.P.; Saied, E.M.; Bendary, F.M.; Ali, A.A. Energy management system for two islanded interconnected micro-grids using advanced evolutionary algorithms. *Electr. Power Syst. Res.* **2021**, *192*, 106958. [CrossRef]
119. Rocha, H.R.O.; Honorato, I.H.; Fiorotti, R.; Celeste, W.C.; Silvestre, L.J.; Silva, J.A.L. An Artificial Intelligence based scheduling algorithm for demand-side energy management in Smart Homes. *Appl. Energy* **2021**, *282*, 116145. [CrossRef]
120. Samuel, O.; Javaid, N.; Khalid, A.; Khan, W.Z.; Aalsalem, M.Y.; Afzal, M.K.; Kim, B.S. Towards Real-Time Energy Management of Multi-Microgrid Using a Deep Convolution Neural Network and Cooperative Game Approach. *IEEE Access* **2020**, *8*, 161377–161395. [CrossRef]
121. Leonori, S.; Paschero, M.; Frattale Mascioli, F.M.; Rizzi, A. Optimization strategies for Microgrid energy management systems by Genetic Algorithms. *Appl. Soft Comput. J.* **2020**, *86*, 105903. [CrossRef]
122. Elkazaz, M.; Sumner, M.; Thomas, D. Energy management system for hybrid PV-wind-battery microgrid using convex programming, model predictive and rolling horizon predictive control with experimental validation. *Int. J. Electr. Power Energy Syst.* **2020**, *115*, 105483. [CrossRef]
123. Tayab, U.B.; Zia, A.; Yang, F.; Lu, J.; Kashif, M. Short-term load forecasting for microgrid energy management system using hybrid HHO-FNN model with best-basis stationary wavelet packet transform. *Energy* **2020**, *203*, 117857. [CrossRef]
124. Morad, M.; Nayel, M.; Elbaset, A.A.; Galal, A.I.A. Sizing and analysis of grid-connected microgrid system for Assiut University using HOMER software. In Proceedings of the 2018 Twentieth International Middle East Power Systems Conference (MEPCON), Cairo, Egypt, 18–20 December 2018; IEEE: Piscataway, NJ, USA, 2018; pp. 694–699.
125. Çetinbaş, İ.; Tamyürek, B.; Demirtaş, M. Design, analysis and optimization of a hybrid microgrid system using HOMER software: Eskişehir osmangazi university example. *Int. J. Renew. Energy Dev.* **2019**, *8*, 65–79. [CrossRef]
126. Rozlan, M.B.M.; Zobaa, A.F.; Abdel Aleem, S.H.E. The optimisation of stand-alone hybrid renewable energy systems using HOMER. *Int. Rev. Electr. Eng.* **2011**, *6*, 1802–1810.
127. Martinez-Velasco, J.A.; Guerra, G. Reliability Analysis of Distribution Systems with Photovoltaic Generation Using a Power Flow Simulator and a Parallel Monte Carlo Approach. *Energies* **2016**, *9*, 537. [CrossRef]
128. De Araujo Pegado, R.; Rodriguez, Y.P.M. Distribution network reconfiguration with the OpenDSS using improved binary particle swarm optimization. *IEEE Lat. Am. Trans.* **2018**, *16*, 1677–1683. [CrossRef]
129. Li, J.; Ma, X.Y.; Liu, C.C.; Schneider, K.P. Distribution system restoration with microgrids using spanning tree search. *IEEE Trans. Power Syst.* **2014**, *29*, 3021–3029. [CrossRef]
130. Al Faruque, M.A.; Ahourai, F. GridMat: Matlab Toolbox for Gridlab-D to Analyze Grid Impact and Validate Residential Microgrid Level Energy Management Algorithms. In Proceedings of the ISGT 2014, Washington, DC, USA, 19–22 February 2014. [CrossRef]

131. Mathews, D.; Ó Gallachóir, B.; Deane, P. Systematic bias in reanalysis-derived solar power profiles & the potential for error propagation in long duration energy storage studies. *Appl. Energy* **2023**, *336*, 120819. [CrossRef]
132. Brouwer, A.S.; van den Broek, M.; Zappa, W.; Turkenburg, W.C.; Faaij, A. Least-cost options for integrating intermittent renewables in low-carbon power systems. *Appl. Energy* **2016**, *161*, 48–74. [CrossRef]
133. Vellingiri, M.; Rawa, M.; Alghamdi, S.; Alhussainy, A.A.; Ali, Z.M.; Turky, R.A.; Refaat, M.M.; Abdel Aleem, S.H.E. Maximum hosting capacity estimation for renewables in power grids considering energy storage and transmission lines expansion using hybrid sine cosine artificial rabbits algorithm. *Ain Shams Eng. J.* **2023**, *14*, 102092. [CrossRef]
134. Almalaq, A.; Alqunun, K.; Refaat, M.M.; Farah, A.; Benabdallah, F.; Ali, Z.M.; Aleem, S.H.E.A. Towards Increasing Hosting Capacity of Modern Power Systems through Generation and Transmission Expansion Planning. *Sustainability* **2022**, *14*, 2998. [CrossRef]
135. Nguyen, T.A.; Byrne, R.H. Software Tools for Energy Storage Valuation and Design. *Curr. Sustain. Energy Rep.* **2021**, *8*, 156–163. [CrossRef]
136. Tozzi, P.; Jo, J.H. A comparative analysis of renewable energy simulation tools: Performance simulation model vs. system optimization. *Renew. Sustain. Energy Rev.* **2017**, *80*, 390–398. [CrossRef]
137. Ul Abideen, M.Z.; Ellabban, O.; Al-Fagih, L. A review of the tools and methods for distribution networks' hosting capacity calculation. *Energies* **2020**, *13*, 2758.
138. González Ordiano, J.; Waczowicz, S.; Hagenmeyer, V.; Mikut, R. Energy forecasting tools and services. *Wiley Interdiscip. Rev. Data Min. Knowl. Discov.* **2018**, *8*, e1235. [CrossRef]
139. Stadler, M.; Groissböck, M.; Cardoso, G.; Marnay, C. Optimizing Distributed Energy Resources and building retrofits with the strategic DER-CAModel. *Appl. Energy* **2014**, *132*, 557–567. [CrossRef]
140. Sharma, H.; Mishra, S. Optimization of Solar Grid-Based Virtual Power Plant Using Distributed Energy Resources Customer Adoption Model: A Case Study of Indian Power Sector. *Arab. J. Sci. Eng.* **2022**, *47*, 2943–2963. [CrossRef]
141. Jiang, M.; Rindt, C.; Smeulders, D.M.J. Optimal Planning of Future District Heating Systems—A Review. *Energies* **2022**, *15*, 7160. [CrossRef]
142. Mohammed, O.H.; Amirat, Y.; Benbouzid, M.E.H.; Feld, G.; Mohammed, O.H.; Amirat, Y.; Benbouzid, M.E.H.; Design, G.F.O.; Man, E. Optimal Design and Energy Management of a Hybrid Power Generation System Based on Wind/Tidal/PV Sources: Case Study for the Ouessant French Island. In *Smart Energy Grid Design for Island Countries*; Springer: Berlin/Heidelberg, Germany, 2017.
143. Arrinda, M.; Berecibar, M.; Oyarbide, M.; Macicior, H.; Muxika, E.; Messagie, M. Levelized cost of electricity calculation of the energy generation plant of a CO2 neutral micro-grid. *Energy* **2020**, *208*, 118383. [CrossRef]
144. Belderbos, A.; Delarue, E.; Kessels, K.; D'haeseleer, W. Levelized cost of storage—Introducing novel metrics. *Energy Econ.* **2017**, *67*, 287–299. [CrossRef]
145. Jülch, V. Comparison of electricity storage options using levelized cost of storage (LCOS) method. *Appl. Energy* **2016**, *183*, 1594–1606. [CrossRef]
146. Pena-Bello, A.; Barbour, E.; Gonzalez, M.C.; Patel, M.K.; Parra, D. Optimized PV-coupled battery systems for combining applications: Impact of battery technology and geography. *Renew. Sustain. Energy Rev.* **2019**, *112*, 978–990. [CrossRef]
147. Raugei, M.; Peluso, A.; Leccisi, E.; Fthenakis, V. Life-Cycle Carbon Emissions and Energy Return on Investment for 80% Domestic Renewable Electricity with Battery Storage in California (U.S.A.). *Energies* **2020**, *13*, 3934. [CrossRef]
148. Han, X.; Garrison, J.; Hug, G. Techno-economic analysis of PV-battery systems in Switzerland. *Renew. Sustain. Energy Rev.* **2022**, *158*, 112028. [CrossRef]
149. Al-Wreikat, Y.; Attfield, E.K.; Sodré, J.R. Model for payback time of using retired electric vehicle batteries in residential energy storage systems. *Energy* **2022**, *259*, 124975. [CrossRef]
150. Tsai, C.T.; Ocampo, E.M.; Beza, T.M.; Kuo, C.C. Techno-economic and sizing analysis of battery energy storage system for behind-the-meter application. *IEEE Access* **2020**, *8*, 203734–203746. [CrossRef]
151. Saevarsdottir, G.; Tao, P.C.; Stefansson, H.; Harvey, W. Potential use of geothermal energy sources for the production of lithium-ion batteries. *Renew. Energy* **2014**, *61*, 17–22. [CrossRef]
152. Schneider, S.F.; Novak, P.; Kober, T. Rechargeable batteries for simultaneous demand peak shaving and price arbitrage business. *IEEE Trans. Sustain. Energy* **2021**, *12*, 148–157. [CrossRef]
153. Mathews, I.; Xu, B.; He, W.; Barreto, V.; Buonassisi, T.; Peters, I.M. Technoeconomic model of second-life batteries for utility-scale solar considering calendar and cycle aging. *Appl. Energy* **2020**, *269*, 115127. [CrossRef]
154. Wankmüller, F.; Thimmapuram, P.R.; Gallagher, K.G.; Botterud, A. Impact of battery degradation on energy arbitrage revenue of grid-level energy storage. *J. Energy Storage* **2017**, *10*, 56–66. [CrossRef]
155. El-Ela, A.A.A.; El-Seheimy, R.A.; Shaheen, A.M.; Wahbi, W.A.; Mouwafi, M.T. PV and battery energy storage integration in distribution networks using equilibrium algorithm. *J. Energy Storage* **2021**, *42*, 103041. [CrossRef]
156. McKenna, E.; McManus, M.; Cooper, S.; Thomson, M. Economic and environmental impact of lead-acid batteries in grid-connected domestic PV systems. *Appl. Energy* **2013**, *104*, 239–249. [CrossRef]
157. Kucevic, D.; Englberger, S.; Sharma, A.; Trivedi, A.; Tepe, B.; Schachler, B.; Hesse, H.; Srinivasan, D.; Jossen, A. Reducing grid peak load through the coordinated control of battery energy storage systems located at electric vehicle charging parks. *Appl. Energy* **2021**, *295*, 116936. [CrossRef]

158. Liu, D.; Xu, L.; Sadia, U.H.; Wang, H. Evaluating the CO_2 emission reduction effect of China's battery electric vehicle promotion efforts. *Atmos. Pollut. Res.* **2021**, *12*, 101115. [CrossRef]
159. Liu, Z.; Song, J.; Kubal, J.; Susarla, N.; Knehr, K.W.; Islam, E.; Nelson, P.; Ahmed, S. Comparing total cost of ownership of battery electric vehicles and internal combustion engine vehicles. *Energy Policy* **2021**, *158*, 1–41. [CrossRef]
160. Khezri, R.; Mahmoudi, A.; Aki, H. Resiliency-Oriented Optimal Planning for a Grid-Connected System with Renewable Resources and Battery Energy Storage. *IEEE Trans. Ind. Appl.* **2022**, *58*, 2471–2482. [CrossRef]
161. Lee, H.; Lim, D.; Lee, B.; Gu, J.; Choi, Y.; Lim, H. What is the optimized cost for a used battery?: Economic analysis in case of energy storage system as 2nd life of battery. *J. Clean. Prod.* **2022**, *374*, 133669. [CrossRef]
162. Yang, T.; Mok, K.T.; Tan, S.C.; Lee, C.K.; Hui, S.Y. Electric Springs With Coordinated Battery Management for Reducing Voltage and Frequency Fluctuations in Microgrids. *IEEE Trans. Smart Grid* **2018**, *9*, 1943–1952. [CrossRef]
163. Zobaa, A.F.; Aleem, S.A. *Uncertainties in Modern Power Systems*; Academic Press: Cambridge, MA, USA, 2020; ISBN 0128208937.
164. Ebeed, M.; Aleem, S.H.E.A. Overview of uncertainties in modern power systems: Uncertainty models and methods. In *Uncertainties in Modern Power Systems*; Zobaa, A.F., Abdel Aleem, S.H.E.B.T.-U., Eds.; Academic Press: Cambridge, MA, USA, 2021; pp. 1–34. ISBN 978-0-12-820491-7.
165. Refaat, M.M.; Abdel Aleem, S.H.E.; Atia, Y.; Ali, Z.M.; El-Shahat, A.; Sayed, M.M. A mathematical approach to simultaneously plan generation and transmission expansion based on fault current limiters and reliability constraints. *Mathematics* **2021**, *9*, 2771. [CrossRef]
166. Mohamed, N.; Aymen, F.; Ali, Z.M.; Zobaa, A.F.; Abdel Aleem, S.H.E. Efficient power management strategy of electric vehicles based hybrid renewable energy. *Sustainability* **2021**, *13*, 7351. [CrossRef]