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Review

Review on Recent Strategies for Integrating Energy Storage Systems in Microgrids

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Abstract: Energy security and the resilience of electricity networks have recently gained critical momentum as subjects of research. The challenges of meeting the increasing electrical energy demands and the decarbonisation efforts necessary to mitigate the effects of climate change have highlighted the importance of microgrids for the effective integration of renewable energy sources. Microgrids have been the focus of research for several years; however, there are still many unresolved challenges that need to be addressed. Energy storage systems are essential elements that provide reliability and stability in microgrids with high penetrations of renewable energy sources. This study provides a systematic review of the recent developments in the control and management of energy storage systems for microgrid applications. In the early sections, a summary of the microgrid topologies and architectures found in the recent literature is given. The main contributions and targeted applications by the energy storage systems in the microgrid applications is defined for each scenario. As various types of energy storage systems are currently being integrated for the reliable operation of the microgrids, the paper analyses the properties and limitations of the solutions proposed in the recent literature. The review that was carried out shows that a hybrid energy storage system performs better in terms of microgrid stability and reliability when compared to applications that use a simple battery energy storage system. Therefore, a case study for a DC microgrid with a hybrid energy storage system was modelled in MATLAB/Simulink. The presented results show the advantages of hybrid energy storage systems in DC microgrids.

Keywords: distributed energy sources; energy storage; microgrids; hybrid energy storage system; photovoltaic system

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1. Introduction

A microgrid is an interconnected group of loads, energy storage systems (ESSs) and distributed generators that can exchange power with the main grid through a single point of common coupling (PCC) [1]. Microgrids (MGs) have the capability of working together with the main grid, and as separate entities (i.e., as islands). Therefore, MGs can be deployed to provide electricity in remote areas, thereby facilitating the generation, distribution, and regulation of the power flow to the local consumers. MGs are being considered as one of the key concepts that will enable the deployment of high penetrations of renewable energy sources (RESs) in our electricity networks [2]. Amongst present and emerging RESs, RES integration in MGs typically consists of technologies including photovoltaic (PV) modules, small-capacity hydro units, ocean energy, and wind turbines. MGs can improve the energy security and reliability of the local energy network through the integration of complimentary distributed renewable sources. MGs are the key enablers for future smart grids, which have the potential to transition the present, centralised electricity networks into fully distributed architectures. MG architectures are categorised as alternating current microgrid (ACMG), direct current microgrid (DCMG) and hybrid microgrid (HMG). The

HMG combines the advantages of the ACMG and DCMG architectures since the AC and DC buses are interlinked by a power electronic converter.

Power generation from RESs is typically intermittent and variable as the output power depends on the environmental conditions. Examples of this type of behaviour are the fluctuations in PV generation due to cloud coverage and the variable output characteristics of wind turbines. These uncertainties in RES generation can disrupt conventional planning by utilities. Any large unplanned fluctuations in non-dispatchable generators (i.e., RESs) can potentially affect the stability of the system [3–6]. Novel dispatch strategies are essential to maintaining the balance between generation and demand in scenarios with high penetrations of distributed RESs. Due to their hierarchical control architecture, MGs can maintain the voltage, phase angle, and frequency changes under permissible levels during fluctuations in RES generation. The hierarchical architecture enables the integration and management of distributed energy storage technologies that can provide the required additional reliability and energy security. High penetrations of distributed energy sources also cause power imbalances in the LV distribution network and can affect the transient stability. Local MG control strategies can maintain the voltage and frequency as stable, thus providing a reliable electricity supply to consumers during all possible modes of operation (islanded operation, grid-connected, and transitions between the two modes of operation) [7]. It is also a known phenomenon that high penetrations of distributed energy sources can also cause power imbalances, especially in cases where there are single-phase residential prosumers [8].

The authors in [9] examine the impact of integrating a PV system, an ESS, and electric vehicles into the distribution network of a campus. The authors applied an EMS to the campus microgrid while considering future integrations of RESs. A linear optimisation approach implemented in MATLAB was used to investigate the optimal PV and ESS scenarios. Without the local PV system, the utility provided for the entire energy needs of the campus under a time-of-use (ToU) tariff system. The integration of the PV and ESS, determined from the linear optimisation approach, predicted a reduction of up to 44.80% in the daily energy consumption costs. Investigations were also conducted into the effects of additional local issues such as power outages.

In [10], the authors mapped the interval forecast data from a PV system to the solution space with various weight assignment schemes for day-ahead optimisation. A thorough case study was conducted that shows a significant increase in the hybrid vessel's operational flexibility. The dispatching system that was used in this study uses a multi-objective function to schedule the ship operation in scenarios with competing objectives. The operational cost is the main objective that is addressed by the optimisation scheme while the degradation in the lifetime of the ESS is minimised.

Economic load dispatch was also proposed in [11] to meet the load demand while reducing the overall operational costs by distributing power across several ESSs. In [11], the authors propose a multi-agent consensus-distributed control strategy that was designed to achieve multiple goals simultaneously. The multi-agent consensus-distributed control strategy considers the frequency/voltage droop controllers and the BESSs' hierarchical control architecture. The presented results show that with this strategy, several BESSs tracked the time-of-use-based pricing-generated SoC reference trajectories during a 24 h period with a variable load. The multi-agent consensus strategy also distributes the load active and reactive power, and simultaneously achieves frequency and voltage management (using the leader-follower consensus approach). However, each BESS requires information from nearby BESSs, in addition to the local information. The suggested communication strategy includes plug-and-play functionality and robustness against communication-link failure and transmission delays of up to 15 ms.

A mixed-integer, nonlinear programming model for PV-battery systems was proposed by the authors in [12], which considers long-term battery deterioration. The main objective was to minimise the lifecycle cost by using a novel two-layer optimisation method that takes into account the self-consumption ratios, optimum battery capacity, and two types of tariff systems. The results showed that the battery degradation could cause an increase in operational costs. By taking the battery degradation into account in the optimisation strategy, the resulting battery capacities and lifecycle costs show a significant increase when compared to the scenario without the battery degradation effects.

In [13], a methodology is created which enables the efficient and effective management of the numerous measurements and uncertainties that come with renewable energy sources. By characterizing the measured data by representative days, clustering algorithms were employed to address these two problems. Historical data was used to reflect the specificities of the considered grid. The architecture that was created can successfully govern across various time horizons. HOMER Pro® (Boulder, CO 80301, USA) was employed for planning purposes, while other pertinent indicators were gathered through a day-ahead optimal scheduling tool. A case study shows that the proposed methodology can be used to identify the best battery technology and DOD strategy. The selection criteria for the battery storage were based on parameters such as the lifetime and annual operating costs of each battery technology. Results for the specific case study have shown that, even though NiCd batteries have the best operational costs, their profitability is limited due to their high fixed costs. From an economic standpoint, Li-ion batteries have shown similar behaviour. On the other hand, lead-acid and NaS batteries appeared to be profitable alternatives for the considered microgrid. However, further studies on various microgrid and nanogrid configurations are necessary in order to further corroborate these results.

The authors in [14] examined current research topics that are crucial for the planning, control, and operation of campus microgrid architectures. Several approaches for different types of campus microgrids were studied and compared. These campus microgrids were investigated using a variety of optimisation methodologies, modelling tools, and energy storage technology types. It was determined that different campus microgrids throughout the world lack effective energy management strategies. Most of the evaluated campus microgrids have outdated energy management methods as there have been several advancements in this field that can be deployed to further improve the energy management of their systems.

In [15], the authors identify a trade-off between minimizing energy usage and maximizing user comfort caused by the existing scheduling systems' disregard for user activities. The trade-off between user comfort and electricity cost was alleviated by directly involving user actions in a proposed load-optimisation technique. This trade-off was taken into account, and optimisation models for various home appliances were designed and implemented. An analysis of the simulation's outcomes was performed in terms of occupancy, cost, and energy-consumption reduction.

In [16], the authors discuss energy-efficient power grid technologies. A thorough analysis was performed that takes into account the numerous difficulties in smart-grid demand-side management. The authors propose that line planning and low-cost scheduling make up the first two tiers of the demand-side load management architecture. Demand response is at the third level and is a topic which has seen considerable research activity in the past decade. This study investigates the viability of reprogramming consumer goods under heavy loads and system overloads to meet distribution system requirements.

Energy storage systems (ESSs) are critical elements in MGs as these can allow the effective integration of RESs with loads while maintaining transient stability and reliability. ESSs in microgrids are flexible resources that can provide a range of functions, such as grid resiliency (e.g., seamless transitions to/from islanded operations) and power-quality mitigation (e.g., voltage regulation and harmonic compensation). There are a few review papers that have been published in recent years that mainly discuss ESS sizing strategies, hierarchical control of MGs, and the state of the art in ESS technologies. The main contribution of the present study is to highlight the latest contributions in the literature on the optimal integration of ESSs with a specific focus on microgrid applications.

The remainder of the paper is organised as follows: Section 2 gives an overview of microgrid operating modes and architectures. Energy storage methods and their applications are discussed in detail in Section 3. Section 4 provides a description and analysis of a case study that considers the integration of a hybrid energy storage system (HESS) in a DC microgrid. The conclusions of the paper are presented in Section 5.

2. Microgrid Operation Mode and Architectures

Microgrids can operate in grid-connected and islanded operation. A brief overview of these two modes of operation now follows. A detailed description of these modes of operation is widely available in the literature and is beyond the scope of this article.

2.1. Modes of Operation

2.1.1. Grid-Connected Operation

In this mode, the MG is connected to the main grid through a single PCC. The MG exchanges power with the main grid depending upon the mismatch in the load power and the power generated by the RESs. Any excess power generated by the RESs (i.e., when the load demand is low, and the generation is high) can be used to charge the ESS. In scenarios where the ESS is fully charged, any excess power generated within the microgrid can be exported to the main grid. On the other hand, in case of partial shading or cloudy conditions (i.e., when the generation is lower than the load demand), the load may be supplied by the ESS, depending on the available SoC. When the ESS reaches its lower SoC limit, the required power may be imported directly from the main grid. Hence, the RES, ESS, and main grid need to work together to maintain the reliability and stability of the microgrid. Hence, the power flow through a PCC can be bidirectional.

2.1.2. Islanded Mode of Operation

Faults occurring in the main grid may cause abnormal conditions at the PCC of the microgrid. In this scenario, the microgrid can be isolated from the main grid and continue to operate as an islanded microgrid. In this mode of operation, the local frequency and voltage are regulated by the distributed RESs (e.g., wind and solar PV) and ESSs [17]. In this mode, ESSs are critical elements of the MGs that can maintain the energy balance, minimise power fluctuations, and improve the reliability and system efficiency [18]. The ESSs absorb excess RES generation when the generation exceeds the demand. The ESSs can be used to supply power to the MG in periods where the demand exceeds the local generation. This minimises any instances where RES power curtailment and/or load shedding should be carried out. In addition, ESSs can also be used to improve the voltage and frequency regulation of the islanded microgrid.

2.2. Microgrid Architectures

As described in an earlier section, MG architectures can be categorised into ACMGs, DCMGs, and HMGs. This section provides a brief overview of the main characteristics of each architecture.

2.2.1. AC Microgrids (ACMGs)

In ACMGs, the local RESs, ESSs, and loads are all connected to a common AC bus. Any DC generating units (e.g., PV panels) and ESSs (e.g., batteries) must connect to the common AC bus through dedicated DC-to-AC inverters [19]. The control and management of ACMGs is difficult due to the presence of critical and non-critical loads that require harmonic currents [20]. In ACMGs, harmonic suppression is achieved either by the introduction of passive/active filters or through the addition of special functionality in the primary control loops of the power electronic converters in the microgrid. While AC microgrids can be easily integrated into the main grid, re-synchronisation of the ACMG with the main grid is complex. Synchronisation of the MG involves matching the voltage amplitude, frequency, and phase at the PCC with that of the main grid. In the literature, there are three main AC distribution architectures for microgrids, namely, single-phase, three-phase with neutral, and three-phase without neutral.

2.2.2. DC Microgrids (DCMGs)

In these MGs, the local RES generation, ESSs, and loads are connected to a common DC bus. Any AC sources and loads must be connected to the common bus through dedicated AC-to-DC passive/active rectifiers. In the literature, one can find three main types of DC microgrids: monopolar, bipolar, and homopolar distribution systems. A monopolar DC grid consists of a two-wire distribution system, between which the DC bus voltage is defined. On the other hand, the bipolar and homopolar DC grids are three-wire DC distribution systems. In addition to the ground return conductor, the bipolar DC grid has two low-voltage conductors with different polarities, while the homopolar DC grid has two low-voltage conductors with the same voltage polarity. DCMGs have several advantages over their AC counterparts. These include greater reliability, higher efficiency (fewer power electronic converters), and improved stability. DC microgrids have been recently employed in special applications, such as shipboard microgrids, EVs, and telecommunication systems. However, the main limitation of DC microgrids is the complexity and high cost of the protection system when compared to AC microgrids [21].

2.2.3. Hybrid Microgrids (HMGs)

In HMGs, the AC sources and loads are connected to the AC bus, while DC sources and DC loads are connected to the DC bus. HMGs have the advantages of both ACMGs and DCMGs, and they result in fewer power conversion stages since these can simultaneously support both AC and DC sources/loads. The AC and DC sub-grids are interconnected via a bidirectional interlinking converter. This converter is the most important part of the HMG as it manages and coordinates the power flow between and within the sub-grids. The HMG uses a transformer to convert voltage on the AC side and a DC–DC converter for voltage conversion on the DC side [21,22]. Depending upon the load requirement and the condition of main grid, HMGs can also be made to work in grid-connected or islanded mode.

3. Recent Microgrid Architectures and Applications

Table 1 summarises the applications and main contributions described in the recent literature on microgrids that include ESSs. The remainder of this section provides a detailed review of the work carried out in these articles.

The authors in [23] performed an extensive review on the integration of RES with the main grid, while focusing on commercial applications. This study has shown that the role of ESSs in microgrids becomes crucial to ensure the continuous power supply to the loads due of the intermittent nature of the RES. In addition, the authors also provide a detailed analysis for the design of microgrids for commercial applications, with a specific focus on reliability criteria. Hybrid energy storage systems (HESSs) were proposed by the authors so as to benefit from the advantages of the combined types of ESSs. In [24], a HESS was used to overcome the inherent limitations of individual ESSs and thus achieve reliable storage solutions. A centralised control strategy is used with the conventional method for managing the HESS, whereby a filter-based technique is typically used. Both centralised and distributed control strategies were evaluated by the authors in order to improve the reliability of the ESS. Independent SoC recovery was performed to maintain the SoC of the HESS within the permissible limits.

An intelligent-control strategy aimed at scheduling the power purchasing in a microgrid consisting of wind turbines and BESSs was described in [25]. A carbon tax was also proposed by the authors to complement the RES generation since this would result in additional reductions in the dependency on fossil fuels. Quantum-based particle swarm optimisation was applied to a number of case studies to improve performance. The optimisation strategy was aimed at minimizing the generation cost while ensuring that the RES generation was used to the maximum and was increased using the optimisation and control technique. The authors in [26] proposed a self-sustainable microgrid architecture that can work with minimal dependence on the utility grid. BESSs were used to support the microgrid in the absence of the main grid. The sizing strategy for the BESS was based on minimizing the tie line flow from the utility grid. The test microgrid and control scheme were successfully implemented in a region in Thailand, and measures regarding the ways this strategy can be applied to other similar regions were also provided.

Table 1. Categorisation of recent microgrid publications, including ESSs, available in the literature.

MG Configuration	Regulatory Control	Mode of Operation	Application	Contribution	Year	Reference
DC	Distributed	Grid connected	Commercial	Reliability	2020	[23]
DC	Centralised	Grid connected	Industrial	Enhances system reliability, voltage regulation, and SoC recovery	2015	[24]
DC	Distributed	Grid connected	Commercial	Reduces the generating cost and enhances the power capacity	2015	[25]
DC	Distributed	Autonomous	Commercial	BESS sizing for system reliability	2015	[26]
AC	Distributed	Grid connected	Industrial	Power losses and battery sizing are strategies for economic benefits of the microgrid	2017	[27]
DC	Distributed	Grid connected	Residential	Battery life and reduction of the voltage fluctuations	2017	[28]
AC	Distributed	Grid connected	Commercial	Optimal sizing of the ESS, enhances the battery life	2017	[29]
DC	Distributed	Autonomous	Residential	Cost of BESS is highlighted for reducing overvoltages, energy loss, and emissions	2018	[30]
DC	Distributed	Autonomous	Commercial	System reliability, reduction of energy costs using intelligent techniques	2018	[31]
DC	Distributed	Grid connected	Commercial	Energy cost is analysed for efficient BESS operation	2017	[32]
DC, AC	May be applied to al	May be applied to all	May be applied to all	Cost and capacity of the ESS to reduce the peak-load demand	2019	[33]
DC, AC	Centralised	Autonomous	Commercial	Power loss and cost minimisation of the ESS	2017	[34]
DC	Decentralised	Autonomous	Industrial	Cost and sizing of the storage system	2019	[35]
DC, AC	Decentralised	Grid connected	Industrial	Cost, capacity, and sizing of ESS	2017	[36]
AC	Centralised	Grid Connected	Commercial	Operation and sizing of an ESS for a windfarm	2020	[37]
Hybrid	Decentralised	Both	Household	Cost	2020	[38]
DC, AC	Decentralised	Autonomous	Residential	Hybrid power system; limit the power and energy for efficient ESS operation	2021	[39]
DC, AC	Grid connected	Autonomous	Commercial	Two control techniques are proposed for the charging and discharging of ESSs	2021	[40]
DC	Decentralised	Both	Commercial	An ESS is integrated with a microgrid for reliability in normal and abnormal conditions	2021	[41]
DC, AC	Centralised	Both	Industrial	Hybrid ESS for resilient microgrid operation	2022	[42]
DC	Centralised	Grid connected	Residential	Intelligent method for estimating the battery SoC	2021	[43]
DC	Centralised	Autonomous	Commercial	Hybrid energy storage approach is used to minimise the operating cost in the microgrid system and minimise waste energy	2021	[44]

The authors in [27] propose an optimisation strategy that serves two purposes: minimising the cost and minimising the power losses. Traditionally, there is a trade-off between these two objectives. Hence, a fuzzy logic strategy was proposed by the authors in order to reach the optimal solution. A cost-efficient model was proposed to determine the optimal size and location of the ESS units. Demand response was used for the load management, where the peak loads were shifted to off-peak periods. The optimal siting of the BESS for voltage-balancing applications in grid-connected microgrids with high penetrations of RESs was explored in [28]. A genetic algorithm-based optimisation technique was utilised for voltage-deviation mitigation while considering the maximisation of the battery lifetime. A qualitative cost model was designed to minimise the overall cost of the system. In addition, a sensitivity analysis was performed for varying costs.

Intelligent methods were applied in [29] for the optimal sizing of the ESS while maximising the battery life by avoiding overuse. The CAPEX of BESSs is highlighted in [30] in applications that target the reduction of overvoltages, energy losses, and emissions. Intelligent techniques were applied in [31] to reduce the cost and improve the reliability of the system. The authors in [32] analyses the energy costs by effectively utilising the BESS. Cost and capacity of the ESS are highlighted, and a reduced peak-load demand is achieved in [33]. Power loss and the cost of the ESS is discussed in [34] for hybrid microgrids using a centralised control scheme. The cost and capacity of the ESS is analysed in [35] for a DC microgrid.

Optimal sizing and cost of the ESS are considered in [36] for a hybrid microgrid. Charging and discharging strategies for a storage system used in a microgrid that includes a wind farm are discussed in [37]. The proposed system explores the most economical ESS for a wind-based microgrid. The cost and charging and discharging patterns of the ESS are discussed in [38] for a hybrid microgrid. The system was found to be environmentally friendly. The hybrid power system based on different scenarios was compared in [39]. The limits of the power and energy for efficient ESSs are also discussed and analysed. Two control strategies were applied to regulate the unbalanced power in the microgrid and to control the charging/ discharging of the storage system in [40]. The authors in [41] propose an ESS integrated in a microgrid for reliable system operation by balancing demand and supply in normal and abnormal conditions. The authors in [42] propose a hybrid ESS for improving the resiliency of microgrids. The authors in [43] use an intelligent method for estimating the SoC of a battery in a microgrid system. A hybrid energy storage approach is used to minimise the operating cost in the microgrid system and minimise the waste energy in [44].

3.1. Energy Storage Systems for Microgrid Prosumers

With the integration of renewable energy generation into the existing power system, many users are becoming prosumers by playing the combined roles of producer and consumer. The main grid may be negatively impacted by the huge amount of PV and WT feed-in; the feed-in pricing is substantially lower than the retail pricing to entice prosumers to use RES. Prosumers must also deal with inconsistency in the load demand and the unpredictability of the RES output. All of these requirements have led to a pressing demand for prosumer energy storage resources. The broad use of personal energy storage systems is hampered by the high investment cost, and in many cases, it is still not economical for the prosumers to install their own storage systems. Community ESSs for the shared use of prosumers is a workable solution to the issue [45]. Consumers who use community-scale ESSs have a distinct financial advantage over all other consumers who use personal energy storage systems. Many studies have recently concentrated on the energy exchange between prosumers and community ESSs. For instance, the authors in [46] developed a two-stage paradigm for CESSs and prosumers to share energy storage, in which community ESSs determine the price of virtual storage capacity in the first stage, and prosumers determine capacity and charging/discharging power in the second stage. In [47], a revised two-stage approach for shared energy storage is introduced. A distributed energy capacity trade and operation game proposed in [48] allows consumers to choose capacity bidding actions and day-ahead charging and discharging routines.

3.2. Machine Learning in the Energy Management System of Microgrids

The electric power system is undergoing a drastic modernisation process, which is being driven by the most recent developments and implementations of smart-grid technologies. Microgrids are a crucial component of the modernisation of electricity networks because they offer a flexible means of integrating distributed RESs into the electrical grid. Distributed RESs, like solar and wind, can, nevertheless, be quite unpredictable and intermittent. It is challenging to properly operate an MG because of these erratic resources, load demand, and the random variations on the supply and demand sides. Many studies have been performed to address this issue and provide energy management strategies for the real-time scheduling of an MG, taking into account the adequacy of renewable energy, electricity prices, and load demand uncertainty [49]. In [50], a learning-based solution is provided which does not require an explicit model of the uncertainty, in contrast to traditional model-based approaches that call for a predictor to estimate the uncertainty. The goal of energy management is to reduce the daily running costs using a Markov decision process [51]. A deep reinforcement learning strategy was devised to resolve the Markov decision process. The deep Q-network algorithm was used to train the neural network in the deep reinforcement learning approach, which uses a deep feedforward neural network to approximate the ideal action-value function [52,53]. The necessity of an explicit system model and a predictor to manage the uncertainty can be relaxed by learning-based approaches. The MG is treated as a mysterious black box, and by interacting with it, they develop an almost ideal strategy. Deep reinforcement learning techniques were suggested as potential solutions to the issues a few years ago by the machine learning community. DRL methods use deep neural networks' end-to-end learning capabilities to circumvent the difficulty of learning from high-dimensional state inputs. A deep learning architecture based on a convolutional neural network (CNN) was developed to extract knowledge from historical time series of energy consumption and PV generation.

4. Energy Storage Methods

ESSs play a crucial role in microgrids, and various types of ESS technologies have been considered in the literature. Figure 1 shows abroad classification of ESSs that encompasses many technologies into six main categories. Table 2 lists the different energy storage methods and outlines their main benefits and their disadvantages.

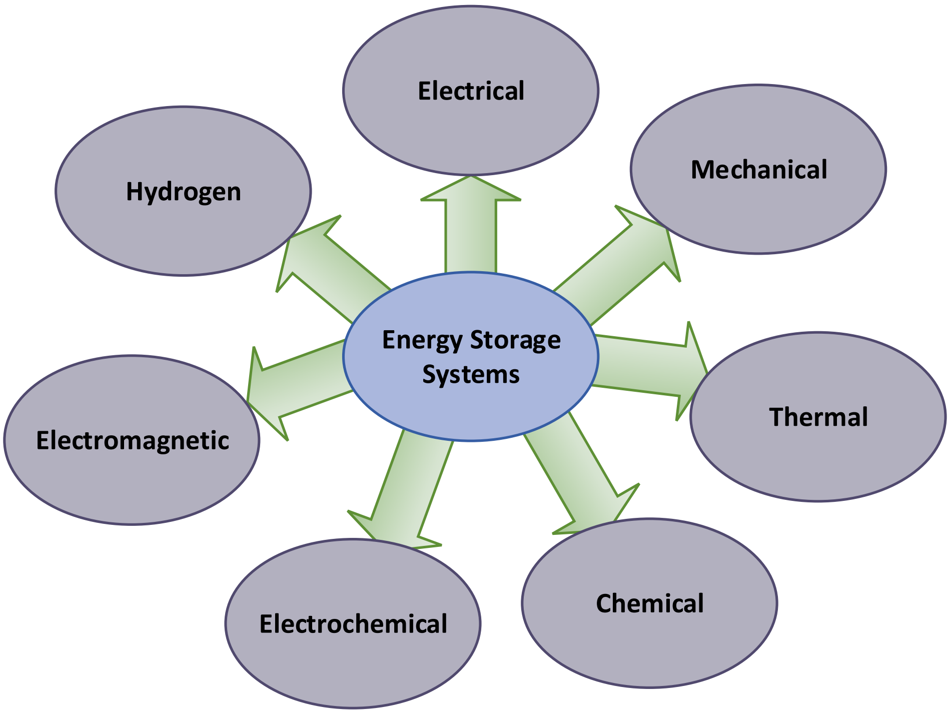

Figure 1. Classification of energy storage systems.

Table 2. Advantages and Disadvantages of available energy storage technologies.

Type of ESS	Advantages	Disadvantages	Reference
Flywheel-based	Environmentally friendly, efficient system, power density is high, low maintenance cost, longer lifespan	Large capital investment, high self-discharge rate, low energy density	[54–56]
Compressed-air-based	Peak shaving performance, provides better control, better quality of air, more stable, smoothened power	Implementation is difficult as appropriate geographical regions needs to be chosen, large capital investment, water loss	[57,58]
Gravity-based	Difference in elevation is not an issue, can be coupled with high-voltage transmission system easily	Capacity of storage system needs to be high, bigger in size, shorter lifetimes	[59,60]
Electrochemical	Low losses, different sizes are available	Uneconomical, Low energy density, shorter lifespan, requires maintenance	[61,62]
Battery	Enables better utilisation of DGs, reliable in grid-connected as well as islanded mode, Provides better control	Shorter lifespan, high maintenance required, SoC limits needs to be maintained	[63–65]
Thermal	Economical, environmentally friendly, rate of self-discharge is low	Temperature needs to be varied for the energy to be stored, unpredictable lifespan, capacity of storage system needs to be high	[66–68]
Chemical	High duration of energy storage, high storage capability	High energy losses, high cost high, low energy density, maintenance is required	[69,70]
Electrical	Better power quality, better response during peak hours, high power density	Uneconomical, high self-discharge rate	[63,71]
Hybrid	HESS has high energy density and power density because of the presence of both BESS and SC both, their energy storage capability is also high, making the system more reliable and stable	HESS has high energy density and power density because of the presence of both BESS and SC, their energy storage capability is also high, making the system more reliable and stable	[72–74]
Hydrogen-based	High energy density, independent charge/discharge rate	relatively low round-trip efficiency	[75,76]

4.1. Mechanical Energy Storage Systems

Mechanical ESSs encompass technologies such as pumped hydro, compressed air and gravity storage devices. The flywheel-based ESS is a robust and efficient method to store electrical energy as kinetic energy in a rotating mass with low frictional losses. Flywheel-based ESSs have low maintenance costs that result in long lifecycles but have very high capital costs. These storage systems are mainly suitable for enhancing the transient stability of microgrids due to their fast repost times. These storage systems typically have high power densities and low energy densities, which limits their flexibility. Thus, this ESS is not ideal for microgrid energy storage applications [54–56].

4.2. Compressed-Air Energy Storage Systems

The compressed-air ESS (CAESS) is a technically mature storage technology in which electricity is stored as compressed air that can be used when required. CAESSs can be built for small-scale and large-scale applications as backup power systems. CAESSs can be used for black start applications and peak shaving; however, their moderate-to-long time constants and spatial constraints (due to the storage tank) limits their widespread application in microgrid systems. Large-scale deployments also require significant capital investments, and the siting of a CAESS is not a trivial task [57,58].

4.3. Gravity-Based Energy Storage Systems

A gravity-based ESS (GESS) is a new solution for large-scale energy storage in which energy is stored as potential energy by the hydraulic lifting of a large mass. It can be coupled with a high-voltage transmission system easily but has a shorter lifespan. The authors in [59,60] examine and survey current gravity-based energy storage technologies. This storage method provides the means for high-capacity energy storage as well as a pollution-free, cost-effective, and extended lifespan. GESSs have quite a significant potential and could be employed in the future to reserve sustainable power to complement existing large-scale energy storage solutions. However, a significant number of studies and innovations must be performed to put these systems into practise and make them interoperable with other ESSs.

4.4. Electrochemical Energy Storage Systems

Secondary batteries, supercapacitors (SC), and fuel cells (FC) fall into the category of electrochemical energy storage. Batteries use an electrochemical reduction reaction to transform the chemical energy found in their active components into electric energy. SCs are high power density devices with time ranges from seconds to minutes as only the electrode surface of material is used, unlike in BESSs and FCs. Electrochemical ESSs have low losses and are available in different sizes [61,62].

4.5. Battery Energy Storage Systems

The battery-based energy storage system (BESS) is a reliable type of electrochemical energy storage which enables better utilisation of distributed generation. If necessary, the battery discharges to supply local loads. The most common technologies that are available on the market for BESSs include lithium-ion, lead-acid, nickel–cadmium, and nickel–metal hydride. Each battery type has unique performance details that define BESS implementations and impact the efficiency of the BESS. The SoC of a battery-based ESS needs to be maintained, otherwise it directly affects the battery's lifetime. It provides better control but requires more maintenance [63–65]. Peak shaving, flexibility, and load shifting are the main advantages of BESSs.

4.6. Thermal Energy Storage Systems

Each year, renewable energy makes up more of the total energy produced throughout the world. Apart from hydroelectric energy, renewable energy sources, such as solar energy and wind energy are among the most used. Due to being intermittent energy sources, they cannot be utilised to their full potential yet. The sun does not always shine, and the wind is not always blowing. If this intermittent energy can be stored, it can be employed even during times when the sources are not actively providing energy. Thermal energy storage is a viable solution. It can be described as storing energy as heat or cold in a storage medium to be used later. Thermal energy storage's main use is to overcome the imbalance between energy generation and energy use. A few essential requirements for an effective thermal energy storage system are a storage material with a high energy density, very good insulation to ensure minimal heat loss, a storage material that is chemically stable, and a completely reversible process that can be repeated numerous times. There are three main types of thermal energy storage systems: sensible heat storage, dealing with a mild increase or decrease in the temperature of a storage material; latent heat storage, which involves the phase change of a storage material; and thermochemical energy storage, where a reversible chemical reaction with high energy involved is used to store energy. The main limitation of these systems is that the change in temperature required for the energy to be stored. A thermal ESS is an economical and environmentally friendly way to store energy that has a low self-discharge rate and a high storage capacity [66–68].

4.7. Chemical Energy Storage Systems

A chemical ESS has high storage capability but low energy density. Their cost is usually high, and the losses are even greater. More maintenance is required for such systems [69,70]. Electrical ESSs provides high power density and better power quality. They show a better response during peak hours, but their self-discharge rate is very high [63,71]. Hybrid ESSs area reliable and stable solution to these problems as they have high energy density as well as high power density due to the presence of both BESSs and supercapacitors. Their energy storage capability is also high. The drawback is that their control is comparatively complex [72–74]. Figure 2 summarises the main applications of ESSs from small-scale systems to large-scale systems.

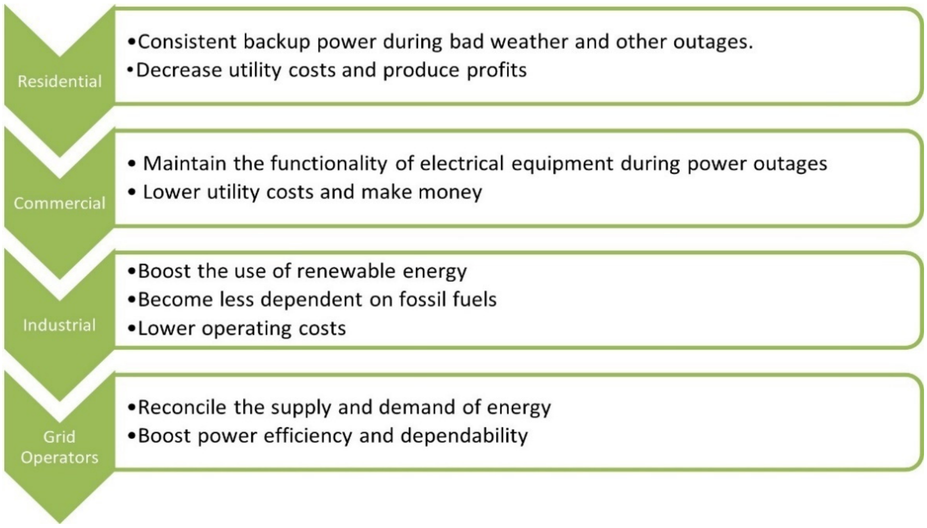

Figure 2. Applications of energy storage systems.

4.8. ESS Integration in Microgrids: Research Gaps

Table 3 summarises the main contributions to the field of ESS integration in microgrids by recent studies, together with the identified research gaps. A thorough review of energy storage methods and their respective analyses are discussed in [77]. However, the shortcomings of battery ESSs and their optimisation approaches were not considered in that work. In [78], a comprehensive review of energy-storage-based applications was performed. The drawbacks with respect to the degradation in the battery lifetime were discussed, but no solutions were provided to maximise the expected lifetime of the ESS. In [79], PID- and ANN-based control methods for frequency control in an ESS are discussed. Their results showed that the ANN-based methods show better performance, and PID controllers have certain limitations. The stability of a microgrid with high penetrations of renewable energy sources was improved in [40] by the introduction of complex controllers designed to regulate the SoC of the ESSs. Different sizing methods for battery ESSs are discussed in [80]. However, only a few of the considered optimisation methods are considered in sufficient detail to benefit academic and industrial applications. A battery's lifetime depends on its operational conditions [81], with the developed model identifying and including the main variables in the degradation process of lithium-ion batteries in V2G applications.

Table 3. Energy Storage Methods and research gaps.

Proposed Research	Research Gaps	Year	Reference
Control techniques are used to reduce the instability of a microgrid during the huge integration of renewable energy sources in load consumption	The numbers of controllers are designed to regulate the SoC conditions.	2021	[40]
Microgrid network, which predicts the uncertainties using deep learning techniques for efficient energy management	The sample batch size is reduced, which impacts the performance of the system.	2019	[49]

Table 3. *Cont.*

Proposed Research	Research Gaps	Year	Reference
Detailed techniques for battery life and SoC condition	The bus voltage is not considered, and battery SoC shows minor fluctuations.	2017	[74]
A thorough explanation of ES methods and their applications	For BESS techniques, the difficulties and problems are not discussed. The optimisation approaches are also not provided.	2016	[77]
Energy-storage-based applications are discussed in detail	The issues related to batteries' life cycles are identified, but solutions are not suggested.	2017	[78]
PID- and ANN-based control methods are discussed for frequency control	The ANN-based methods show excellent results, but the PID methods have some limitations	2020	[79]
Different sizing methods of BESSs for renewable energy systems	Details of the optimisation approach for sizing BESSs is limited to a few approaches.	2017	[80]
BESSs are delivered based on a confined forecast horizon of uncertainties and bound by the SoC constraints	The present BESS dispatch decisions can be appropriate for the current period but not for day-ahead planning.	2016	[81]
A two-stage coordinated technique is introduced to reduce operational costs	Energy losses, uncertainties, and real-time electricity prices are not considered.	2020	[82]
Charging and discharging among different microgrid networks	The real-time connections failed in some microgrid networks.	2015	[83]
A rule-based controller is used to reduce the annual cost and save the operational cost of ESSs	This method is limited to one ESS.	2020	[84]
Performance optimisation of residents in multi-microgrid networks	All four MPC techniques have their drawbacks in terms of size and communication channels.	2015	[85]
Deep learning techniques for energy management, cost reduction, and energy savings	This work lacks accuracy. So, more feasibility is required.	2021	[86]
PV-battery system for residential loads. Battery scheduling and electricity cost reduction are considered	This research is restricted to one consumer.	2021	[87]
Various decision-making approaches in microgrids are discussed	The related works do not involve the sizing of batteries and optimisation methods.	2019	[88]
Deep learning techniques are implemented for microgrid network hybrids	Time-based(day/hour) consumption does not distinguish between day and night.	2021	[89]
Application and principles of lead-acid batteries are discussed for different countries	The battery sizing and optimisation approaches are not included. It is only focused on lead-acid batteries.	2018	[90]
Smart homes have reduced energy costs and temperature fluctuations for energy management	Energy cost and temperature variations are effectively discussed but show the variations in grid parameters' performance.	2019	[91]
Energy sizing techniques for decarbonisation	The attributes are not discussed clearly.	2020	[92]
Categorised into four parts: electrical, mechanical, thermal, and chemical	Sizing and optimisation methods are not included.	2021	[93]

A two-stage coordinated technique was introduced in [82] to reduce the operational costs in microgrids. However, energy losses, uncertainties, and real-time electricity prices were not considered in the two-stage coordination technique, thereby limiting its practicality. Control techniques were proposed in [74] to control the SoC and improve the battery lifetime. However, minor fluctuations can still be observed in SoC conditions using the proposed technique. In [83], model predictive charging and discharging of energy storage was used to schedule the power exchanges between microgrid clusters. The proposed cooperation among grids shares similar limitations with centralised architectures when it comes to the failure of real-time communication. A rule-based controller was used in [84] to reduce the annual costs and reduce the operational cost of the ESS. The main drawback of this controller is that it is limited to only one ESS. The performance of residential ESSs in multi-microgrid networks was also considered by the authors in [85]. All four MPC techniques have their drawbacks in terms of size and communication channel. Deep learning techniques were proposed in [86] to deal with network complexity for the better energy management, cost reduction, and energy saving of a TESS. However, there are still numerous challenges that need to be addressed before deep learning techniques can find their way into the consumer market. The authors in [87] deal with battery scheduling and electricity cost-reduction for a hybrid PV-battery system in a residential setting. However, this research was restricted to one consumer, thereby limiting its applicability. The prediction of uncertainties using deep learning techniques for the efficient energy management of microgrids is considered in [49]. The sample batch size is small, which impacts the performance of the system. Various decision-making approaches are discussed in [88] for the integration of BESSs within microgrids. The related works do not involve the sizing of batteries or optimisation methods. Deep learning techniques are also implemented in [89] for hybrid microgrid networks. The time-based (day/hour) consumption, however, does not distinguish between day and night. May et al. [90] discuss the properties and applications of lead-acid batteries for utility-scale applications based on the operational experiences of different countries. However, the study does not describe battery sizing and optimisation approaches. Smart homes have reduced energy costs and temperature fluctuations for energy management [91]. The energy cost and temperature variations are effectively discussed but show the variations in grid parameters' performance. The grid-connected and standalone modes of operation are discussed in [92] for energy sizing techniques for decarbonisation. It is categorised into four parts, such as electrical, mechanical, thermal, and chemical [93]. The sizing and optimisation methods are not included.

Table 4 shows the comparative study of different approaches for the integration of ESSs into microgrids. The authors in [23] discuss a microgrid consisting of a PV and a BESS for smart grid applications. The exergy principle was applied in [94] for multiple energy sources with different energy levels and qualities. Using a multi-objective optimisation technique, the overall efficiency of the system was found to be improved, while the energy cost was reduced. Branch-and-cut was utilised to combat the trade-off between the cost and exergy objective functions. The proposed technique ensures minimum economic cost and improved efficiency. A comprehensive review of optimal energy management techniques was performed in [95]. Power flow stability was discussed for a complex power system consisting of utility grid, DER, ESS, DC loads, etc. Intelligent energy management technologies utilising optimisation approaches were discussed for coordination in the power flow of the smart grid. The smart grid ensures resilient and reliable demand and supply management. The energy internet was found to be a novel approach for a multi-energy system in a microgrid. A multi-level HESS topology and novel energy management scheme was proposed in [96] to improve battery life. A comparison of various HESS approaches was also performed by the authors. The system was found to be technically and financially viable when compared to existing ESSs. The life of an ESS is improved while the operational cost is minimised using the proposed technique. A novel coordination control algorithm is introduced in [97] for the control of voltage and frequency within the permissible limits. A BESS is connected to the microgrid to improve the efficiency and power quality of the system. The BESS is controlled by the main control centre, which controls the charging and discharging of the BESS. BESSs are divided into master BESSs and slave BESSs, depending upon their capacities. The BESS with a larger capacity, i.e., the master BESS, contributes to the charging/discharging process first. When the SoC limits of the master BESS are reached, the control centre sends a signal to the slave BESS to serve the purpose. Lesser deviations in voltage and frequency are obtained as compared to the on-load tap-changer technique.

Table 4. Comparative study of different approaches for energy storage system integration with the microgrid.

Storage Type	Renewable Energy Type	Highlights	Year	Reference
BESS	PV	Smart grid storage application,	2020	[23]
BESS	Hybrid	Energy cost is reduced, overall energy efficiency is improved	2015	[94]
ESS	Hybrid	Optimal energy management, reducing energy cost	2019	[95]
HESS	PV	Energy management, minimising the energy cost, comparison of HESS approaches	2017	[96]
BESS	RES is not included	Voltage and frequency control, central control of BESS, novel coordination control algorithm is introduced	2015	[97]
BESS	PV	Voltage and SoC control, local ESS controller is used.	2014	[98]
HESS	PV	ESS is centralised control, active distribution network is considered, IEEE-34 test feeder	2014	[99]
BESS	PV	Coordination control to manage the charging and discharging conditions, implemented on are al dataset	2018	[100]
BESS	PV	Predictive control methods used for managing the energy storage condition	2018	[101]
HESS	PV	Droop control and LPF is used to control the battery conditions, communication traffic is minimised	2021	[102]
HESS	PV	Designed an energy management system to increase the performance of the optimisation approaches used in the control scheme	2021	[103]
HESS	PV	Augmented filters used to increase the life of the battery; PI controller is used to control the reference current of the battery	2021	[104]
HESS	PV	Hybrid optimisation approach is used for energy management and battery sizing, predictive control method is implemented	2021	[105]
HESS	Hybrid	Reviews the energy storage approaches and applications for hybrid renewable power system	2022	[106]

The PV feed-in tariffs are lower than the utility grid electricity consumption rates in countries such as Germany. Hence, PV plants with ESSs are emerging in such locations. With high penetrations of PVs into the power system, the voltage tends to increase since the peak of the PV generation and the peak electricity demand do not coincide. Self-consumption does not necessarily imply an advantage for distribution networks with significant PV penetration. Voltage control techniques also need to be applied in such microgrids in addition to self-consumption strategies. The local PV storage control achieved in [98] ensures reactive power compensation and PV power curtailment, while managing the BESS charging, depending on the voltage. Grid simulations and an economic evaluation are used to determine their capacity to facilitate PV–grid integration while boosting self-consumption.

A coordinated control scheme was designed in [99] to regulate the charging/discharging of BESSs. By combining the local droop-based control method with a distributed control scheme, the voltage can be maintained within the permissible levels. Two distinct consensus algorithms were used. The first algorithm is employed to assess the BESSs' ability to participate in terms of their installed capacity, while the second algorithm basically performs voltage control. The latter adjusts the SoC of the BESSs to avoid over-charging/discharging of the BESS, thereby ensuring that the BESS is utilised effectively for various scenarios. The predictive control method was used to manage the energy storage units in [100] for a microgrid with a PV and a BESS. Droop control is used to control the battery SoC in [101] in a microgrid with PV and HESS. The advantage of this proposed algorithm is that the communication traffic is also minimised. In [102], an augmented filter was used to increase the lifetime of the battery, while a PI controller was used to control the reference current of the battery. A hybrid optimisation approach was used for the energy management and the battery sizing in [103]. The predictive control method was implemented for proper energy management. An extensive review of the energy storage approaches and applications for hybrid renewable power systems was performed in [104].

5. Case Study

A standalone microgrid with an energy storage system is an attractive alternative for remote electrification. Since BESSs have a short lifespan, they are unreliable and expensive to operate as the predominant solution for sustainable microgrids. In an effort to extend the lifetime of a BESS, the hybridisation of the ESS by combining elements with complimentary characteristics and their associated energy management strategies was investigated.

A MATLAB/Simulink model of a test microgrid was developed to evaluate the effectiveness of a HESS for accurate power sharing and voltage-deviation mitigation in dynamic power-exchange scenarios. The schematic diagram of the small-scale test standalone DC microgrid simulated in MATLAB/Simulink is presented in Figure 3. The test microgrid is composed of a PV source, a battery, a supercapacitor, and a load. A 120 W PV source is interfaced with the DC bus using a DC/DC boost converter, which implements a perturb-and observe-based MPPT technique. A 24 V, 14 Ah lithium-ion battery pack having an initial SoC of 50% and a 32 V, 29 F supercapacitor were connected to the DC bus through their respective bidirectional DC/DC converters. Tables 5–7 show the parameters of the PV, SC, and BESS, respectively. It can be observed that, for the varying power scenarios, the HESS supports the system such that the load is served all the time. It can further be observed that the DC-link voltage is maintained at a constant value, except for the negligible fluctuations during a change in PV power. These fluctuations during transients are minimised by the action of the SC, while the BESS maintains this DC-link voltage during a steady state.

Energy management in the microgrid is achieved by ensuring adequate coordination between the BESS and the SC. The PV was implemented with maximum power point tracking (MPPT) mode, using the well-known perturb and observe technique. The duty cycle is maintained depending on the SoC of the BESS and the deviation of the voltage from the reference value (50 V). Switching signals are sent to the boost converter interfacing the PV with the DC bus.

The DC-link voltage and reference voltage are compared, and the error signal is fed to the PI controller. This PI controller generates the reference current for the BESS. Now, the battery current reference is compared with the measured battery current, and their difference is fed to the PI controller. The output of the PI controller is sent to the PWM generator, which sends switching signals to switches S1 andS2 of the DC/DC bidirectional buck–boost controller, which in turn controls the charging and discharging process of the BESS. If the generation is more than the demand, a rise in voltage is observed, and the BESS works in buck mode. On the other hand, when a dip in voltage is observed, the BESS works on boost mode and supports the load. Hence, energy management is achieved while maintaining the DC-link voltage at its reference value [107].

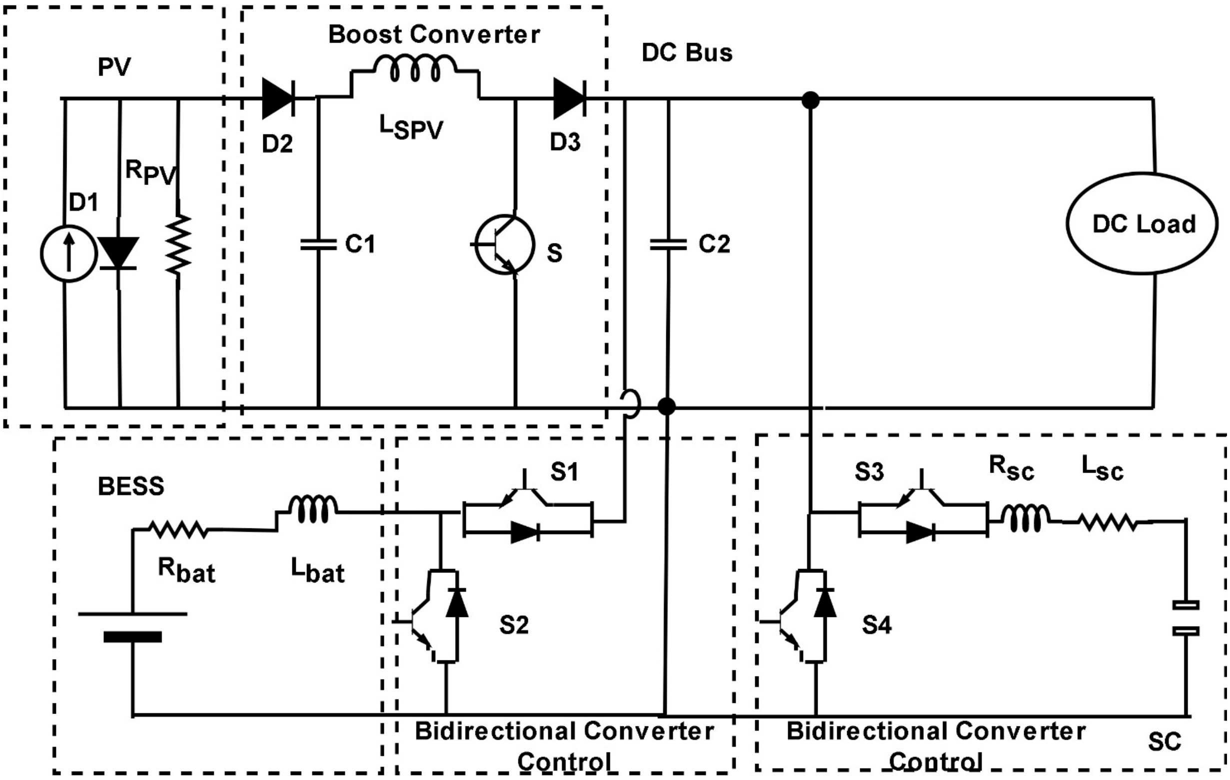

Figure 3. Simplified Schematic of the Test Microgrid structure.

Table 5. PV parameters used.

S. No.	Parameter	Value
1	Maximum power (W)	120.7
2	Cells per module (Ncell)	72
3	Open circuit voltage (V)	21
4	Short-circuit current (A)	8
5	Voltage at maximum power point (V)	17
6	Parallel strings	4
7	Series-connected modules per string	2
8	Operating temperature (Celsius)	25

Table 6. Supercapacitor parameters used.

S. No.	Parameter	Value
1	Rated capacitance (F)	29
2	Equivalent DC series resistance (ohms)	0.003
3	Rated voltage (V)	32
4	Number of series capacitors	1
5	Number of parallel capacitors	1
6	Initial voltage (V)	32
7	Operating temperature (Celsius)	25

The battery reference current and error signal of the voltage generates the SC current reference signal. The SC current reference signal is compared with the SC current, and the error signal is sent to the PI controller. The output of the PI controller is converted to switching signals by the PWM generator. The switching signals are sent to switches S3 andS4 of the DC/DC bidirectional converter connecting the SC and the DC bus. The BESS controls the DC-link voltage during the steady state, while the SC participates in the process during transients. A moving average and low-pass filter are utilised for the power allocation so as to remove the low frequency element and reduce BESS stresses.

Table 7. Battery parameters used.

S. No.	Parameter	Value
1	Type	Lithium-ion
2	Nominal voltage (V)	24
3	Rated capacity (Ah)	14
4	Initial SoC (%)	50
5	Battery response time (s)	0.1
6	Maximum capacity (Ah)	14
7	Cut-off voltage (V)	18
8	Fully charged voltage (V)	27.93
9	Nominal discharge current(A)	6.087
10	Internal resistance (ohms)	0.0171
11	Capacity at nominal voltage (V)	12.66

Figure 4 shows the output PV power for the considered case scenario. Initially, the PV power is increased to 900 W as per the irradiance. At 1.2 s, the PV power is dropped to 400 W. The microgrid serves a constant load of 500 W. Since the PV generation is reduced to less than the load at 1.2 s, PV power is not sufficient to serve the load. Then, the transient supercapacitor comes into action and makes it stable. The supercapacitor power can be observed in Figure 5. The SoC of the SC is shown in Figure 6. It can be observed that, since the supercapacitor works only during the transient, the supercapacitor SoC drops considerably at 1.2 s, which further remains constant.

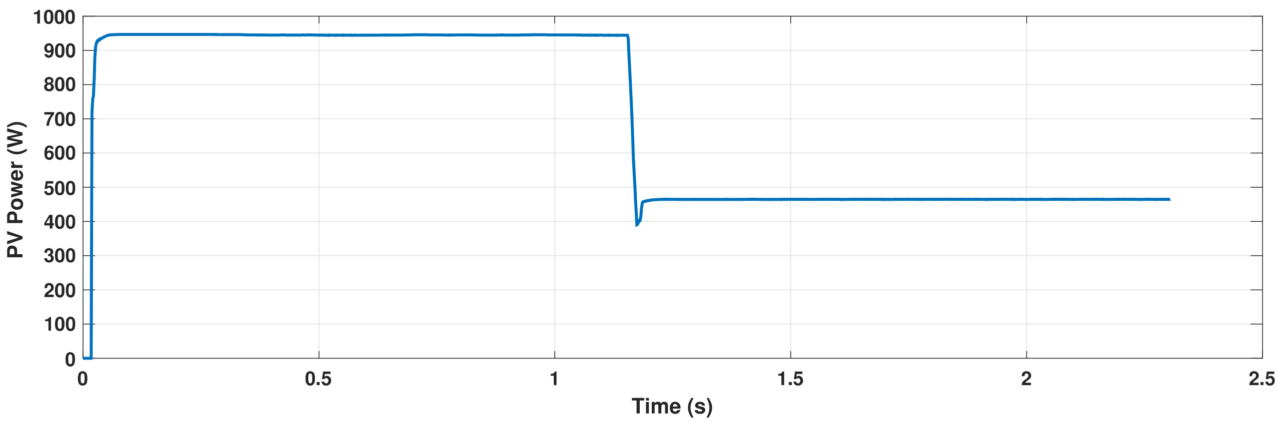

Figure 4. Variations in PV output power with time. The PV power is initially set to 900 W while at 1.2 s the PV power reduces to 400 W.

Figure 7 shows the battery charging and discharging power characteristics for the considered case study. It can be observed that the battery is charging initially until the time that the PV power is more than the load power. However, at 1.2s, the battery starts discharging itself to support the load by providing the deficit amount of power to the load. Variations in battery SoC can be observed in Figure 8. Since the battery is initially charged by the excess amount of power generated by the PV, the battery SoC can be seen to increase, while, after 1.2s, the battery starts being discharged, so the battery SoC also decreases. The DC-link voltage variation is shown in Figure 9. It can be observed from the figure that the DC-link voltage is maintained as constant throughout due to the action of the HESS. Fluctuations in the DC-link voltage can be observed at 1.2s. Due to the action of the HESS, the deviation is mitigated, and the voltage is maintained at the same constant value. Figure 10 shows the variation in battery power and the supercapacitor power with the variation in PV power. It can be observed that a constant load power of 500W is required throughout. Initially, the generated power is sufficient to serve the load; hence, the SC and BESS do not need to discharge. The BESS takes the excess amount of power by charging itself while the supercapacitor acts only during transients. A drop in the generated power can be observed at 1.2s. Now, during this transient condition, the supercapacitor consumes the power to maintain the DC-link voltage. After 1.2s, the generated power is less than that required by the load. The battery comes into action to compensate for the rest of the required power by discharging itself. The DC-link voltage is maintained by the prompt action of the HESS.

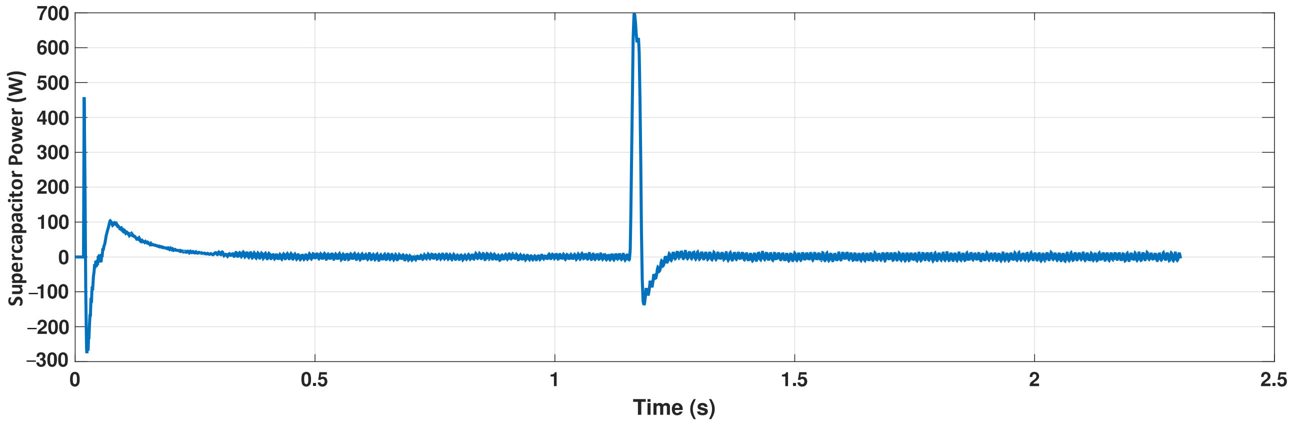

Figure 5. Variation in supercapacitor power with time for a step reduction in the PV output power from 900 W to 400 W at t = 1.2 s.

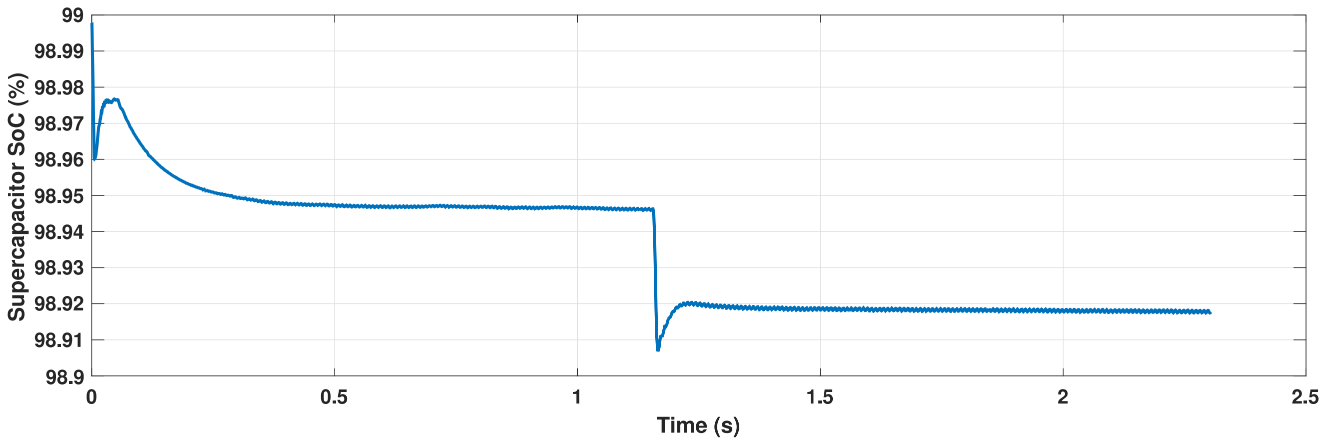

Figure 6. Variation in supercapacitor SoC with time for a step reduction in the PV output power from 900 W to 400 W at t = 1.2 s.

In order to provide a fairly stable DC bus, the battery bank is positioned between the PV and the load. This basic design balances the mismatch between PV generation and load by charging and discharging the BESS. This conventional approach operates effectively when generation and load requirements are steady, but PV microgrids frequently experience fluctuations in generation and load requirements. Hence, the battery is constantly under stress from dynamic supply and absorption, which could possibly shorten its lifecycle.

In the proposed scheme, the SC and BESS are connected in parallel to the DC-link through their respective bidirectional DC/DC converters. It can be observed that, by combining the SC and the BESS, the stress on the battery can be reduced as transient power sharing is assigned to the SC. To minimise DC-link voltage imbalance, the HESS arrangements are meticulously planned because the SC and BESS are on the same DC bus. The SC responds to the high-frequency power exchange or to mitigate the DC-link voltage fluctuations during transients, whereas the BESS, which has a high energy density, is designed to accommodate the low-frequency power variation during steady state conditions.

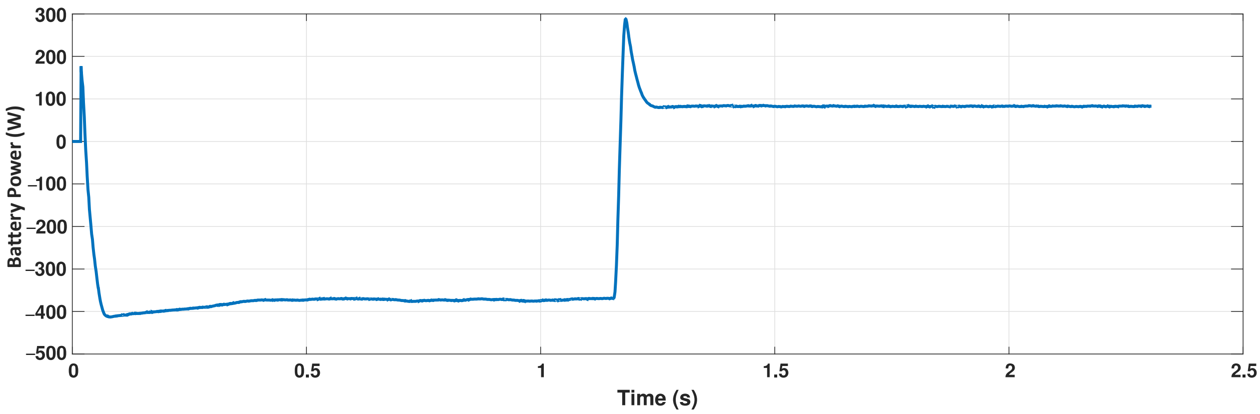

Figure 7. Variation in battery power with time for a step reduction in the PV output power from 900 W to 400 W at t = 1.2 s.

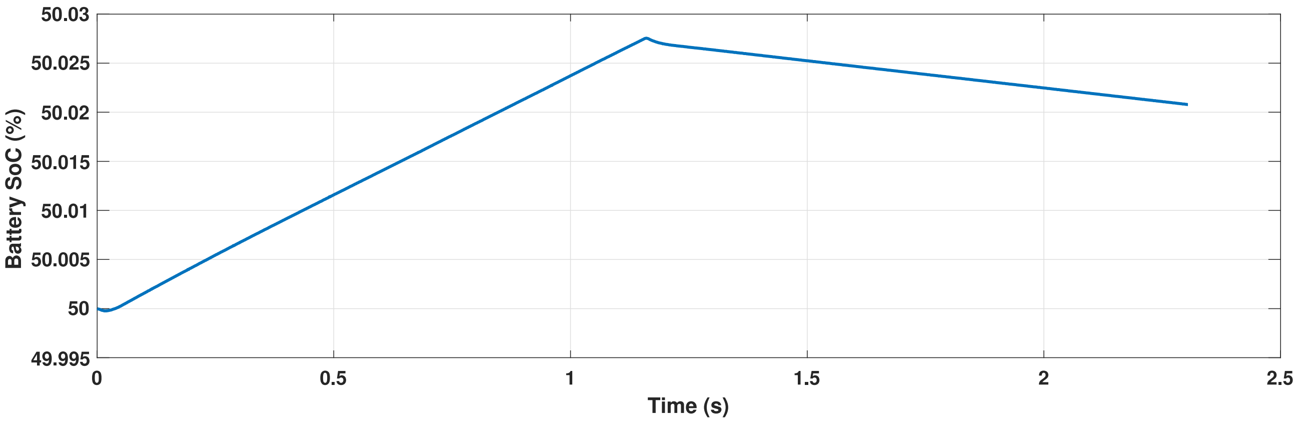

Figure 8. Variation in battery SoC with time for a step reduction in the PV output power from 900 W to 400 W at t = 1.2 s.

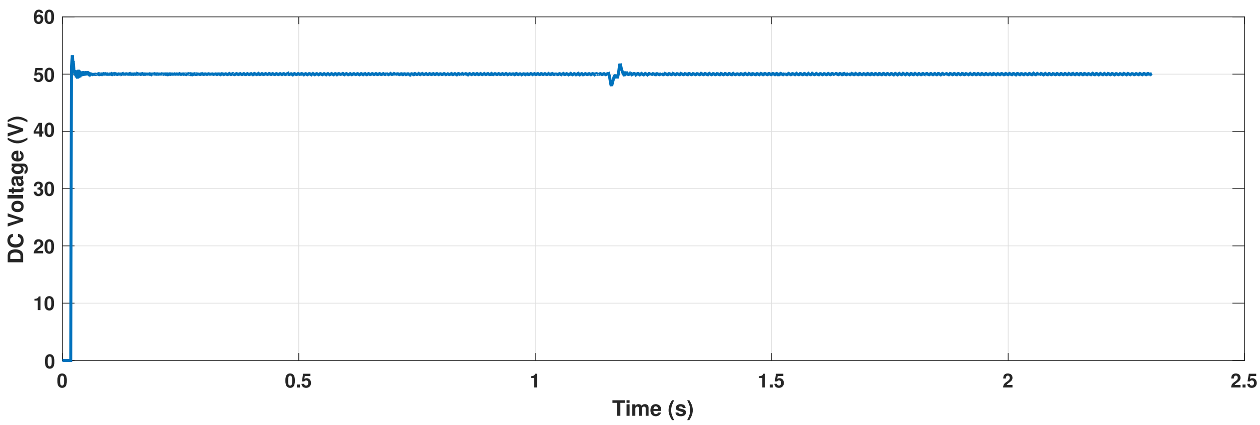

Figure 9. Variation in DC-link voltage with time for a step reduction in the PV output power from 900 W to 400 W at t = 1.2 s.

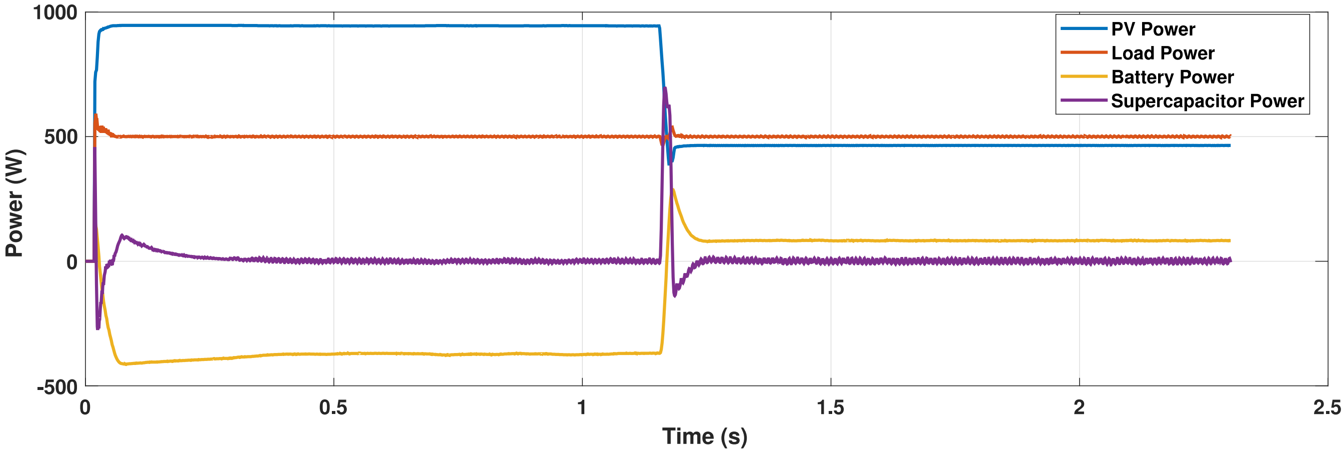

Figure 10. Variation in supercapacitor power/battery power with the variation in demand and supply for a step reduction in the PV output power from 900 W to 400 W at t = 1.2 s.

6. Conclusions

This study provides a systematic review of the recent developments in the control and management of energy storage systems for microgrid applications. One can observe that there is an apparent trend towards shifting from research on AC microgrid topologies to DC microgrid architectures. This can be attributed to the advantages with respect to reducing the number of power electronic converters when integrating storage systems and renewable energy sources in DC microgrids. While battery storage is the predominant system for microgrid applications in the evaluated literature, there was an increase in the studies involving alternative storage systems. The present trends have shifted towards hybrid energy storage systems, combining multiple complementary storage technologies to exploit their advantages. Hybrid energy storage systems perform better in terms of energy security and reliability when compared to applications that use a simple battery energy storage system. Finally, intelligent control strategies have also become prominent in the literature, with a specific focus on machine learning and artificial intelligence starting to become integrated into the management strategies of the storage devices in microgrids.

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