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Review

Review of Latest Advances and Prospects of Energy Storage Systems: Considering Economic, Reliability, Sizing, and Environmental Impacts Approach

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Abstract: Studies have shown that the role of energy storage systems in human life is increasing day by day. Therefore, this research aims to study the latest progress and technologies used to produce energy storage systems. It also discusses and compares the most recent methods used by researchers to model and optimize the size of these tools and evaluates the strengths and weaknesses of each. Investigations have shown that using energy storage systems in hybrid stand-alone power generation systems based on renewable energy increases the reliability of the power generation systems and increases their efficiency. It has also reduced the cost of transmitting the power grid to remote areas. Furthermore, this study showed that advances in energy storage technology in recent years have led to the development and promotion of clean microgrids. In addition, this review paper also addresses energy storage technology issues and proposes practical and applied solutions.

Keywords: energy storage; green microgrid; optimization; modeling; reliability; renewable energy

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1. Introduction

Researchers and experts in the fields of energy and the environment believe that environmental pollution from fossil fuels is the greatest threat to the future of humanity, and the world must move towards new and clean technologies. Many industries today will migrate to zero carbon dioxide technologies. Nowadays, the management and supply of human power consumption are often provided by generators connected or disconnected from the grid. The fuel for these generators is often fossil fuels, which produce carbon dioxide and consequently cause air pollution and damage the environment [1]. Currently, the policies of governments around the world are moving towards decarbonization. It entails producing electricity using clean and new technologies to reduce carbon emissions [2]. In this regard, global policies strongly support renewable energy to produce green and clean energy. Energy storage devices play a significant role in storing, managing, improving performance, and transferring clean power generated by renewable sources. Ensuring a high-reliability energy supply, environmental sustainability, and a cost-effective power supply are the three main goals of clean microgrids to generate electricity with the least pollution. Using renewable energy sources instead of fossil fuels to generate electricity to reduce greenhouse gas and carbon dioxide emissions cannot be achieved without considering the economic aspects and evaluating the potential of renewable energy [3]. So, in addition to the reliability of power systems that use renewable energy sources, the determined size of each part of the green microgrids is also important.

Many studies have been conducted on the use of new technologies to reduce greenhouse gas emissions, and as expected, the rate of carbon dioxide emissions by large power plants will be close to zero by 2050 [4]. Nowadays, stand-alone hybrid renewable energy microgrids have received much attention for producing clean electricity. Because renewable sources are inherently unpredictable, power generation from these sources is violated at certain times of the year. Therefore, energy storage systems play an important role in solving and controlling this problem in these systems [5].

The three scenarios in 2050 were compared to determine the share of renewables in electricity generation. As shown in Figure 1, offshore wind turbines and photovoltaic panels play a significant role in all three scenarios for power generation and decarbonization in the future [6].

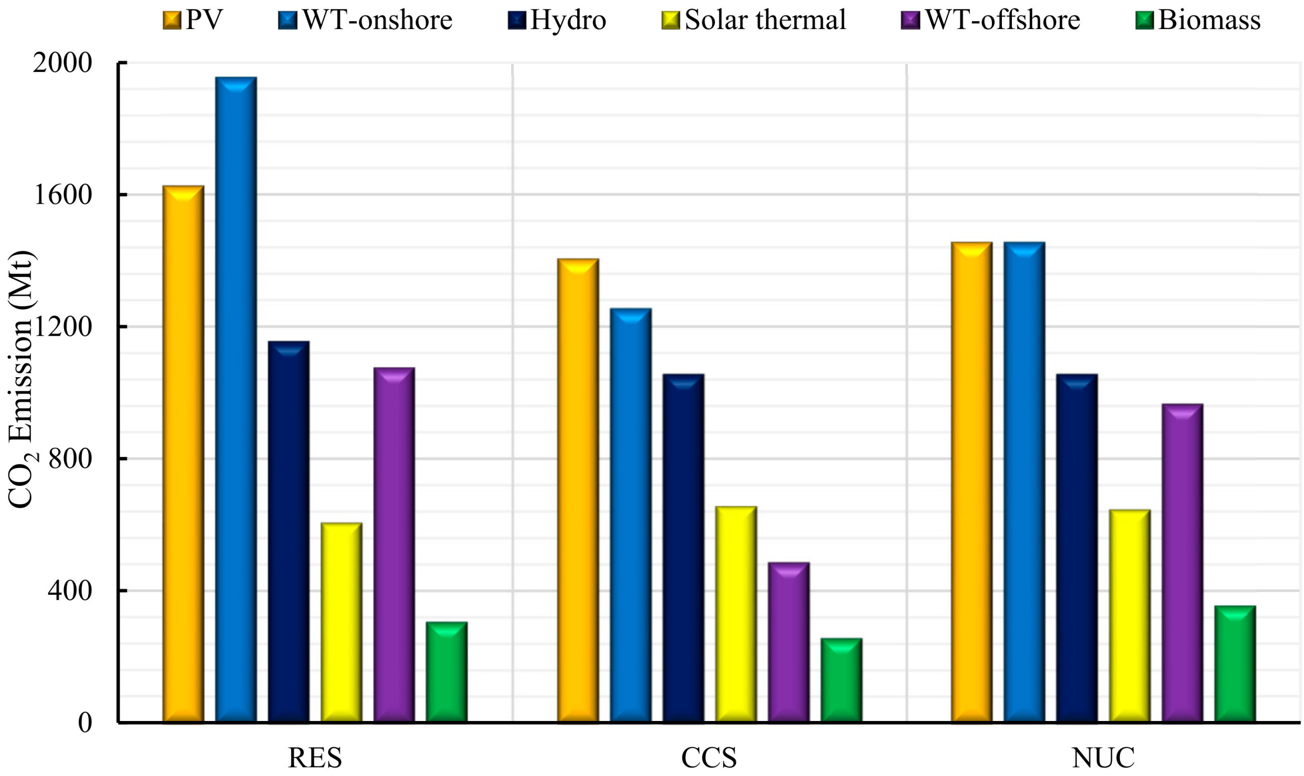

Figure 1. Renewable technologies' contribution to decarbonization in various global scenarios. RES: renewable energy source, NUC: nuclear energy, CCS: carbon capture and sequestration. Adapted with permission from Ref. [6]. Copyright 2018, Ecological economics.

In Reference [7], a renewable energy microgrid consisting of wind turbines, photovoltaic panels, microturbines, and lead-acid batteries was designed and modeled. The life cycle of this clean microgrid is estimated at 20 years. Reducing greenhouse gas emissions, reducing emissions taxes, and achieving the minimum cost have been the goals of developing this green power generation unit. With an increasing share of renewable energy contributing to the power supply of the world's total power demand, the amount of pollutant emissions will also decrease and will be closer to the goal of decarbonization. Energy stores in green microgrids play an essential role [8].

Figure 2 shows the wind-solar energy-based microgrid; and as mentioned, the primary role of these units is to store the excess energy produced by the renewable energy power generation units [9,10]. The size of this energy storage unit should be optimized to have more stable and efficient performance and be more economically interesting [11]. Factors that affect the size of energy storage units include capital costs, maintenance costs, replacement costs, and installation costs. As shown in reference [12], the cost of energy storage increases linearly with the size of this unit. Conventional energy storage devices used in green microgrids have a variety of types that will be mentioned in the following sections of this study. The cost of energy storage devices has a tremendous impact on the development rate of stand-alone renewable energy microgrids. Therefore, finding the optimal size of these units is significant in achieving the carbonation goals [13,14]. In

Reference [14], the researchers optimized the size of the battery bank using an optimization algorithm. These batteries are responsible for storing energy in the microgrid unit and transmitting the required power into the grid when the power supply system is faced with a shortage of productive power. This study focuses more on the economic aspects of the power generation system, and the environmental aspects are not considered.

The authors of the references [15,16], proposed an optimization method that determines the optimal size of the battery bank by considering the peak load and management of renewable energy sources. This study has not investigated the competitiveness of electricity generated by this green microgrid. In reference [17], the energy storage performance of a clean microgrid was optimized. The aim of this study was to maximize the use of renewable energy sources, meet the peak load sustainably, and reduce energy costs. However, in this study, management and regulation of voltage were not examined.

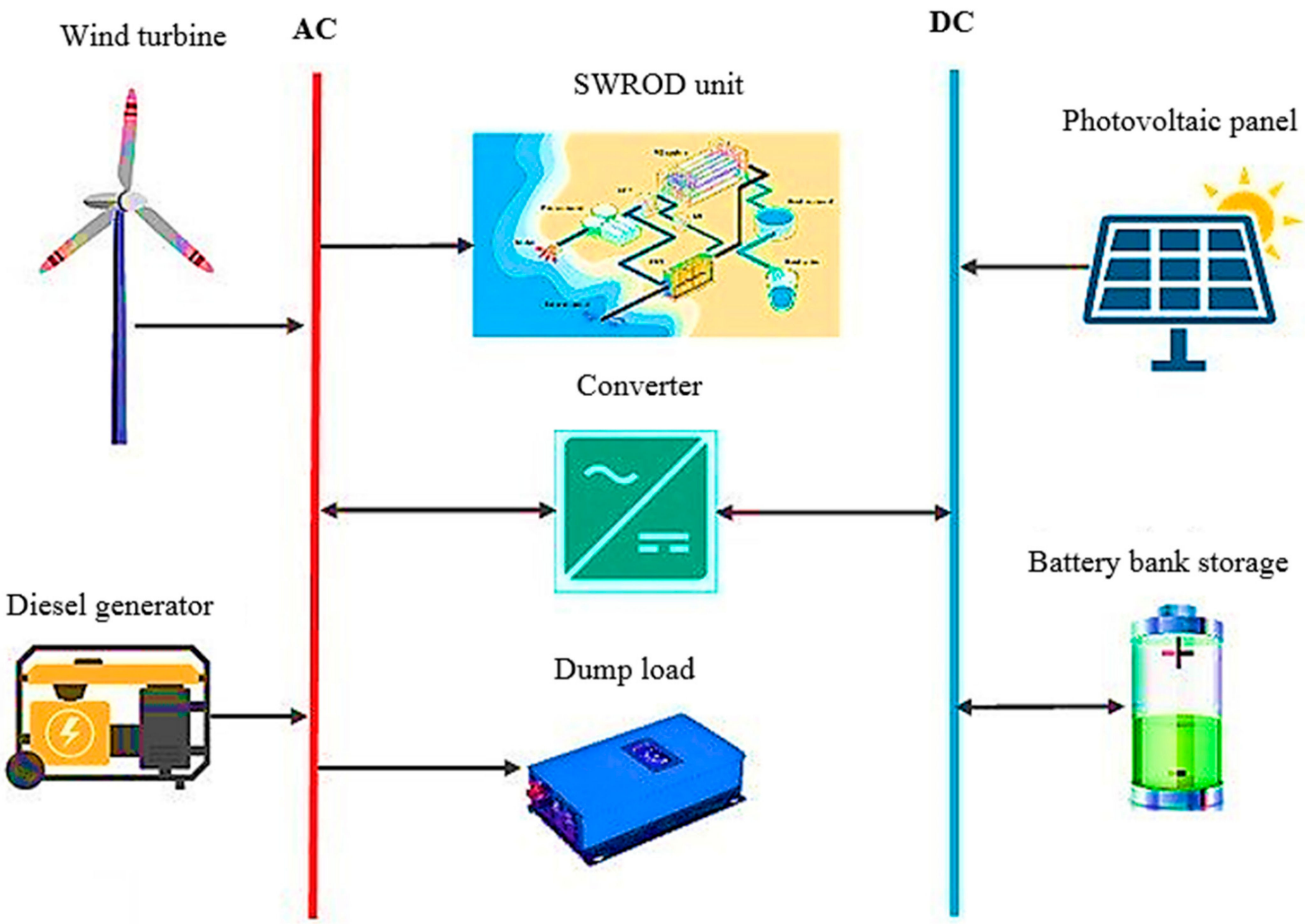

Figure 2. Common configurations for a hybrid renewable-based microgrid. Reprinted with permission from Ref. [18]. Copyright 2014, Energy Conversion and Management.

In reference [19], a detailed and comprehensive study was performed concerning different methods of optimizing the battery bank as an energy storage unit. Different methods of optimizing the battery bank size were compared and assessed in this reference. However, this study did not evaluate optimization algorithms, multi-objective functions, and mathematical modeling. The optimal size of energy storage, management, and power control of these units was evaluated in reference [19,20]. However, the optimization algorithm used in this study was not evaluated and compared in detail. Renewable energy components must be optimized to achieve decarbonization goals. One of the essential components of this system is the production of energy storage power. Limited research has been reported in the literature on optimizing the size of green microgrids' energy storage units to discuss and evaluate different types of energy storage, mathematical modeling, economic modeling, and their reliability. The literature of this study first introduces the common and widely used types of energy storage and evaluates the technologies used in these devices. The mathematical and economic modeling of these units is then reviewed in detail. In the next section, the criteria of reliability will be studied. Then different optimization methods, techniques, and algorithms will be discussed. The limitations, challenges, advantages, and disadvantages of the various techniques used to optimize these units will also be reviewed comprehensively. Finally, suggestions for future research will be provided. The Google Scholar search engine was used for this review, and papers with the keyword energy storage systems were initially searched. Articles related to reliability, economic analysis, and environmental problems related to energy storage systems were also searched and reviewed.

2. Energy Storage Resources

2.1. Conventional Energy

The world's primary conventional energy source is non-renewable sources such as fossil fuels. The electricity required by many of the world's largest power plants, factories, and industries still depends heavily on this conventional energy source. According to the reference [21], about 85% of the global energy needs are met by fossil fuels. These fuels have disadvantages such as damage to the environment and human health due to phenomena such as climate change. On the other hand, these resources are exhaustible, and the level of reserves of this fuel is low [22]. Hence, researchers are looking for alternative sources of fossil fuel that create less environmental burdens to the environment.

2.2. Renewable Energies

Unlike conventional energies, renewable energies are inexhaustible and lead to polluting the environment. In addition, these clean energies are always accessible for free. These benefits of renewable energy have made this green energy the best and most suitable alternative to conventional energy and fossil fuels, and they have also attracted the attention of many energy investors and governments around the world [23,24]. Since these renewable sources are unpredictable and intermittent, the presence of energy storage units in power generation systems from renewable energy sources, such as batteries and fuel cells, is necessary for the power generation system's stability [25].

These energy storage units are comprehensively reviewed in the next section. Solar and wind energy have been extensively studied among all the renewable energies. Researchers consider using more than one renewable energy source integrated with energy storage to be the best way to increase the sustainability of power generation systems from renewable sources [26]. Because renewable energy has very variable amounts at different times, or in other words, has low reliability, researchers have introduced and used different methods to determine the reliability of power generation systems from renewable energy sources, which will be discussed in detail in the following sections. In modeling and designing a clean power generation system equipped with energy storage and considering its reliability, the economic aspects of this system should also be considered. A green power generation system is economical when the size of each of its components is optimized. Researchers propose and use various techniques and algorithms to optimize the size of this power generation unit, which will be reviewed in this study [27–30].

3. Energy Storage Technologies

Energy storage systems are essential components of power generation systems from renewable sources. Most stand-alone power generation systems have an energy storage unit. In addition to storing the excess energy produced by power generation sources, these units are responsible for supplying the power required by power consumption units during peak times or shortages of renewable energy sources. These systems play a vital role in the power generation system's stability, control, and management [31]. Energy storage devices generally have three states of charge (SOC): charge, discharge, and storage (Figure 3). A charging state is a mode in which the amount of electrical energy produced by the units of renewable power is greater than the energy consumed, and the excess energy is sent to storage units to charge the energy storage. When the energy produced by renewable sources is equal to the required energy consumption, the energy storage unit is in storage mode; and in the third case, when the energy produced by renewable energy production units is less than the amount of power consumption, then an energy storage unit is in discharge mode and transmits the electrical power stored into the power grid to compensate for the required energy deficit.

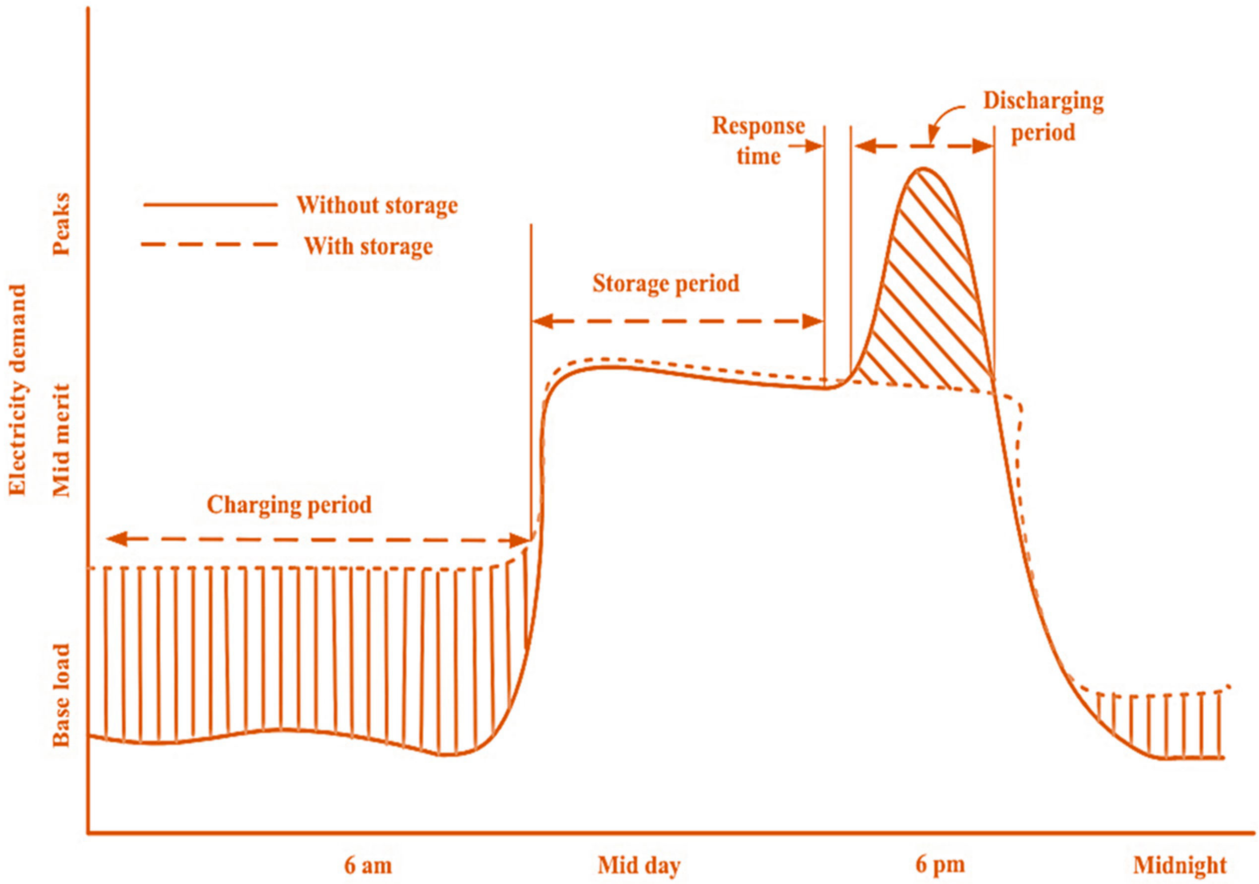

Figure 3. Management of energy production through the use of energy storage. Reprinted with permission from Ref. [32]. Copyright 2014, Renewable and Sustainable Energy Reviews.

Energy storage devices are generally classified according to two principles: (a) duration of storage and (b) form of storage. Based on storage time, energy storage systems are divided into three general categories: short-term, medium-term, and long-term. Also, according to the storage form criterion, these units are classified into electrical, chemical, and mechanical (Figure 4) [33,34]. Today, a very diverse and wide range of energy storage technologies are available that play a role in a particular area according to the needs of each consumer. These technologies will be discussed in detail in the following sections of this research.

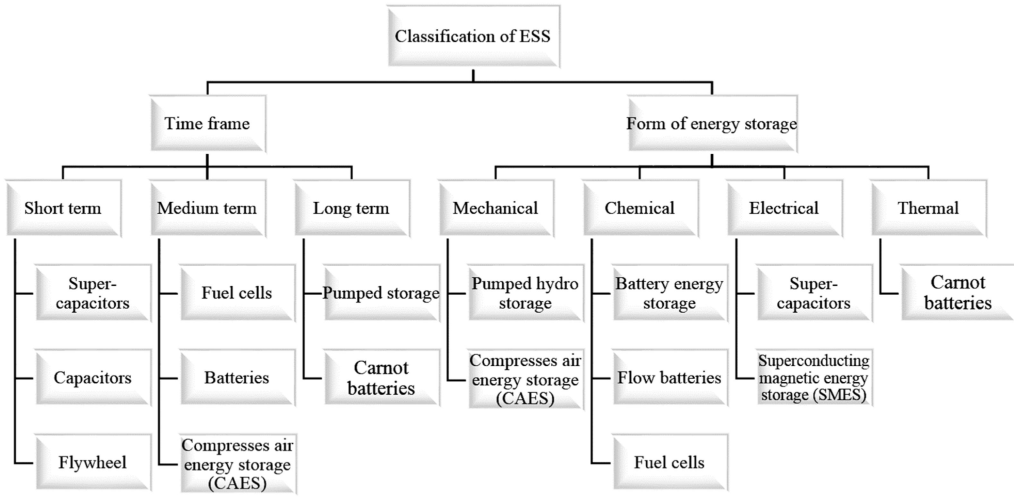

Figure 4. The classification of the energy storage system (EES) [35].

3.1. Battery Storage System

Battery storage banks have been one of the oldest human tools for storing chemical energy. These storage devices are classified into two types: rechargeable and disposable. In this section, we consider rechargeable batteries. These batteries are used in most off-grid green microgrids. The easy access, uncomplicated structure, easy application, and high flexibility of rechargeable battery banks have made them the most widely used type of energy storage. Batteries do not emit pollutant emissions during operation. Another advantage of this energy storage is its high response speed for transmitting electrical power required to power-consuming units. This advantage of batteries means that the power generation system does not face the problem of not responding to the demand load and works stably without interruption. According to research, the battery conversion efficiency is 60–90%. There are various types of battery banks. The most widely used are lead-acid batteries, lithium-ion batteries, sodium-sulfur batteries, and flow batteries. Each of them will be introduced in the following section.

3.1.1. Lead-Acid Batteries

Lead-acid batteries have the same structure as other batteries, meaning that they use two positive and negative electrodes and a separator. The positive electrode consists of lead dioxide, and sulfuric acid is used as an electrolyte and separator of the two electrodes. Sulfate ions supplied by this electrolyte are used to react when the battery is discharged. The following equation shows the chemical reaction of this type of energy storage.

$$PbO_2 + Pb + 2H_2SO_4 \rightarrow 2PbSO_4 + 2H_2O \quad (1)$$

As can be seen from this relationship and Figure 5, both electrodes are discharged to lead sulfate, which is a weak electrolyte, and this electrolyte is diluted over time as the discharge process continues. In the charging state, this process occurs in reverse and increases the concentration of electrolyte sulfate while the specific weight of this electrolyte also increases. This type of battery is used in most off-grid renewable energy-based microgrids. Lead-acid batteries also have drawbacks. This battery bank has an energy density of 30 to 50 watts per kilogram, which is low. In addition, their cycle life is about 500 to 1000 cycles, which is a short life. Lead processing and recycling of this type of battery is another problem associated with their use [36]. A key driver for the prospects of the lead-acid battery scrap market is the abundant use of lead-acid batteries in a wide range of applications due to their low cost. Compared to other electrochemical systems, some advantages of lead-acid batteries are simplicity of design, low cost of manufacture, reliability, and relative safety [37]. However, lead-acid batteries suffer poor power and energy densities and the necessary relatively long recharging times [38]. The uncontrolled emission of PM2.5 containing lead particulates and SO_2 are serious concerns associated with lead-acid batteries because of irreparable problems for humans and the environment [39].

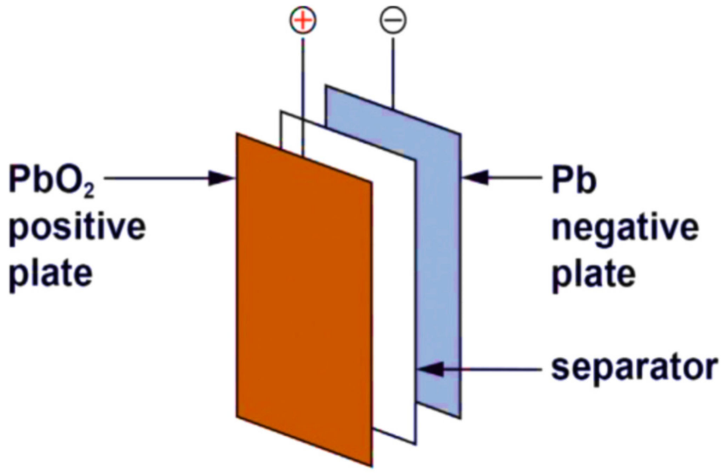

Figure 5. Components schematic of a lead-acid battery [40].

3.1.2. Lithium-Ion Batteries

Lithium-ion batteries, like other batteries, are responsible for storing energy. The positive electrode of these batteries is lithium, and the negative electrode is carbon or graphite. The electrolyte of this type of battery is made of non-aqueous materials such as propylene with lithium salts because lithium reacts very strongly with water. The separators used in the cells of this battery are also fine porous plastic films.

Lithium cobaltite (LCO) is often used as a positive electrode component in lithium-ion batteries. However, other compounds store energy in these batteries in off-grid microgrid applications because it is expensive. These compounds include a combination of oxides of nickel, cobalt, and aluminum (NCA), nickel, cobalt, and manganese (NCM), which are cheaper than lithium cobaltite (LCO). Its negative electrode is mainly composed of carbon or graphite. Lithium-ion batteries are often used in electric vehicles. Since these batteries have a high energy density and a flammable electrolyte, cell construction, charging system, etc., must be done carefully [36]. These batteries' advantages are long cycle life, wide operating temperature range, and high energy density [41].

In comparison, they suffer from high costs, safety issues, and environmental pollution problems [42]. Environmental concerns about these batteries are attributed to the extraction and processing of lithium sources as well as pollution caused by the careless disposal of batteries since they contain toxic materials and heavy metals such as nickel and cobalt [43]. From a technical point of view, these batteries tend to overheat, which leads to damage at high voltages.

3.1.3. Sodium-Sulfur Batteries

A sodium-sulfur battery, like other batteries, consists of two electrodes, in which the positive electrode is in the liquid sulfur electrolyte, and the negative electrode is in the liquid sodium electrolyte. A solid beta-aluminum ceramic electrolyte separates the two electrodes. Positive sodium ions combine with the sulfur in the electrolyte to form sodium polysulfide. For a more suitable transfer of sodium ions, the cell temperature should be 300–350 degrees Celsius. To provide this high temperature, these batteries use their stored energy. The efficiency of these batteries is over 90%, and they have no automatic discharge. The energy density of sodium-sulfur batteries is much higher than the energy density of lead-acid batteries. The cycle life of this type of battery is also long. Since the thermal management of these batteries is very important, it needs a more complex and accurate design, and the cost of capital and maintenance of these batteries is high, so they are often used in large industries and power plants (Figure 6) [44–47]. Although they have their high initial cost and mostly their safety issues since pure sodium is a hazardous material [48], they include higher specific energy as well as higher energy conversion efficiency [49]. Notably, sodium-ion batteries are more eco-friendly, cheaper, and more sustainable than lithium-ion batteries.

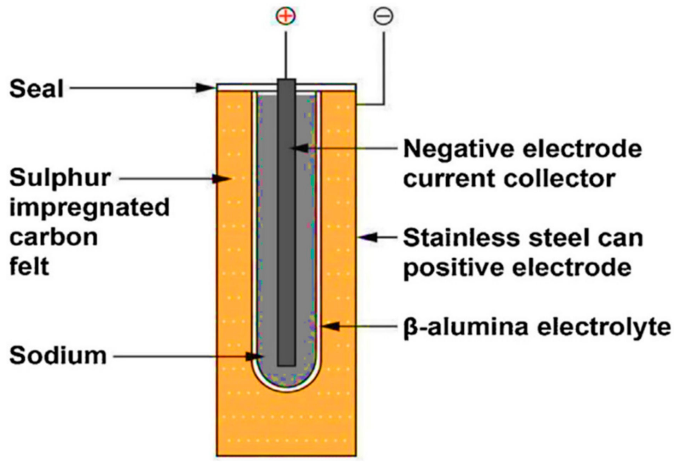

Figure 6. Components schematic of a sodium-sulfur battery.

3.1.4. Flow Batteries

The flow battery consists of electrolytes, membranes, and positive and negative electrodes. Membranes separate the positive and negative electrodes of the flow energy storage. This battery has a high capacity for energy storage, and its different types are vanadium redox battery (VRB), polysulfide bromide battery (PSB), zinc bromide battery (ZnBr), etc.

These batteries are often used in off-grid microgrids, and the most critical issues to consider when using these batteries are cost, reliability, longevity, and depth of discharge [50,51]. Vanadium redox batteries (VRB) have unlimited capacity and are expensive. These flow batteries are mainly used for energy storage in large power plants (Figure 7) [52–54]. Among the advantages of these batteries are the inherent scalability of their capacity and long-term storage of charge [55]. However, the major disadvantage of these batteries compared to other technologies is that the power/energy density is relatively low [56].

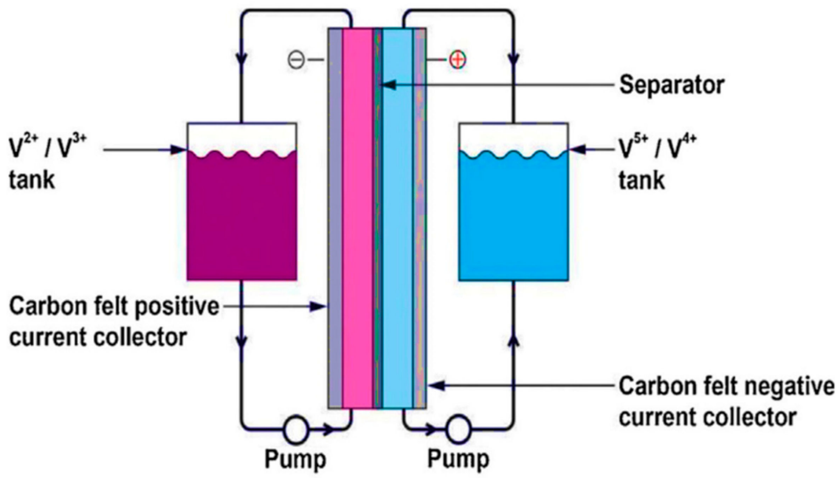

Figure 7. Components schematic of a vanadium redox flow battery.

As Figure 8 shows, zinc-bromide batteries are another type of flow battery. This battery has a shorter life than VRB batteries, but the cost of ZnBr is less than VRB. Bromine emissions are hazardous to the environment and human health, so controlling and managing this type of battery should be done more carefully [57,58]. This issue has limited the use of this type of battery, like other flow batteries [59]. As mentioned, there are other types of flow batteries, but they are not widely used.

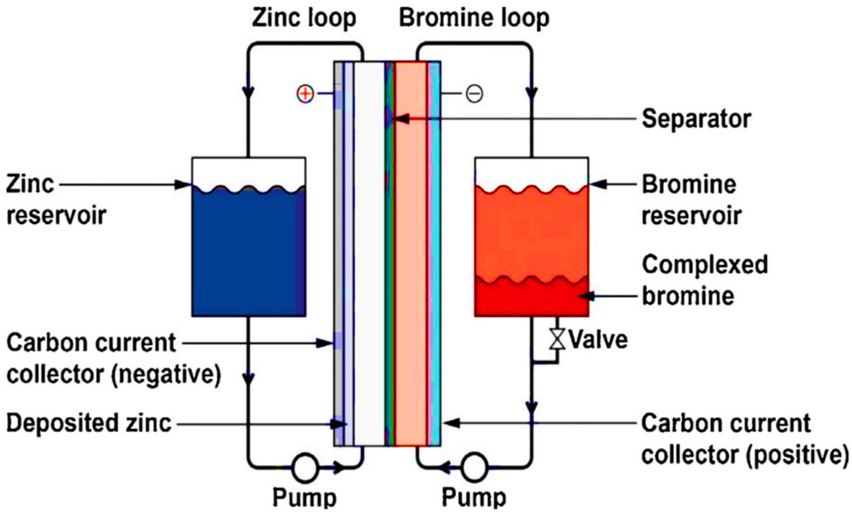

Figure 8. Components schematic of a zinc-bromine battery [40].

Due to the increasing popularity of renewable energy, the use of batteries in the future is expected to increase sharply in various sectors of energy consumption (Figure 9). Therefore, the focus should be on the production and use of environmentally friendly batteries to reduce the environmental consequences of conventional batteries.

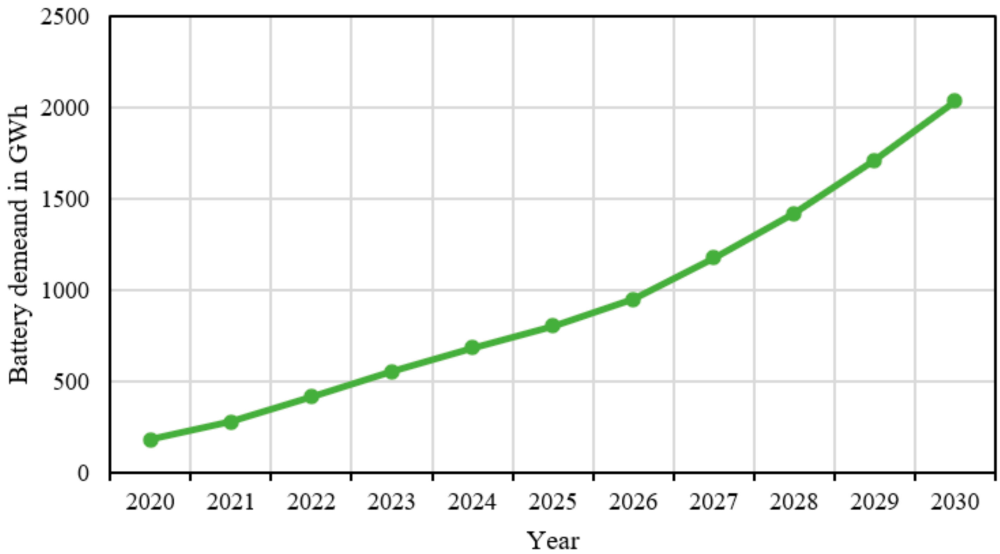

Figure 9. Battery demand worldwide by application 2020–2030 [60].

3.2. Supercapacitors Energy Storage

Another type of energy storage is supercapacitors. In this energy storage, two-layer plates are used to separate the loads from each other. These batteries have a very long life cycle and are suitable for places that require high power and fast response speed. For reliability and safety issues, the voltage of the supercapacitor module is considered in the range of 200–400 volts [61]. The main advantages of supercapacitors over batteries are very specific power and their number of charge-discharge cycles [62]. However, supercapacitors' energy stored per unit weight than batteries is considerably lower [63]. Because its energy density is very low that can be improved by increasing the capacitance [64].

3.3. Flywheel Energy Storage

This energy storage stores the kinetic energy caused by the rotation of the disks around an axis. The energy stored in this energy storage is directly proportional to the square of the moment of inertia of the disk and the wheel's speed. When the consumer needs power, the flywheel energy store uses disk or rotor inertia to convert the stored kinetic energy into electricity and meet the required power [50]. Flywheel energy storage is used as a backup system for power supply and voltage, transportation, etc. To store higher powers, it needs larger wheels. Depending on the number of losses in different parts of this energy storage, its efficiency is set between 95–90% [61]. Relatively high efficiency and fast response time (milliseconds) are the advantages of this energy storage [65,66]. Despite these benefits, compared to batteries and supercapacitors, flywheel energy storage systems have maintenance effort, lower power density, noise, cost, and safety concerns [62].

3.4. Hydrogen Storage

Hydrogen is obtained by the electrolysis of water using electrical energy in a clean method. Hydrogen is produced at low pressures (30–00 PSI) and stored in tanks at high pressures (3000 PSI). The efficiency of these energy storage devices is about 40–60%. There are several ways to produce hydrogen with fuel cell technology, including solid oxide fuel cell, direct methanol fuel cell, molten carbonate fuel cell, and metal-air battery [61]. It should be noted that hydrogen storage has many inherent advantages such as potentially high energy storage densities, ease of disposal, and the absence of toxic components [67]. Nevertheless, based on the storage method, it has various disadvantages listed in Figure 10.

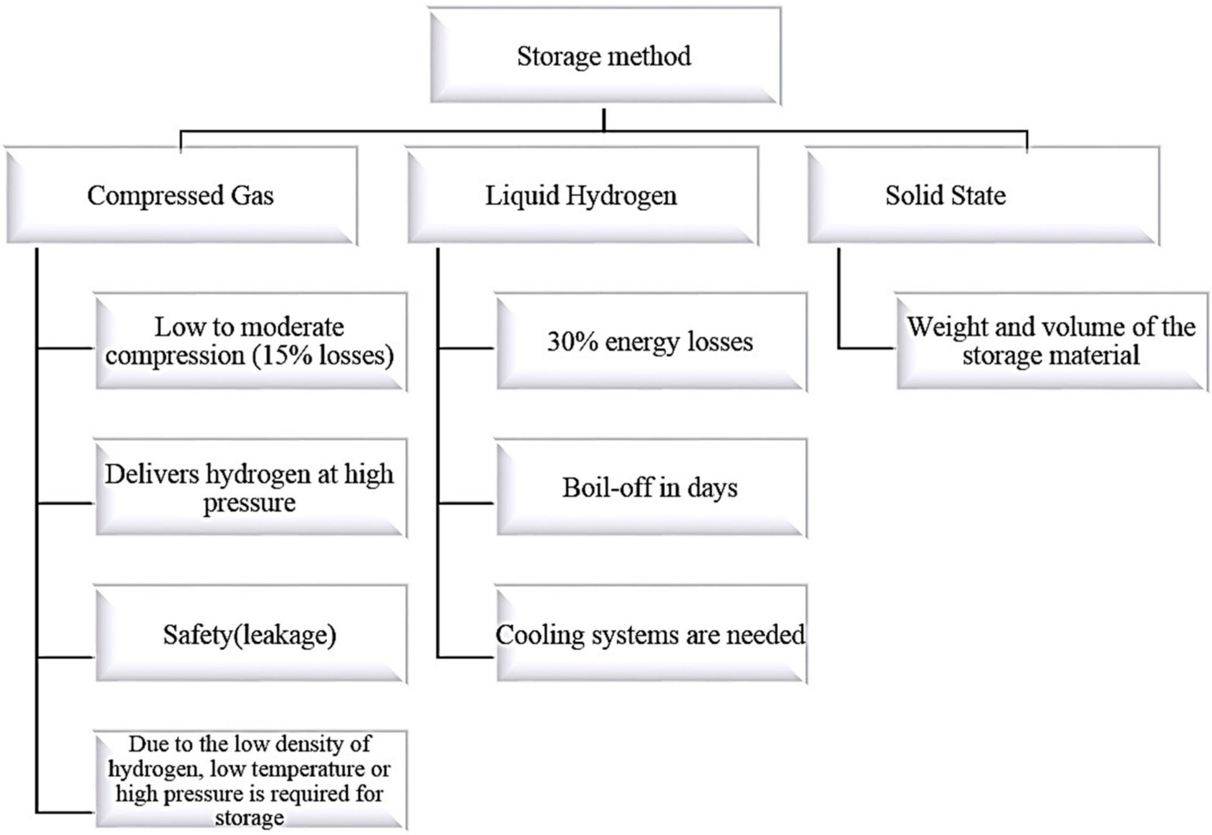

Figure 10. A summary of disadvantages of hydrogen storage methods [68].

3.5. Potential Energy Storage

Potential energy storage is used in pumped storage hydropower (PSH) and compressed air energy storage (CAES) systems [69]. Briefly, PHS is a technology based on pumping water to an upstream reservoir during off-peak or the times that there is surplus power electricity by renewable energy. When electricity is needed, it releases energy through the hydro turbines [70]. Scarcity of available sites for two large reservoirs, long lead time, high cost for construction, and environmental issues are major drawbacks of PHS [71]. CAES has been proposed as an alternative to pumped hydro storage for large-scale. In a CAES, surplus power compress air by a rotary compressor and then store it in an underground chamber. It is released from the chamber and passed through an air turbine that generates electricity from the flow of high-pressure air when the power is required [72]. However, the major disadvantage of CAES is their dependence on geographical location [73].

3.6. Thermal Energy Storage

It simply dissipates into the environment necessitating fossil fuel combustion if the thermal energy is not stored. Thermal energy storage (TES) is known as one key function in thermal energy management [74]. In fact, it is a technology that, by cooling or heating a storage medium, stocks thermal energy to store energy and is used later for power generation and cooling and heating applications [75]. A wide variety of materials are being used for TES that must possess suitable thermophysical properties such as favorable melting point for the given thermal application, high thermal conductivity, high specific heat, and high latent heat. The type of TES material being selected for cold or heat storage classifies TES systems into (1) sensible heat storage systems, (2) latent heat storage systems, and (3) chemical heat storage systems. Sensible heat storage materials are thermally stable and thus have most used for high-temperature applications. Moreover, they are usually low-cost. However, they suffer from temperature stability during the discharge process. Near the phase change temperature, the energy storage density of latent heat storage materials is very high. Because latent heat is 50–100 times larger than sensible heat. However, latent heat storage materials are poor thermal conductivity. Chemical thermal energy storage has the highest density with low heat losses; however, they are still in the laboratory stage. Most commonly TES materials are water, inorganic salts, thermal oils, sand, gravel, and paraffin [74].

4. Energy Storage Modeling

As mentioned in the previous sections, off-grid renewable energy microgrids require an energy storage unit to generate electricity from renewable energy sources with high reliability and cost-effectiveness. It should be modeled and analyzed correctly and carefully, and then its size should be optimized with the proper optimization methods. Therefore, the following section of this study will discuss common and widely used economic modeling and analysis systems, reliability determination, and optimization techniques.

4.1. Economic Analysis

The economic criteria of the network-independent power generating system must be properly modeled and analyzed to produce a cost-effective solution. Energy savers are a member of this clean power generation system, and their role in modeling and economic evaluation of these power generation systems is critical. To evaluate and study the economics of renewable energy power production systems, researchers now employ effective and generally accepted economic methodologies and criteria such as total life cycle cost (TLCC), life cost of energy (LCOE), Internal rate-of-return (IRR), Payback period (PBP), etc., which will be fully described in the following section.

4.1.1. Total Life Cycle Cost (TLCC)

One of the economic methods for calculating the entire cost of a renewable energy microgrid equipped with energy storage throughout the course of a project is the net present cost (NPC) or total life cycle cost (TLCC) (Table 1). This economic criterion considers all the factors affecting the cost of such a project, such as maintenance costs, initial costs, installation costs, etc. [76,77]. This approach provides a complete financial picture by considering all costs and benefits over the project's entire life cycle. Also, it can compare various combinations of measures and select the one that will maximize to save and financial return. These specifications make its application in microgrids with energy storage systems very interesting. However, predictive tools and available databases to estimate operation and maintenance costs are usually inadequate; hence, to apply to real problems, LCC is often very difficult [78].

Table 1. Some important economic models of the green microgrid.

Line	Indices	Remarks	Mathematical Equations
1	CRF	Capital recovery factor	$CRF(i,n) = \frac{i(1+i)^n}{(1+i)^n - 1}$
2	PW	A factor of payment present worth	$PW = C \times \sum_{k=0}^{n} \frac{1}{(1+i)^k}$
3	TLCC	Total life cycle cost	$TLCC\ (A_{WT},\ A_{PV},\ N_{BBS}) = \sum_{m=PV,WT,BBS} LCC_m$
4	LCC	Life cycle cost	$LCC = CC + MC$
5	LCC_{PV}	Life cycle cost of photovoltaic	$LCC_{PV} = CC_{PV} + MC_{PV}$ $CC_{PV} = A_{PV} \times C_{PV} \times CRF$ $MC_{PV} = C_{Mnt-PV} \times A_{PV}$
6	LCC_{WT}	Life cycle cost of wind turbine	$LCC_{WT} = CC_{WT} + MC_{WT}$ $CC_{WT} = A_{WT} \times C_{WT} \times CRF$ $MC_{WT} = C_{Mnt-WT} \times A_{WT} \times \sum_{k=0}^{19} \frac{1}{(1+i)^k} \times CRF$
7	LCC_{BAT}	Life cycle cost of battery	$LCC_{BAT} = CC_{BAT} + MC_{BAT}$ $CC_{BAT} = N_{BAT} \times PW_{BAT} \times CRF$ $MC_{BAT} = N_{BAT} \times C_{Mnt-BAT}$
8	LCC_{INV}	Life cycle cost of Inverter	$LCC_{INV} = CC_{INV} + MC_{INV}$ $CC_{Conv/inv} = N_{Inv} \times PW_{Inv} \times CRF$ $MC_{Conv/Inv} = N_{Inv} \times C_{Inv}$
9	LOCE	Levelised cost of energy	$LOCE(t) = \frac{\sum_{t=1}^{n} \frac{I_t + M_t + F_t}{(1+r)^t}}{\sum_{t=1}^{n} \frac{E_t}{(1+r)^t}}$

4.1.2. Levelized Cost of Energy (LCOE)

Energy generation's average net present value (NPV) during its operating life is measured by the levelized cost of energy (LCOE), also known as the levelized cost of electricity. Additionally, it serves as a tool for comparing and contrasting various techniques of producing power. Lifetime cost of energy (LCOE) "represents the average income per unit of electricity generated to repay the expenses of constructing and maintaining the plant throughout its estimated financial life and duty cycle". It is calculated as the ratio between all discounted costs over the lifetime of an electricity generating plant divided by the discounted sum of the actual energy quantities delivered. The estimator is in charge of selecting inputs for the LCOE. Capital costs, finance costs, fuel costs, decommissioning costs, operating and maintenance costs (both constant and variable), and an assumed utilization rate are all included. The LCOE is a useful method since it combines both fixed and variable costs into a single measurement to simplify analysis. However, it doesn't consider all costs related to an actual financial decision, leading to the oversimplifying project context. It also oversimplifies interest rates and ignores project risks, leading to uncertainty in the results [79].

4.1.3. Annualized Cost of the System (ACS)

The system's annual cost is another economic analysis tool for clean power generation systems. This criterion consists of replacement, capital, and maintenance costs [80]. A limitation of *ACS* is that the discount rate or capital cost must be estimated for each project; it may be inaccurate. Since energy storage systems are generally introduced as a project's capital cost, this limitation can be problematic.

4.1.4. Internal Rate-of-Return (IRR)

The amount of real profit the system generates over the course of the project is known as the internal rate of return (ROI). The time-adjusted rate of return (or return on investment) is another name for this metric. For an execution project, this discount rate equals zero's net present value (NPV) [81]. This method provides the exact rate of return for each project than the investment cost, thus allowing the investor to get a sneak peek into the potential returns. It is very promising in microgrid systems based on energy storage systems, which will be more profitable. However, it can only help decide whether a project is worth investing in. Moreover, IRR cannot account for the project size when comparing projects [82].

4.1.5. Payback Period (PBP)

Payback time is the period during which an investment's initial cash flow may be expected to be recouped using the investment's subsequent cash inflows. Calculating the amount of time it will take to recover your initial investment using the payback period is an important part of any financial planning process. The biggest advantage of using this method is that it is easy to calculate [83]. It may subjectively definite the target payback period; also, it does not note the time value of money [84].

4.2. Power

In addition, a power generation system from renewable sources should be cost-effective and be investigated from a life cycle assessment (LCA) [18,85]; it should be considered in terms of reliability. The dependability of a clean microgrid is evaluated using a variety of methodologies, including the loss of power supply probability (LPSP), the level of autonomy (LA), the expected energy not supplied (EENS), and so on. Several of the most significant, effective, and extensively used tools will be discussed in this section (Table 2).

Table 2. Some important power reliability models of the green microgrid.

Line	Indices	Remarks	Mathematical Equations
1	LPSP	Loss of power supply probability	$LPSP(t) = \frac{\sum_{t=1}^{T} LPS(t)}{\sum_{t=1}^{T} P_L(t)}$
2	LOEP	Loss of energy probability	$LOEP = \sum_j \frac{P_j \times E_j}{E_0}$
3	DPSP	Deficiency of Power Supply Probability	$DPSP(t) = \frac{\sum_0^t P_{df}(t)}{\sum_0^t P_L(t)}$
4	LOEE	Loss of energy expected	$LOEE = \sum_{h=1}^{H} \sum_{i \in S} P_i \times LOE_i$
5	LOLP	Loss of load probability	$LOLP = \sum_j \frac{P_j \times t_j}{100}$
6	LOLE	Loss of load expected	$LOLE = \sum_{h=1}^{H} \sum_{i \in S} P_i \times T_i$

4.2.1. Loss of Power Supply Probability (LPSP)

To assess a renewable energy system's dependability, one method is to look at the chance of a power supply interruption. Using a percentage to indicate the performance of a power production system in load supply is a great way to gauge the system's overall efficiency. When it comes to losing electricity, the odds are always somewhere in the range of 1 to 0. The number zero is the highest, and the number one is the smallest [86]. In fact, LPSP is the probability that an inadequate power supply gives when the generation resources and energy system storage cannot meet the power required [87].

4.2.2. Expected Energy Not Supplied (EENS)

Unsupplied power supply (EENS) is another measure of system reliability. This index reflects the amount of energy that is predicted to be unavailable because of the load conditions or insufficient supply of load. An example of EENS is the energy that will be unavailable when the local power surpasses the available generation, in a more precise sense [88]. It is defined by the expected value for a local power "L" as follows:

$$\text{EENS} = E(max(L - P_h,\ 0)) \tag{2}$$

where P_h is power generated by the system; EENS is calculated per kilowatt-hour [89].

4.2.3. Level of Autonomy (LA)

This reliability index specifies the fraction of time the intended load can be met. Moreover, its value depends on two crucial factors. 1—Total number of hours of activity or work (*HTotal*) and 2—Number of hours in which loss of load (*HLOL*) occurs [90]. LA can be calculated as:

$$\text{LA} = 1 - \frac{HLOL}{HTotal} \tag{3}$$

4.3. Energy Storage System Sizing Techniques

Researchers use different techniques to determine the optimal size of energy storage units for clean power plants. Each of these methods has advantages and disadvantages. The complexity of using these techniques also depends on the type and method of optimization. Green microgrid components can be reduced in size using a variety of strategies, from simple techniques to mathematical and nature-inspired approaches. Here, we'll focus more on procedures that are commonly utilized and found in academic publications [80,81], a variety of optimization strategies, including artificial intelligence, multi-objective design, analytical technique, probabilistic approach, Iterative approach, graphic method building method, and commercially accessible computer software.

4.3.1. Artificial Intelligence (AI)

Artificial intelligence (AI) techniques, such as artificial neural networks (ANN), genetic algorithms (GA), and division algorithms (DA), are one of the most commonly used tools for optimizing components of power generating systems from network-independent renewable energy sources, particle swarm optimization (PSO), harmony search (HS), biogeography-based optimization (BBO), ant colony optimization (ACO), etc. are given in Table 3 of the study conducted by a few of the researchers [91–97]. These algorithms have many advantages; some are summarized in Figure 11. However, there are still various disadvantages to AI methods, such as overfitting, easily getting into local optimum, a relatively low convergence rate, etc. [98–100].

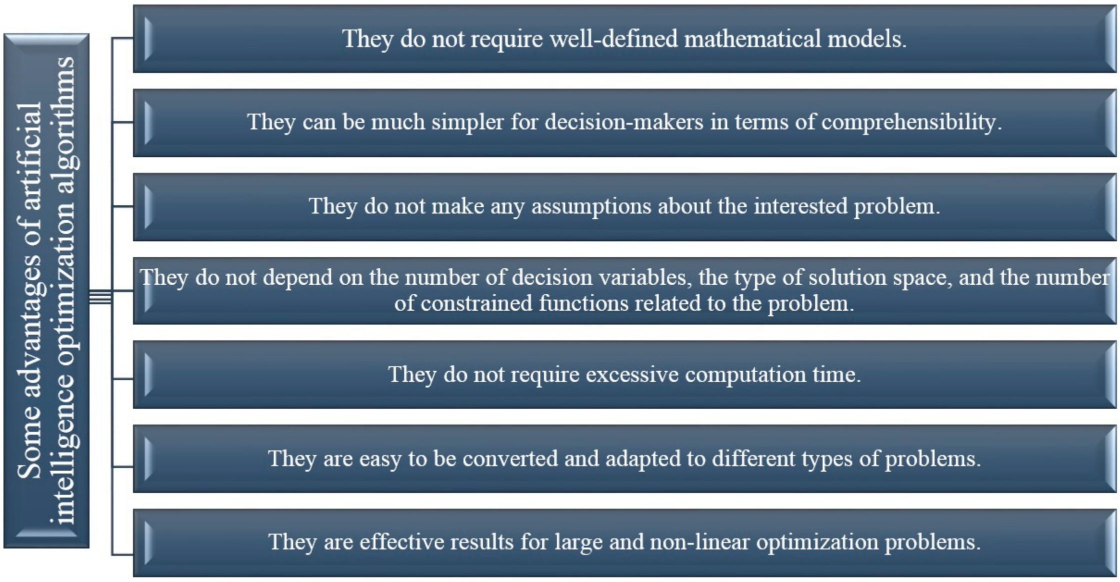

Figure 11. A summary of advantages of artificial intelligence optimization algorithms [101].

4.3.2. Multi-Objective Design

One of the optimization approaches with more than one goal set for optimization in the objective function is multi-objective optimization. This method's general strategy is to combine all of the single goal functions into a single function or to discover the whole set of possible solutions and then assess them to obtain the best response from this set of possible answers [102–107]. When it is applied to solve multi-objective problems, its main advantage is that it typically generates sets of solutions that allow computation of an approximation of the entire Pareto front. Since solving problems related to energy storage systems usually depends on several different objectives (e.g., cost vs. environmental burdens), this approach can be very helpful in solving them. However, it still has its weaknesses. Among the disadvantages of multi-objective optimization is that it cannot tolerate randomness inside the objective function and suffer from a slow convergence rate.

4.3.3. Iterative Approach

The performance assessment of the power generating system is accomplished in an iterative process utilizing a recursive program in this method, resulting in an optimal system. The net present value (NPV) approach, levelized cost of energy (LCOE), or energy cost model is used as an economic indicator for this method, and the LPSP is also utilized to estimate the dependability of the power production system [108–113]. This approach allows developers to find functional/design-related flaws as early as possible to take corrective measures on a limited budget. However, it suffers from high risk and uncertainty, so it may not be appropriate for complex and object-oriented projects.

4.3.4. Analytical Method

Another optimization technique is the analytical method. Using computer models, optimal solutions are analyzed and determined in this process. This tool is used by researchers to calculate the appropriate size for various combinations of green microgrid components [114,115]. However, it can lead to underestimating, unknown, and measurement errors.

4.3.5. Probabilistic Approach

There are several ways to assess all conceivable occurrences, their probabilities of occurrence, and related losses so that a more realistic depiction of risk may be portrayed in the future. This is a broad method. The consequences of climate change are considered when evaluating the ideal size of a microgrid independent of the green grid, and adequate and accurate models for power generation and consumption are created. This results in a risk model. This approach provides vital data for decision-making processes at the operational and planning level [116]. While exhaustive and time-consuming are disadvantages of the probabilistic approach [117].

4.3.6. Graphical Construction Method

The graphic construction technique is dependent on producing enough products to match the average demand. The average quantity of electricity provided by renewable sources like wind and solar will satisfy the average power needs for a clean microgrid. There are just two possible outcomes when using this tool. However, in the optimization process by this method, only two parameters can be included [118].

4.3.7. Computer Tools and Software

For those interested in optimizing the scale of off-grid microgrids from an economic standpoint, there is a variety of computer software available. One of the most popular tools for determining the optimal size of green microgrids is HOMER. User expectations and life cycle costs can be used to model an energy-producing system. HOMER allows the user to select the most cost-effective and efficient setup from a list of options. Additionally, the power generating system size may be precisely optimized with HYBRID2. Opt Quest, General Algebraic Modeling System (GAMS), TRNSYS, LINDO, Photovoltaic Energy Simulation Systems (Sim Pho Sys), WDILOG2, RETScreen, and many more are examples of computer software for developing power production systems [119–135].

Table 3. Summary of studies based on economic, reliability, and optimization approaches.

No.	Authors	Energy Sources		Economic Analysis	Reliability Method	Sizing Techniques	Ref.
		Wind	Solar				
1	Kiehbadroudinezhad et al.	√	√	TLCC	LPSP	DA	[18]
2	Lujano-Rojas et al.	√	√	NPC	EENS	ANN	[136]
3	Tina et al.	√	√	ACS	EENS	Analytical	[137]
4	Yang et al.	√	√	LCOE	EENS	Probabilistic	[138]
5	Bagul et al.	×	√	TLCC	LPSP	TEPD *	[139]
6	Xu et al.	√	√	TLCC	LPSP	GA	[140]
7	Yang et al.	√	√	ACS	LPSP	GA	[141]
8	Abedi et al.	√	√	NPC	LOLP	Fuzzy	[142]
9	Yang et al.	√	√	ACS	LPSP	Iterative	[111]
10	Diaf et al.	√	√	LCOE	LPSP	ANN	[106]
11	Yang et al.	√	√	LCOE	LPSP	Iterative	[113]
12	Borowy et al.	√	√	TLCC	LPSP	Graphical	[143]

* Three event probability density.

It should be noted that computer tools and software can solve mono or multi-objective optimization problems; also, they are comprehensive in terms of optimization variables. However, some of them, such as HOMER cannot enable the user to select appropriate system components intuitively. Moreover, tools, e.g., HYBRIDS, only can simulate one configuration at a time [118].

5. Discussions

This paper reviews various issues related to the most widely used energy storage devices in off-grid renewable energy microgrids. Topics such as energy storage resources, technologies, and the various categories of these storage systems are reviewed. Among energy storage devices, superconducting magnetic energy storage (SMES) is one of the most efficient energy storages with 98% efficiency. However, unlike flywheel storage, energy storage time in the SMES is possible for a short time. Another problem with this storage that can be mentioned is that it is expensive in terms of economics. The issue of safety is another matter that needs to be addressed; this is especially important in some energy storage devices, such as hydrogen storage, because it requires a high-pressure reservoir to store hydrogen. Battery banks are the most reliable and responsive energy storage among other energy storage. Sodium-sulfur (NaS) and current batteries are currently the most cost-effective and efficient types of energy storage batteries. This study also investigates the application and function of these units in renewable microgrids. Energy storage is one of the essential components of grid-independent green power generation units. These energy storage units modulate the unpredictable changes in power generation renewable energy sources. For better performance of energy storage and off-grid green microgrids, these units must be economically and reliably in suitable condition, meaning that the size of the components of the clean power generation units should be optimized to be cost-effective. These units should also be carefully evaluated for reliability so that green power generation systems can meet load demand with high reliability. Therefore, in detail, this article discusses a review of optimization, modeling, and analysis of clean microgrids, including energy storage. In this regard, various and widely used economic modeling and analysis methods were studied.

Furthermore, different techniques for determining the reliability of these systems were fully assessed, and then different tools for optimizing the size of components of clean power generation units were discussed. The strengths and weaknesses of each of these techniques were reviewed and compared. The genetic and PSO algorithms are the most widely used optimization algorithms among artificial intelligence techniques. However, researchers have shown a division algorithm to optimize the size of clean microgrid components equipped with energy storage that has better performance in terms of speed and accuracy of obtained results. HOMER software is one of the most popular computer programs among computer tools. This study described the advantages and disadvantages of each optimization technique in detail (Table 4).

Table 4. A summary of the details reviewed in the present study.

Item	Advantages	Disadvantages
	(1) Energy storage technologies	
Lead-acid battery	• Low cost • Simplicity of design • Reliability and relative safety	• Poor power and energy densities • Long recharging times • Emissions of lead particulates and SO_2
Lithium-ion battery	• Long cycle life • Wide operating temperature range • High energy density	• High cost • Safety issues • Environment pollution problem
Sodium-Sulfur Battery	• High specific energy • High energy conversion efficiency	• High initial cost • Safety issues
Flow battery	• The inherent scalability of capacity • Long-term storage of charge	• Low power/energy density
Supercapacitors energy storage	• More specific power • More number of charge-discharge cycles	• Low energy density
Flywheel energy storage	• High efficiency • Fast response time	• Maintenance effort • Low power density • Noise • High cost • Safety concerns

Table 4. *Cont.*

Item	Advantages	Disadvantages
Hydrogen storage	• Potentially high energy storage densities • Ease of disposal • Absence of toxic components	• Safety • Energy loss • Low temperature or high for storage
Pumped storage hydropower	• A very simple principle	• Scarcity of available sites for two large reservoir • Long lead time, and high cost of construction • Environmental issues
Compressed air energy storage	• Free hydrocarbon fuel	• Dependence on geographical location
Thermal energy storage	• Environmental and economic benefits by reducing the need for fossil fuels	• At every heat source, it is not practical to implement a TES system
	(2) Economic analysis of energy storage systems	
Total Life cycle cost	• Providing a complete financial picture • Comparing various combinations of measures	• Predictive tools and available databases to estimate costs are usually inadequate
Levelized cost of energy	• Simplify analysis	• Oversimplifying project context • Oversimplifying interest rates • Ignoring project risks
Annualized cost of system		• Incorrect discount rate and capital cost
Internal rate-of-return	• Allowing investors to get a sneak peek into the potential returns	• Ignoring project size
Payback period	• Easy	• Ignoring the time value of money
	(3) Energy storage system sizing techniques	
Artificial intelligence	• Relatively simple	• Overfitting • Easily getting into local optimum • Relatively low convergence rate
Multi-objective design	• Solving problems with several conflicting goals	• Lack of tolerating randomness inside • Slow convergence rate
Iterative approach	• Finding functional/design-related flaws	• High amounts of risk and uncertainty
Analytical method		• Underestimate • Unknown • Measurement errors
Probabilistic approach	• Providing vital data for processes of decision making at the operational and planning level	• Exhaustive and time-consuming
Computer tools and software	• Solving mono or multi-objective optimization problems • Comprehensive in terms of optimization variables	• Simulating one configuration at a time • They cannot intuitively select appropriate system components

6. Conclusions

To provide the power needed by power-consuming units, hybrid power generation systems from renewable energy sources are the best alternative to conventional systems that run on fossil fuels. Energy storage devices are one of the most critical components of these green microgrids. Therefore, this article covers a comprehensive review of all aspects related to energy storage, including their types, the technology used, their management and control, modeling, optimization, and comparison. Sodium-sulfur batteries are viable for balancing power generation systems among various energy storage technologies. In this paper, various methods of optimizing the size of power generation systems were investigated. This study showed that artificial intelligence techniques were more accurate in finding optimal solutions. Optimization algorithms such as genetic algorithm, particle swarm optimization, and harmony search are the most widely used optimization algorithms to determine the optimal size of power generation systems and have been widely used by researchers. In addition, much work has been done in this area. However, more research and efforts are needed to improve the performance of energy storage devices and their longevity and reduce the cost and maintenance of these energy storage devices.

7. Challenges and Future Works

Energy storage is an efficient and valuable tool for human beings, and today the rate of production and use of energy storage has become very high. These devices are used in almost all different industries, but the main and most important challenge in using this tool is these storage units' production and recycling process. Energy storage wastes such as batteries are hazardous to human health and the environment due to heavy metals and materials such as plastics, lead, aluminum, gold, silver, and heavy metals such as mercury, cadmium, and arsenic. Recycling energy storage is one of the biggest challenges facing this technology. The presence of heavy metals in the waste of these units is a concern because the gases emitted from the landfill and leakage into groundwater pollute the environment and cause damage to ecosystems and human health.

In the future, the following things can be done to increase the efficiency and improve the performance of these energy storage systems:

- Use technologies to produce energy storage devices with minimal damage to the environment and human health;
- Introducing a new generation of green batteries that, like fuel cells, use clean and renewable sources to generate and store energy;
- Optimize the size or number of energy storage devices used in systems such as clean microgrids;
- Increase the efficiency of energy storage devices;
- Increase the life cycle of energy storage devices;
- Reduce the cost of energy storage;
- Reduce the size of these storage devices, which makes transportation easier and occupies less space;
- Use fewer hazardous materials and heavy metals in producing this power storage tool;
- Create a platform for the faster and easier recycling of energy storage devices with minimal environmental damage.

In the future, focusing on increasing energy storage efficiency, using environmentally friendly materials, increasing the energy discharge duration of energy storage, reducing the charging duration of energy storage, and finding methods to make recycling easier and safer will make the industry more prosperous, the environment safer, and minimized the damage to human health.

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