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Review

Multi-Objective Optimization Algorithms for a Hybrid AC/DC Microgrid Using RES: A Comprehensive Review

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Abstract: Optimization methods for a hybrid microgrid system that integrated renewable energy sources (RES) and supplies reliable power to remote areas, were considered in order to overcome the intermittent nature of RESs. The hybrid AC/DC microgrid system was constructed with a solar photovoltaic system, wind turbine, battery storage, converter, and diesel generator. There is a steady increase in the utilization of hybrid renewable energy sources with hybrid AC/DC microgrids; consequently, it is necessary to solve optimization techniques. Therefore, the present study proposed utilizing multi-objective optimization methods using evolutionary algorithms. In this context, a few papers were reviewed regarding multi-objective optimization to determine the capacity and optimal design of a hybrid AC/DC microgrid with RESs. Here, the optimal system consisted of the minimum cost of energy, minimum net present cost, low operating cost, low carbon emissions and a high renewable fraction. These were determined by using multi-objective optimization (MOO) algorithms. The sizing optimization of the hybrid AC/DC microgrid was based on the multi-objective grey wolf optimizer (MOGWO) and multi-objective particle swarm optimization (MOPSO). Similarly, multi-objective optimization with different evolutionary algorithms (MOGA, MOGOA etc.) reduces energy cost and net present cost, and increases the reliability of islanded hybrid microgrid systems.

Keywords: hybrid microgrids; hybrid renewable energy system; renewable energy sources; evolutionary algorithms; multi-objective optimization

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1. Introduction

All over the world, energy demands will increase by 53% by 2035 [1]. In recent years, fossil fuel resources have gradually decreased; due to this, renewable energy sources have become essential resources for generating power. These sources are integrated with a hybrid microgrid to obtain reliable power, protect the environment, overcome the intermittent nature of the RESs and reduce pollution caused by fossil fuel emissions [2]. Like the power system, the microgrid's operational factors are considered due to the increasing importance of renewable energy sources in the present scenario.

There are many similarities between microgrids and conventional grids, but both are used to supply power for locally dedicated loads [3,4]. As a result, it is asserted that early isolation techniques are now being reviewed as microgrids, which have the unique capacity to incorporate grid connections when required [5]. However, the distribution of renewable energy sources and the various countries' investments in hybrid microgrid deployment are not similar. As predicted, the power strategies of a country directly impact the level and quality of energy generated [6]. The smaller the dependency on conventional sources, the higher the integration of renewable sources. According to Aleasoft energy forecasting, the total energy produced from non-renewable sources in India is shown in Figure 1.

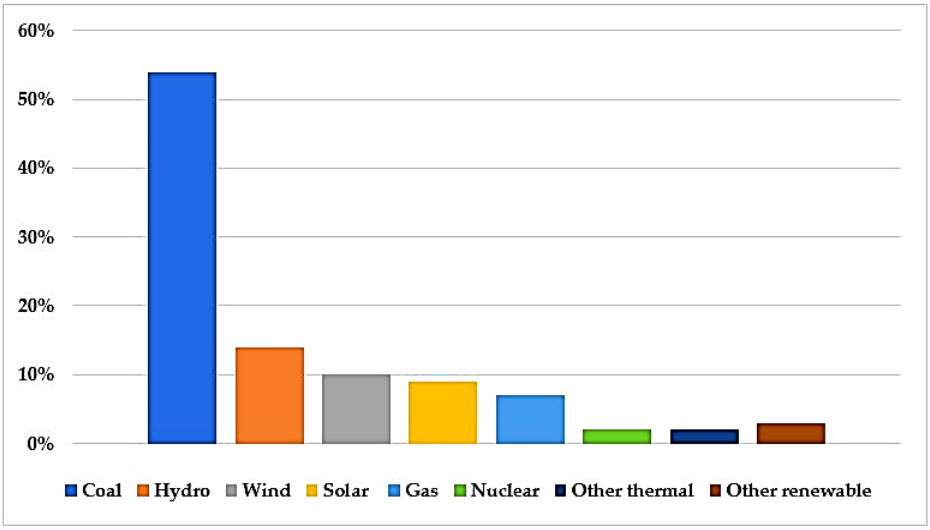


Figure 1. Total generating capacity of India in MW [7].

By incorporating renewable energy systems with utility grids, the power distribution model has been moved towards a decentralized structure, resulting in the research of hybrid microgrids. In DC systems, power electronic-based distributed generator (DG) and energy storage of static devices, such as batteries, is more efficiently used. However, AC systems still dominate most of the loads in the power system. This encourages the development of hybrid microgrids combining the benefits of DC and AC systems [8,9].

In [10], the authors proposed how to position a capacitor using a brand-new mine Blast algorithm (MBA). In addition to reducing power loss, consideration was also given to enhancing the voltage profile and minimizing the net annual cost. In [11], the authors suggested decreasing annual costs and power loss by strategically placing capacitors in radial distribution networks (RDNs). The objective function was to minimize active and reactive power losses and the cost and installation of capacitors, which are required to sustain reactive power and maintain the voltage profile. In [12], the authors looked at incorporating several DGs into the IEEE 33-bus radial distribution system (RDS) to reduce operational losses and enhance voltage profiles. In the case of optimum power factor (OPF-DG) and unity power factor (UPF-DG), the research attempted to discover the best locations and sizes of one to seven DGs to be interconnected. In [13], the authors discussed the multi-objective optimal scheduling in standalone power systems, which consisted of multiple pulsed loads, optimal mobility, and the maximum multiple pulsed-load performance value.

The authors examined the techno-economic viability of a hybrid renewable energy system (HRES) for sustainable rural electrification in Benin [14] using the case study of the village of Fouay. Optimization, modelling, and sensitivity analysis were carried out using HOMER software. Additionally, the potential energy resources and the distance between the power plant and the recipient played a significant role in determining whether HRES was the most cost-effective. In [15], the authors presented an optimum method for a RES-based generating system to be integrated with the current power system of Azad Jammu and Kashmir (AJK), which is experiencing power shortages and load shedding. In [16], the authors set power-related efficiency levels from the point of view of reliability. This included power system availability, expected power deficiency, accumulated power deficiency, instantaneous power capacity, and accumulated power capacity for a hybrid power system (HPS) in a generic smart grid. In [17], the authors presented a three-port bidirectional converter with a single conversion stage. The converter's modified form has fewer active and passive parts, which improves the converter's performance and enhances efficiency. In [18], the authors proposed a DC-DC Multiple-Input Multiple-Output (MIMO) Buck/Boost converter with two input sources, a primary solar power input and a secondary battery input. A secondary bidirectional port explicitly designed for charging and discharging hybrid electric vehicles (HEV) was supported in addition to the converter's two other outputs, which include a fixed voltage output.

The authors in [19] suggested a high-gain multiport bidirectional DC-DC converter. It may be used in AC/DC microgrid and hybrid electric cars. It is capable of bidirectional energy transfer and multi-source power sharing. Both identical and different voltage sources may be employed with it. In [20], the authors constructed and analyzed a 15-level reduced switch inverter with varying modes of operation. The proposed inverter is asymmetric and uses unequal DC voltage sources. This inverter architecture was examined for multiple objectives, such as fewer switches, capacitors, and low total harmonic distortion (THD) for generating maximum output voltage steps.

Different factors and issues must be considered when the discussion is mainly about the multi-objective optimization problem (MOOP) of a hybrid system. Some of the topics included in the system are cost optimization, design and control, acceptable power quality, reliability, and placement. In [21], the authors presented evolutionary algorithms for multi-objective (MO) challenges by using a heuristic approach; there has been a growth in their use in recent research for renewable energy unit optimization. In [22], the authors explained research conducted to solve one of these problems using MOOP. Multi-objective evolutionary algorithms (MOEAs), categorized as population-based approaches, are appropriate for this issue because they can achieve the global optimum. However, among many of the research papers on HRES optimization, only a few studies have used evolutionary algorithms (EA) to solve many objectives in HRES optimization. Finally, the recent research developments will outline the multi-objective optimization methods used in an HRES. In [23], the authors reviewed the multi-objective optimization technologies in wind energy forecasting and introduced the fundamental theories and techniques related to multi-objective optimization. In [24], the authors presented a new formulation for the optimal allocation and sizing of distributed energy resources and the operation of energy storage systems (ESSs) to enhance the voltage profiles and decrease the annual costs. The multi-objective multiverse optimization method (MOMVO) was a solution tool. In [25], the authors presented a new multi-objective optimization model to enhance voltage profiles, decrease DG and battery energy storage system (BESS) costs, and maximize power transfer between off-peak and peak hours. These objectives were rectified using the multi-objective grasshopper optimization algorithm (MOGOA).

The main objective of this research was to design an optimal hybrid AC/DC microgrid for remote locations. Here, the optimal system consisted of a low cost of energy, minimum net present cost, low carbon emissions, minimum operating costs, and a higher renewable energy fraction. All these objectives were obtained by applying the MOO algorithms to the proposed system. The use of MOO algorithms reduced the complexity of the mathematical equations-solving procedure.

Organization of the Paper

Section 2 of this paper describes hybrid renewable energy systems. Section 3 presents an overview of the microgrid. Section 4 describes the multi-objective optimization. Section 5 explains the optimization, and conclusions are presented in Section 6.

2. Hybrid Renewable Energy Systems

There are enough power-producing resources worldwide to meet the increasing electrical demand. However, the electricity provided by RESs is poor because of their intermittent nature. As a result, a non-single combination of these non-conventional energy sources will be required to complete the transformation from conventional to renewable generation. Renewable energy sources such as solar, hydro, biomass, geothermal, wind, nuclear, hydrogen and fossil fuels must work as a single unit in various combinations to supply demand, as shown in Figure 2.

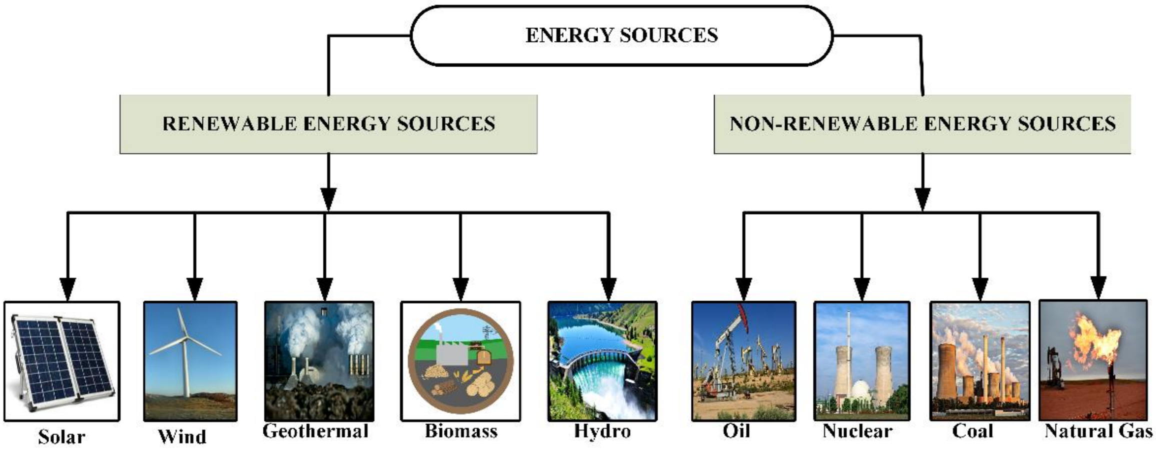


Figure 2. Types of energy sources [26].

The first power generation technologies, such as hydro, biomass, and geothermal power, have been employed since the end of the 19th-century industrial revolution. The second power generation technologies, such as wind power, solar heating, and bioenergy, evolved due to R&D activities in the nineties [27]. The 1970s oil crisis increased the awareness of fossil fuel degradation, promoting the development of alternative energy sources. However, the growth of sustainable green energy has been driven by an increasing concern for environmental conservation. Due to further development, third-generation technologies, such as biomass, geothermal, and ocean energy, have emerged.

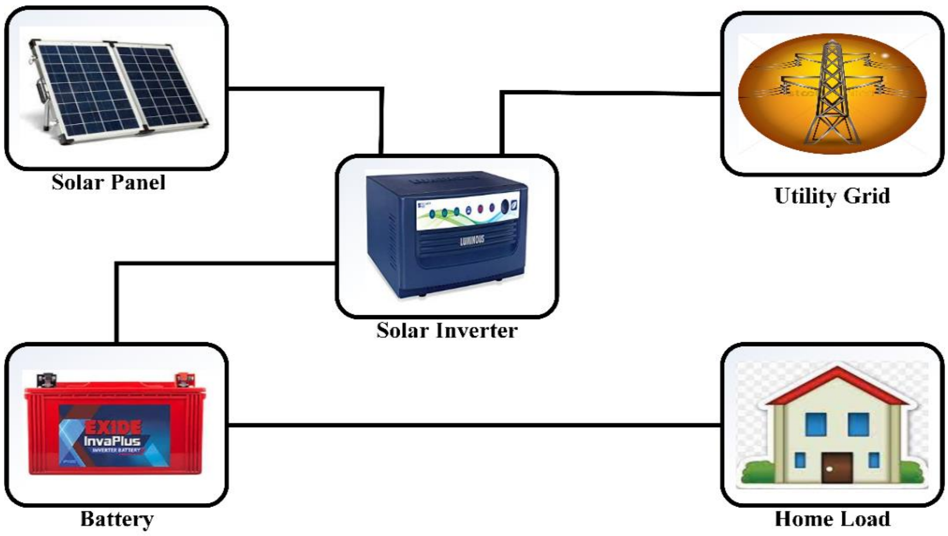
In [28], the authors focused on HRES systems that integrate solar, diesel, wind and battery energy storage technologies. In the last decade, the use of solar and wind technologies to generate electricity has increased worldwide because they are numerous, clean, and site-specific. However, they are incredibly cost-effective due to their low maintenance costs. However, this shows that combining solar and wind energy systems are becoming more common due to their complementary nature, which explains why hybrid renewable energy source modelling was included. Table 1 shows some of the benefits and limitations of RES.

Table 1. Benefits and Limitations of RES [29,30].

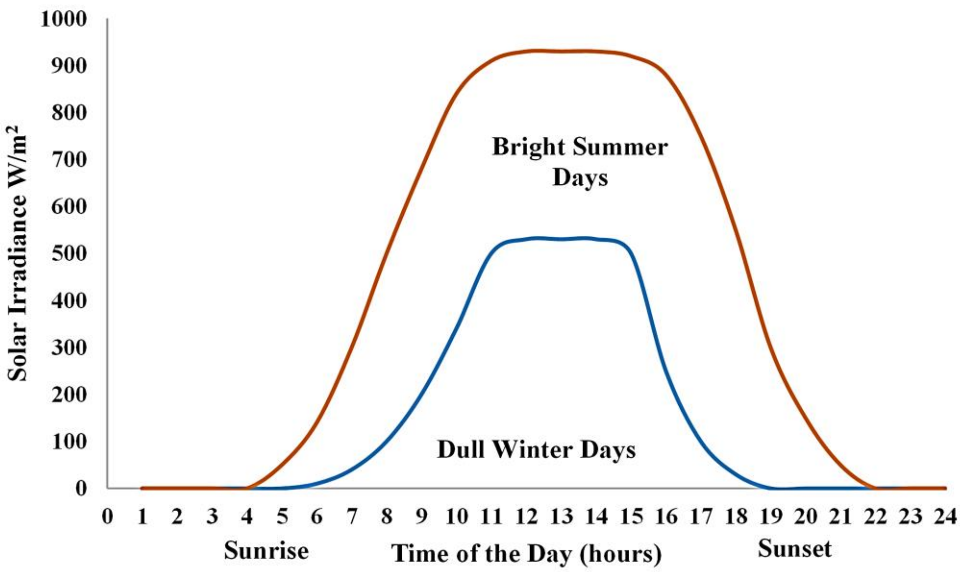
Benefits	Limitations
RES, such as solar, wind, geothermal, etc., are free of cost.	RES, such as solar, wind etc., depends heavily on the weather conditions.
Economic Advantages: RES's cost of fuel consumption and O&M is low.	High Capital Cost: RES power plants' installation cost is quite higher.
Benefits to the Environment: Pollution-free or enormous natural resources. A reliable source of energy: Solar and wind energy plants are spread over all geographical regions and weather conditions in one part will not shut down power to any area.	Difficult to generate a high amount of energy as those created by coal stations. Many photo voltaic (PV) panels and wind turbine (WT)-developing farms need to be set up to meet the high power generated by fossil fuels.

2.1. Solar Energy

A photovoltaic array turns light photons into electrons in the PV system. This operation produces a DC, which can be amplified with DC-DC converters before being inverted to supply AC power to the loads, as shown in Figure 3a,b. As a result, power electronic devices play a vital role in connecting PV panels to the grid. A unique maximum power point tracking (MPPT) is also used to allow the PV to capture the maximum amount of energy from the Sun by varying the slanting angle of its beams during the day. Finally, the electricity is controlled with a lowpass filter before entering the grid to remove any undesired harmonics [31]. Semiconducting crystalline elements are used in the majority of PV cells. PV cells come in various shapes and sizes, including mono-crystalline, poly-crystalline, and thin-film PV cells. In [32], the authors described the Levy flight and fitness distance balance (FDB)-based coyote optimization algorithm (LRFDBCOA) for enhancing the automated generation control (AGC) of three different interconnected PV-based power systems.



(**a**)



(**b**)

Figure 3. (**a**) The basic diagram of the solar system with inverter [33]; and (**b**) average Solar Irradiance in a day [34].

2.2. Wind Energy

Among all renewable energy sources, wind energy is the most promising source. The power production is related to the cube of the wind velocity; hence a minor change in the wind causes a considerable variation in the available power and generation cost. Wind generators have a 20-year of lifespan. Wind energy generally works best in 'wind farms' m^2or 'wind energy plants,' with capacities ranging from a few megawatts to hundreds of megawatts [35]. Although windmills cover a vast geographical region, their actual "footprint" covers a small percentage of the land. As a result, transformers have access to enormous amounts of land to produce more income, strengthening the rural economy. Figure 4 depicts the essential wind energy system operation with the conventional grid.

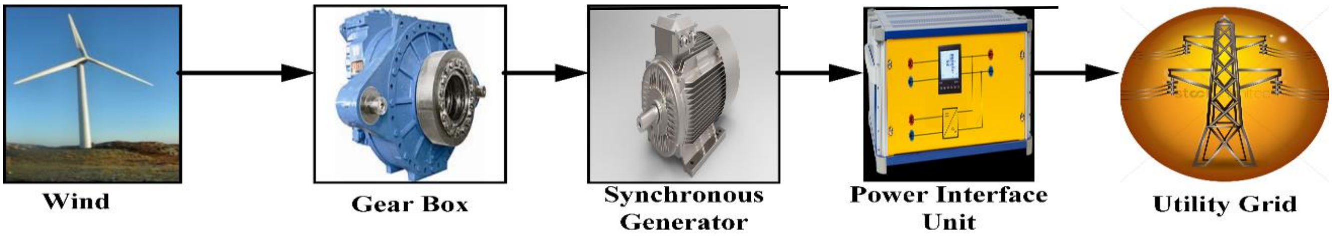


Figure 4. Basic wind energy system with the utility grid [36].

Due to the growth of wind energy used to develop wind turbines and additional equipment, the size of wind turbines has increased in recent years due to exhaustive research in this area, and the installation cost has decreased. Low wind speed was identified as a limitation, so proper planning and forecasting techniques became more essential. The operating system, wind speed prediction, and farm site selection determine the potential of wind energy. The optimal structure of wind farms consists of the wind turbine design and farm layout, which are the primary interests of researchers. The lack of wind prediction data compared to solar estimation data makes it difficult to build up new wind farms [37,38]. It is a well-known fact that solar energy is more reliable than wind energy. As a result, wind farm siting is an essential requirement that necessitates extensive research and study of the wind in the area.

In [39], the authors analyzed the controller's performance for optimal power management by creating the doubly fed induction generator and its power converter. They also developed a doubly fed induction generator wind turbine model that includes a distribution network rearrangement and efficient reactive power control. Figure 5 shows the electrical power production of solar photovoltaic and wind energy systems and describes the battery energy storage capacity throughout India up to 2023.

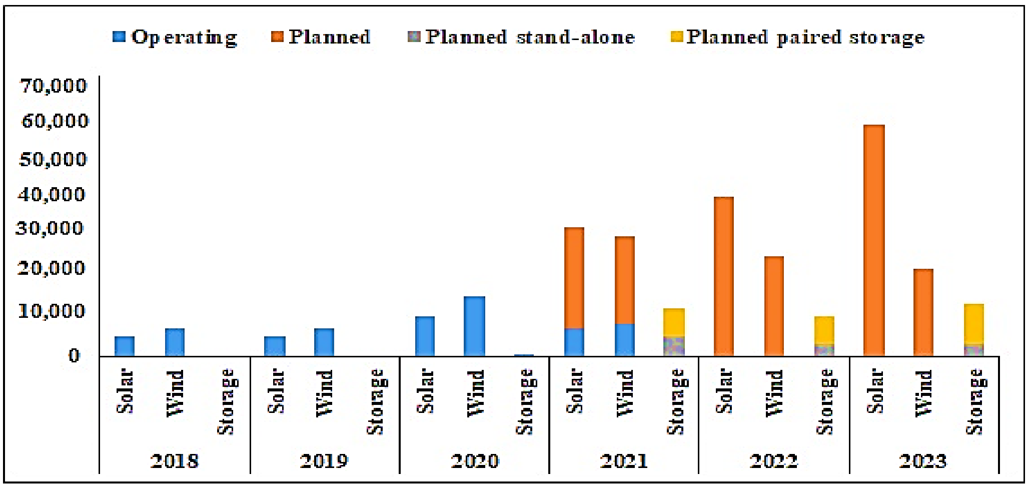


Figure 5. The annual installed capacity of wind, solar and battery storage [40].

2.3. Diesel Generator

DGs are presently widely utilized as backup devices in the HRES to encourage green power. DGs are used when RES and battery systems fail to meet the load requirements. Many factors influence the selection of DGs, including different loads, fuel prices, cost of transportation, and so on. In [41], the authors looked at DG sizing in two scenarios:

when the DG is directly connected to the load, and when it is utilized as a battery charger. The generator operation is economical at a total load of 70–80%. As a result, DGs help augment power during peak load hours and afterwards for recharging energy storage units as needed.

2.4. Energy Storage Systems

The power produced from RES cannot be stored for later utilization, which is the main drawback compared to conventional sources. Because of that, it is not easy to get much power from them when they are still available. Furthermore, they depend on the environmental conditions of the particular site; hence they cannot be guaranteed to be uniform and focused at all times. Therefore, they are unpredictable and unreliable. For example, the electricity generated by a wind turbine is particularly susceptible to harmonic distortions and associated faults, which might affect the system's functioning due to the highly unpredictable behavior of wind energy. An ESS is required to smooth out the fluctuations and improve the power quality [42]. The essential functions of the ESS are to control the energy outputs and supply the auxiliary services as needed. Because of that, they are a vital source of energy for achieving high levels of renewable system penetration. If an ESS operates as a buffer, the energy imbalance between the load and production systems can compensate. For example, a microgrid in an islanded operation will rely on an ESS to maintain total power balance due to some distributed generators' malfunction. Even if the issue is solved by bringing up other production systems, the ESS is crucial for quickly replacing the power gap. ESSs are required when the micro grid (MG) is in a grid-connected mode to maintain power quality and control reactive power. Some ESSs are now being used in microgrids with HRES.

2.4.1. Flywheel Energy Storage

One way to store electrical energy is mechanical energy, which can be divided primarily into kinetic and potential energies. Mechanical energy storage devices may be designed using these kinetic and potential energies along with the energy conservation equation. Flywheel energy storage is one such mechanical storage device [43].

2.4.2. Supercapacitor and Ultra-Super Capacitor

A high-capacity capacitor with a capacitance value much greater than ordinary but with lower voltage restrictions is referred to as a supercapacitor or ultra-capacitor. It connects rechargeable batteries with electrolytic capacitors. It can take and distribute charges considerably quicker than batteries and withstand many more charge and discharge cycles than rechargeable batteries [44]. It stores 10 to 100 times more energy per unit mass volume than electrolytic capacitors. Instead of long-term compact energy storage, supercapacitors are used in applications needing several quick charge/discharge cycles.

2.5. Hybrid Solar–Battery System

Stand-alone solar production systems are a desirable and essential electricity source for security camera devices, streetlights, electric signs, and weather observation systems. The conventional solar PV and battery systems are shown in Figure 6. In addition, the stand-alone PV generation system requires energy storage equipment. The critical point to increasing the efficiency of the generation system is to control battery charging and to discharge with the highest power of the solar PV array [45,46]. The PV panel does not use battery charging because of their unreliable output and dependence on atmospheric conditions, so there is no charge/discharge cycle, leading to a low-charge state [47]. Depending on the application of the PV system, the batteries are changed every three to five years, and improving the size of the PV panel depends on cost. Here, optimization of the battery hybrid storage system includes reducing battery size and extending the battery life by avoiding deep discharges through high currents [48]. In [49], the authors considered the uncertainties of distributed photovoltaics, a multi-objective robust optimization strategy for active distributed networks to maximize renewables' utilization and simultaneously minimize network losses. In [50], the authors proposed a quantitative techno-economic comparison method of battery, thermal energy storage, pumped hydro storage and hydrogen storage in wind–photovoltaic hybrid power systems from the perspective of multi-objective capacity optimization. The multi-objective capacity optimization models are developed based on minimizing the levelized cost of energy and loss of power supply probability.

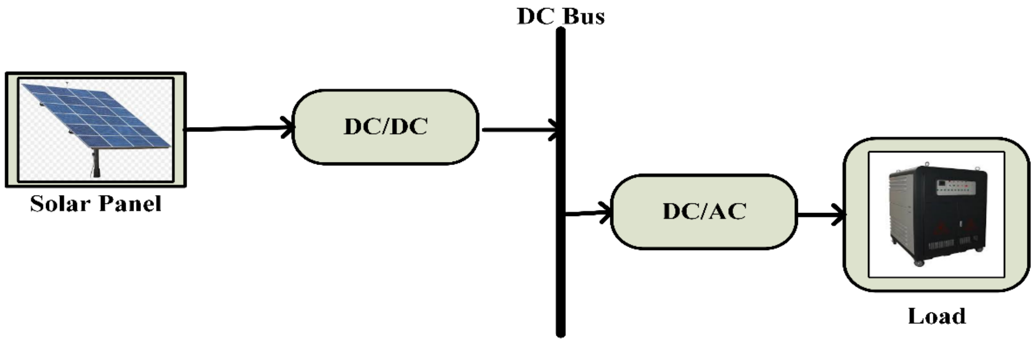


Figure 6. Block diagram of a conventional PV–battery system [51].

2.6. Hybrid Solar–Wind–Battery System

The hybrid solar-wind-battery system operates as an islanded system to confirm the availability of the load requirement, as shown in Figure 7. A controller monitors the availability status and an available source with the load [52]. The pictorial representation of the hybrid solar-wind-battery system is in the following diagram. MPPT of the solar system and pitch control of the blade angle of WTs were incorporated to increase the system's performance under various environmental situations. In [53], the authors proposed a method for designing and constructing hybrid solar–wind systems and their planning and analysis using discrete cost function optimization and energy balance calculations. In [54], the authors proposed an optimal hybrid renewable system design using solar, wind energy, battery storage, thermal loads, thermal load controller, boiler, and a diesel generator for the considered site. The techno-economic analysis was carried out using HOMER Pro (Micro grid analysis 3.14.2 (Pro Edition) by Peter Lilienthal, UL 1790 30th St, Suite 100, Boulder, CO, USA) software to meet the load demand requirement of the village. In [55], the authors focused on the design and sizing optimization of the entire system and delivered three main contributions. First, this paper proposed a retired electrical vehicle battery model based on the model of capacity fading of lithium battery cells, which could allow a more realistic result for the design. Second, a power management strategy was presented to regulate the energy flow for protecting the retired electrical vehicle battery and other system components. Third, multiple objectives were considered in the optimization model, including minimizing loss of power supply, system cost, and a new indicator, namely, potential energy waste.

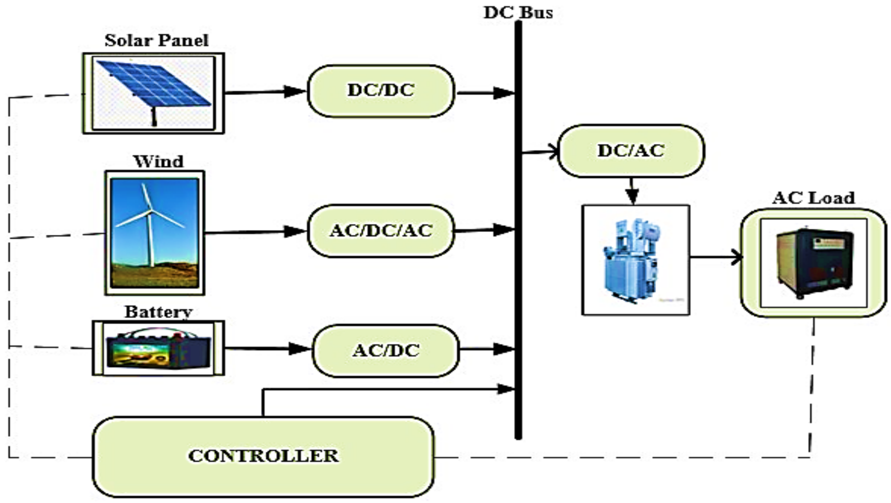


Figure 7. Block diagram of a conventional PV–wind–battery system [56].

2.7. Hybrid Solar–Wind–Diesel–Battery System

Nowadays, researchers are focusing on PV–wind or PV-wind-diesel hybrid systems with battery storage. The installation cost of hybrid solar–wind systems is more expensive, which consists of a DG, and frequently has a minimum installation cost than mono-type renewable systems. Among all hybrid systems, this is the most commonly used system. In [57], the authors implemented a two-objective optimization of a hybrid solar–wind–diesel–battery system. They took two objectives and designed a linear programming model: reducing total cost and carbon-dioxide emissions. In [58], the authors proposed the strength Pareto evolution algorithm's application to the two-objective optimization method of an off-grid hybrid solar-wind-diesel system, including battery storage systems. The minimized objectives are the cost of energy (COE) and the equivalent carbon-dioxide life cycle emissions (LCE). In [59], the authors described a method of sizing optimization of an off-grid hybrid wind–solar-diesel–battery energy system to reduce the overall cost of the system when they are present. Figure 8 shows the circuit diagram of a non-renewable and solar–wind–diesel–battery system.

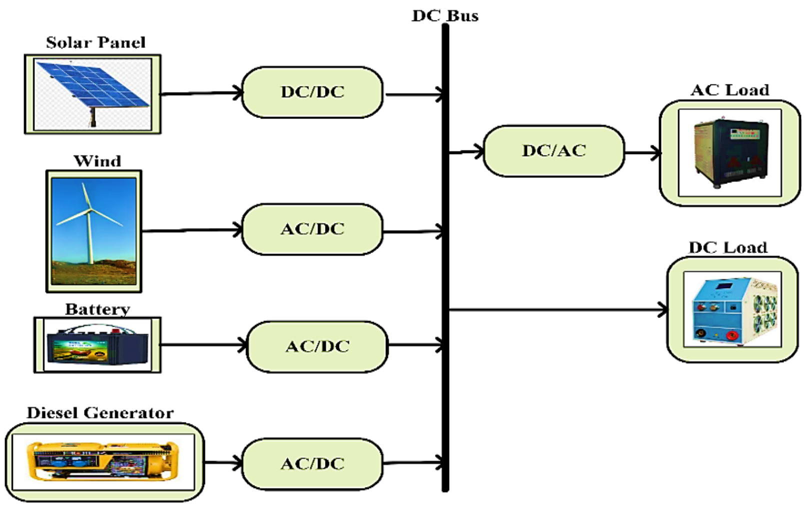


Figure 8. Non-Renewable and Solar PV–wind–diesel–battery systems [60].

3. Microgrid Overview

The early power network was an isolated DC microgrid made primarily of DC power stations. Although, the existing power network was created for various reasons, including challenges in obtaining the appropriate potential difference levels and line losses. Unified control is the electrical energy network's current prevalent operation approach. This controlling technique has enormous problems due to investment necessities in production and transmission because of load growth and a lack of government resources to invest in such areas [61]. Furthermore, the unified control system has lost its admiration because its efficiency must be enhanced, particularly in industrial regions, and not all industries are keeping up with technological developments. Therefore, microgrids determined their methods for the electricity network operation to decrease the operating and maintenance costs of the present electricity network with the earlier mentioned disadvantages. For various kinds of microgrids, many configurations have been suggested. Microgrids are classified into three broad types based on the general topologies shown in Figure 9.

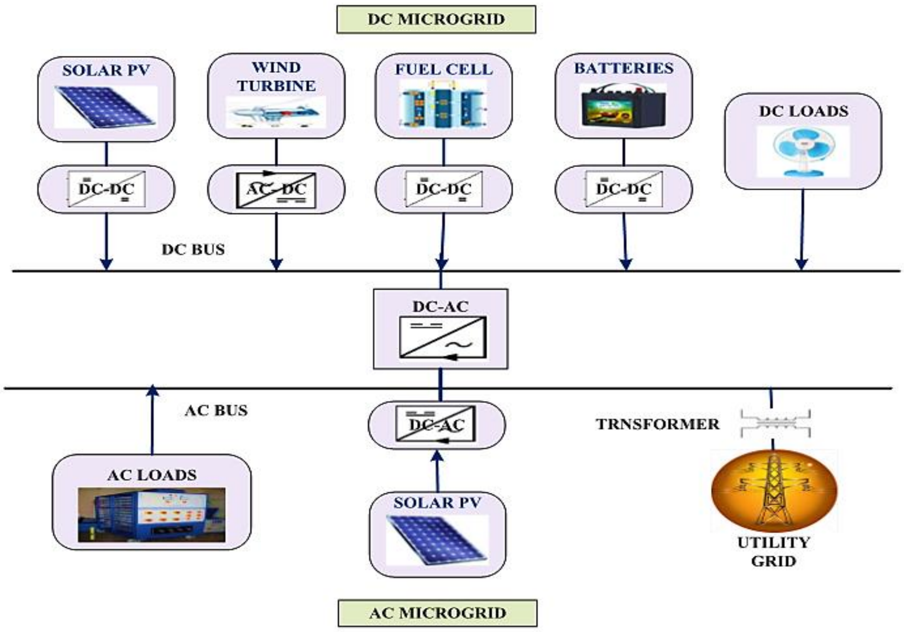


Figure 9. Hybrid AC/DC Microgrid [62].

In [63], the authors reviewed and compared the optimal power flow approaches mainly related to intelligent distribution grids. This work compares the main optimal power flow approaches in terms of their objective functions, constraints, and methodologies. In [64], the authors proposed a novel optimization model that sizes the most cost-efficient renewable power capacity mix of an autonomous microgrid supported by storage technologies. The proposed algorithm considered operational, technical, and land-use constraints. The problem was formulated using linear programming, and was tested and scrutinized with sets of historical weather, load demand and installation prices data, and was modelled hour-by-hour. In [65], the authors discussed definitions and classification of microgrid stability, considering pertinent microgrid features such as voltage-frequency dependency, unbalancing, low inertia, and generation intermittency. In [66], the authors proposed differences in allocations and sizes of all the equipment based on the assumed specific structure for each MG catalogue. Then, the MATLAB (version R2022b, MathWorks, Natick, MA, USA) working platform utilized the non-dominated sorting genetic algorithm-II to compute the multi-objective functions associated with the minimized system cost, the loss of power supply probability, and the greenhouse gas emissions for each MG catalogue.

3.1. DC Microgrid

A DC microgrid mainly consists of DC sources and loads. The essential benefits of DC microgrids are energy storage system incorporation, improved total efficiency because of low AC-DC-AC conversion losses, and the removal of DG co-ordination. Therefore, because of the inability of the produced DC electricity to be transported over long distances, it has lost the admiration of researchers over time. The DC sources, such as PV modules, fuel cells (FCs), etc., are supplied with DC power and used to provide DC loads. Integrating the microgrid design with the power distribution system is one of the issues that must be solved in this microgrid [67]. In [68] the authors focused on the operation and control framework in both grid-connected and islanding modes to provide the guideline for where we currently stand on the migration path from the overwhelming fully AC microgrids to more flexible DC microgrids.

3.2. AC Microgrid

As we know, it is a fact that AC systems have more benefits than DC systems. Therefore, they can be used in most applications for many years. The benefits include quickly changing the voltage levels by using the low-frequency transformer, bearing the faults and preservation can be handled. AC RESs. such as wind turbines, biogas, tidal, and wave turbines, have been combined with AC microgrids in the past few years. The major issues in AC microgrids are DG synchronization problems and reactive power compensation, which may increase the transmission system losses.

Furthermore, because AC renewable sources are sensitive to geographical and atmospheric variations, controlling microgrids' frequency that uses the AC RESs is complex [69]. In [70], the authors proposed a control strategy for renewable-interfaced hybrid energy storage systems under grid-connected/islanding conditions. A second harmonic-based phased locked loop is employed for effective synchronization/resynchronization of the microgrid system under contingency conditions. In [71], the authors implemented a hybrid unit of typical coupling-based architecture for multiple microgrids where microgrids are grid-connected via the AC interfaces and interconnected via the DC interfaces. Based on the proposed architecture, coordinated control schemes under different operation scenarios are finally created.

3.3. AC and DC Microgrid

This structure combines the advantages of both AC and DC microgrids and makes it easier to integrate AC and DC loads with their respective sources. This arrangement has several advantages, such as voltage transformation, economic feasibility, and harmonic control [72]. Despite all the benefits mentioned, a hybrid AC/DC microgrid has minor limitations, such as protection concerns and complex coordination among the units, which can be overcome by adopting optimal operation approaches [73]. However, the overall superiority of the hybrid AC/DC microgrid to other microgrids is a suitable case for evaluating operational issues. In the islanded mode of operation, the system is disconnected from the network, and the ESS plays a significant role, which incurs an additional operational cost. Apart from that, the extra energy will not be able to be stored. This operating mode gives more importance to the local loads, so it is more suitable for remote places and is mainly employed for seasonal purposes. PV systems comprise most islanded MG's capacity because they are the most cost-effective RES [74–76].

The primary concentration of the AC islanded MG's converter is that of multiple AC-DC-AC conversions and serves as a frequency and voltage reference. In [77], the authors proposed high-efficiency distribution architectures combining AC and DC networks. This testing facility provided a research testbed for investigating different aspects of microgrid systems, employing a total of 15.5 kW of reconfigurable Solar PV and 80 kWh of lithium energy storage on a 145 kVA commercial building load. In [78], the author designed a microgrid test model based on the 14-busbar IEEE distribution system. This model can constitute an essential research tool for analyzing electrical grids in their transition to grids. In [79], the authors reviewed other interconnection methods and control challenges of AC and DC microgrids. Then they presented an overview of various control strategies of bidirectional interlink power converters presented in the literature; all were carried out comprehensively. In [80], the authors proposed a new decentralized control strategy for an HMG that regulates a common bus's voltage magnitude in each microgrid. Unique droop characteristics for sources across microgrids and interlinking were proposed in this regard. In [81], the authors explained a comprehensive approach to improve the primary voltage and frequency controls in hybrid AC/DC microgrids. The proposed method ends in an efficient autonomous power-sharing task in the islanded operations through the interlinking converter. An improved droop-based power control was presented and then applied to the interlinking converter (IC) between the AC and DC MGs. In [82], the authors proposed an advanced system-level energy management system (EMS) for residential AC/DC microgrids by taking advantage of the innovations offered by digitalization. Finally, the proposed EMS supports green transition as it was designed for an MG that includes renewable energy sources, batteries, and electric vehicles.

4. Multi-Objective Optimization

Multi-objective optimization problems have received interest from researchers since the early 1960s. In a MOO, issues and functions must be optimized simultaneously. In the case of multiple objectives, a solution that is best for all goals does not necessarily exist because of the differentiation between objectives [83]. For example, a solution may be best for one purpose but worse for another. Therefore, there usually exists a set of solutions for the multiple-objective case, which cannot simply be compared with each other.

For such solutions, called Pareto optimal solutions or non-dominated solutions, no improvement is possible in any objective function without sacrificing at least one of the other objective functions. Thus, by using the concept of Pareto optimality, we can find a set of optimal solutions that compromise the conflicting objectives [84]. Pareto optimality is a concept used in economics, game theory, etc. In the past few years, there has been an overall development in applying genetic algorithms (GAs) to solve the MOO problem, known as MOEA. The population-to-population approach is beneficial in exploring Pareto-optimal solutions. However, the main issue in solving MOO problems using GAs is determining individuals' fitness values according to multiple objectives.

4.1. Multi-Objective Optimization Algorithms

Many metaheuristic algorithms take their fundamental concepts from the natural world, including the development of organisms, animal predatory behavior, physical processes, and geographic context. Metaheuristic optimization methods can combine random algorithms and local search algorithms. Metaheuristic algorithms are more generic algorithms that may be used more broadly to address actual issues than heuristic algorithms, which rely on a particular situation [85]. The metaheuristic algorithm's procedure is iterative, enabling efficient development and exploration of the search space and the search for approximations of ideal solutions. Single-objective optimization algorithms and multi-objective optimization algorithms are two categories under which metaheuristic optimization algorithms fall [86]. The development and use of multi-objective optimization algorithms are required to solve multi objective problems (MOPs) effectively and achieve Pareto optimum solutions. True Pareto optimum solutions for MOPs may be successfully and precisely approached by the solutions produced by multi-objective optimization algorithms.

4.1.1. Multi-Objective Optimization Algorithm Based on Evolution

Global random search algorithms replicating biological evolution are known as "evolution-based algorithms." The fundamental tenet of evolution-based algorithms is that organisms with high environmental adaptation have a greater likelihood of surviving [87].

4.1.2. Non-Dominated Sorting Genetic Algorithm 2

The term "genetic algorithm" (GA) refers to a metaheuristic algorithm influenced by genetics and natural selection principles. It works well for searching. The GA can look over most search spaces without converging to extreme regional values. Additionally, the GA is simple to use and quite sturdy. Consequently, the GA is excellent for solving the MOPs. The fitness assignment, elitism, and diversification approaches are the key distinctions across the various multi-objective GA versions [88]. One of these variants, and the most successful multi-objective GA, is the non-dominated sorting genetic algorithm II (NSGA-II). The NSGA-II uses elitism principles and the diversity preservation method to achieve Pareto optimal solutions.

4.1.3. Multi-Objective Differential Evolution Algorithm

The differential evolution (DE) algorithm uses evolution to solve ongoing global optimization issues. The DE method may provide more accurate optimization results in less time than a straightforward genetic algorithm [89]. The DE algorithm employs adaptive search criteria throughout the evolution phase. This may cause a significant population fluctuation initially, allowing for a worldwide search. The population progressively condenses to a concentrated region as the population evolution process progresses, and the accompanying population disturbance is decreased adaptively, which may guarantee local search capability at the conclusion. As a result, the DE algorithm often has a quicker convergence rate. The multi-objective differential evolution (MODE) method is suggested as a way to adapt the DE algorithm to the solution of MOPs.

4.1.4. Multi-Objective Optimization Algorithm Based on Swarm Intelligence

Swarm intelligence-based optimization algorithms are often motivated by the population's collective behavior. Although individuals within a population are generally straightforward and have limited talents, cooperation among the people may result in complex behaviors [90].

4.1.5. Multi-Objective Ant Lion Optimization Algorithm

An optimization system called the Ant Lion Optimizer (ALO) replicates the predatory behavior of ant lions and their interactions with ants in traps. The multi-objective ant-lion optimization (MOALO) method was proposed by Mirjalili et al. [91] and is the multi-objective variant of the ALO algorithm. The algorithm includes the larval stage and the adult stage, which are both significant phases. The former is mainly in charge of preying, while the latter is primarily in order of repopulating. The method uses leader selection and archive maintenance strategies to produce a Pareto optimal collection with a lot of variation. The results demonstrate that the newly created MOALO method has good convergence and coverage compared to the NSGA-II and the MOPSO algorithms. MOPSO was used for comparison analysis in order to assess the suggested model thoroughly.

4.1.6. Multi-Objective Particle Swarm Optimization Algorithm

The Particle Swarm Optimization (PSO) technique mimics fish or bird movement. The PSO algorithm's basic idea is relatively straightforward, and changing its parameters is not too difficult. The PSO algorithm's effectiveness may be highly influenced by the individual experiences and behaviors of the particles as well as the social experiences of the overall population. To fulfil the use of the PSO technique on MOPs, the multi-objective particle swarm optimization (MOPSO) algorithm is presented [92]. The Pareto dominance idea is connected to the direction of a particle's flight in the MOPSO algorithm. Other particles will utilize the non-dominated vectors discovered by the MOPSO algorithm to direct their flight once stored in a global repository. Finally, an echo state network was optimised using the MOPSO technique to combine the intermediate results from three artificial neural networks (ANNs).

4.1.7. Multi-Objective Grey Wolf Optimization Algorithm

The grey wolf optimizer (GWO) is an optimization method that mimics grey wolves' hunting behavior. Predation by grey wolves mainly consists of clustering the leadership, surrounding the prey, updating the victim's location, and hunting. In [93], the authors introduced the multi-objective grey wolf optimization (MOGWO) method, a multi-objective optimization technique based on the GWO. The Pareto archive and leader selection procedures must be implemented to support MOPs. The former is used to save the Pareto optimal results from each iteration.

In contrast, the latter is used to perform the roulette method-based selection of the alpha, beta, and delta wolves in the archive, which may aid in maintaining the best non-dominated results. The weights and thresholds of an extreme learning machine (ELM) were optimized and modified using the MOGWO technique [94]. When compared to single-objective methods, it has the best average predicting performance. This demonstrates the superior effectiveness and efficiency of the MOGWO algorithm. According to comparison trials with several different multi-objective optimization models, the model optimized by the MOGWO method can produce the best results on all evaluation metrics in most instances. In [95], the authors proposed a technique known as multi-objective grasshopper optimization algorithm-Fractional order frequency Proportional-Integral-Derivative (MOGOA-FOPID), which aims to reduce both the frequency deviation and the control signal of the microgrid's frequency control. By minimizing both the frequency deviation and the control signal simultaneously using the multi-objective grasshopper optimization algorithm (MOGOA), it is possible to manage frequency effectively while limiting battery capacity, flywheel jerk, and excessive diesel fuel consumption.

4.1.8. Multi-Objective Multiverse Optimization

Mirjalili et al. [96] introduced the multi-objective multi-verse optimization (MOMVO) method, which combines physics research with optimization. The multiverse hypothesis served as an inspiration for the algorithm. Multiverse is the opposite of the universe, which acknowledges the existence of multiple universes, and verse is the plural form of the universe. The MOMVO algorithm considers the fundamental celestial body ideas of black holes, white holes, and wormholes. The MOMVO algorithm may achieve the solution's mutation under the assurance of various mechanisms, which is a significant benefit. This way, the search space may be discovered and explored, and the Pareto solutions set can be improved along with avoiding local extremes. The MOMVO algorithm treats the universe of possible MOP solutions as a whole. As a result, the solutions are seen as things in the cosmos. This algorithm's expansion rate notion is thought to match the goal functions [97]. The wormhole may randomly transfer the item to the best universe so far acquired, which offers a random factor for the algorithm's exploration and helps the MOMVO algorithm explore more effectively. To assess its effectiveness, the MOMVO algorithm's performance was compared to that of the multi-verse optimization (MVO), GA, firefly algorithm (FA), DE, GWO, neural network algorithm (NNA), and biogeography-based krill herd (BBKH) algorithms. The MOMVO method has strong optimization capabilities and often achieves the lowest cumulative errors across various assessment measures.

4.2. Hybrid Multi-Objective Optimization Algorithms

The flaws of the individual algorithms may be eliminated by the hybrid algorithm, which is made up of two or more separate algorithms. The hybrid algorithms may often converge more quickly than the different methods [98].

4.2.1. Multi-Objective Bat-Search Flower-Pollination Algorithm

The bat-search flower-pollination algorithm (BSFPA) and multi-objective optimization make up the multi-objective bat-search flower-pollination algorithm (MOBSFPA). The bat search (BS) algorithm, which was proposed to enhance the convergence performance of the flower-pollination algorithm (PFA), is a component of the BSFPA. To maximize the weight coefficients in an ensemble forecasting model for wind speed, Qu et al. suggested and used the innovative MOBSFPA [99]. To assess the ensemble model optimized by the MOBSFPA, the accuracy and stability of the model optimized by the BSFPA were compared.

The experimental findings demonstrated that the MOBSFPA-optimized model may provide more accurate and stable forecasting predictions.

4.2.2. Immune Selection Multi-Objective Dragonfly Optimization Algorithm

The immune algorithm and the dragonfly algorithm comprise the immune selection multi-objective dragonfly optimization algorithm (ISMODA). The issue that the dragonfly optimization algorithm (DA) may easily fall into local optimization can be improved by introducing the immune algorithm (IA), which will also increase global optimization capability [100]. To demonstrate the superiority of the ISMODA, which can be shown using the multi-objective dragonfly algorithm, FA, and cuckoo search (CS) algorithm (MODA), In comparison to the other three algorithms, this ISMODA is the best. Similar optimization processes are used in multi-objective optimization algorithms, often better than their single-objective counterparts. A uniform distribution of solutions in the solution set must be sought, and the algorithm must also sort, compare, and store the optimum solutions acquired in each iteration [101]. Because of this, multi-objective algorithms often need to include various processes, such as archiving, leader selection, roulette techniques, elitism, etc. The temporal complexity reflects the effectiveness of the multi-objective optimization technique. Table 2 explains the literature review on the different MOO algorithms.

Table 2. Literature review on MOO with evolutionary techniques.

Author & Reference	Published Year	Different MOO Algorithms	Different Sources	Objectives
Yu Qian Ang, et al. [102]	2022	Multi-disciplinary, multi-objective optimization	solar, wind, and marine energy	Optimization of cost, energy utilization, carbon emission reduction and power deficit
Yi He, et al. [103]	2022	MOEA-DM	Wind-solar battery system integrated with the hybrid battery-thermal energy storage system.	Reduction of net present cost (NPC) and loss of power supply probability to determine the optimal operation threshold and sizing decision variables
Jinzhao Xu, et al. [104]	2022	Multi-objective optimization and NSGA-II	solar and geothermal energy	To increase the energy benefits, minimise the cost and carbon emissions
Ting Wu, et al. [105]	2021	MO-MFEA-II	Biogas-solar-wind	To optimize the operational cost, carbon emission and energy loss
Kalim Ullah, et al. [106]	2021	MOWDO & MOGA	Solar and wind	To minimize the operating cost and emissions and maximise the availability of RES
Gourab Das, et al. [107]	2021	MOPSO	RES such as Solar, wind etc.	To reduce the cost of generating units as well as carbon emission
Davide Aloini, et al. [108]	2021	MOO based on economic and environmental decision making criteria.	RES such as Solar, wind etc.	Carbon emissions and differential cost
Martin János Mayer, et al. [109]	2020	Multi-objective design framework	Solar, wind turbine	Least cost and the least environmental footprint options
Joy Bandopadhyay, et al. [110]	2020	HMOMFO	Solar, wind, battery storage, diesel generator	Minimum values of loss of power supply probability (LPSP)
Ahmed M.A. Haidara, et al. [111]	2020	MOPSO	Solar, battery energy storage	Lowest cost of energy and NPC

Table 2. *Cont.*

Author & Reference	Published Year	Different MOO Algorithms	Different Sources	Objectives
Peng Li, et al. [112]	2019	Multi-objective optimal operation method (source-network-load coordination)	RES such as Solar, wind etc	To optimize the consumption rate of renewable energy and the operation cost
Amirmohammad Behzadi, et al. [113]	2019	MOGA	Solar, TEG	High hydrogen production rate, lower payback period and total cost rate.
Mohammad Ghiasi, et al. [114]	2019	MOPSO	Solar, wind turbine	To reduce network losses and increase efficiency

Evolutionary techniques have been key instruments for solving real-world problems in multi-objectives in recent decades. On the other hand, analyses of single-objective approaches, presented as problems to find the "optimal" response, which relates to the maximum or minimum value of a single optimization problem, group all multiple optimization problems into one. Hence, multi-objective techniques allow decision-makers to consider the exchange between the various benefits of various objects and select the best option [115,116]. Many genuine issues have several objectives, such as cost minimization, performance maximization, reliability enhancement, etc. These are complex but actual issues.

The most important and time-consuming process in MOO is determining the Pareto front from a set of points in a multi-objective field. This is generally accomplished by a process known as no-dominant sorting [117]. Hence, in sustainable and renewable energy, heuristic techniques, Pareto-based MOO, and parallel processing are exciting research topics. In [118] the authors proposed a multi-objective approach that not only calculates the traditional Pareto frontier but also compiles near-optimal solutions that enlarge the options portfolio for microgrid developers. The proposed iterative approach stores all the simulated answers and post-processes them to provide the developer with multiple design options. A modified version of multiple-objective particle swarm optimization, with improved convergence criteria based on the quadratic mean of the crowding distances and spread, is developed and used. In this [119], the authors maximize the RES penetration and improve the system's voltage profile modelled by minimizing the operation cost through a multi-objective optimization model. In [120], the authors presented a novel approach using a decomposition-based multi-objective evolutionary algorithm to optimally design a PV/wind/diesel hybrid microgrid system considering load uncertainty. Loss of power supply probability and cost of electricity were the optimization problem's objective functions. In [121], the authors proposed a rule-based EMS optimized by a nature-inspired grasshopper optimization algorithm for long-term capacity planning of a grid-independent microgrid incorporating a photovoltaic wind turbine, a battery bank, and a diesel generator. In addition, a rule-based algorithm was used to implement an EMS to prioritize the usage of RES and coordinate the power flow of the proposed microgrid components. Table 3 explains the different objective functions and sources of the different MOO algorithms.

Table 3. Brief discussion on multi-objective optimization algorithms.

Authors/References	Sources	Objectives
J graca Gomes et al. [37]	RESs	Study of optimization methods, energy storage system optimization, developing reliable power, optimal operation of hybrid MG, Levelized cost of energy and net present cost.
Jose Maurilio Raya-Armenta et al. [48]	RESs	Developing reliable power, supply environmentally friendly energy supply, energy management optimization, and economic and emission reduction.
Halil Cimen et al. [55]	RES, BS, EVs	Energy management optimization, reduction in operating cost.
Davide Fiority et al. [77]	RESs	Calculates the traditional Pareto-Frontier and compiles near-optimal solutions.
Heydar Chamandoust et al. [78]	RESs	Improve the voltage profile, improve reliability, maximise renewable energy penetration, and minimise operating costs.
Houssem Rafik El-hana Bouchekara et al. [79]	PV, WT, DG	Load uncertainty, power supply probability loss, and electricity cost.
Abba Lawan Bukar et al. [80]	PV, WT, BS, DG	Minimize the cost of energy, deficiency of power supply probability, reduction of emission, and reduced fuel consumption.
Harish Kumar et al. [93]	PV, WT, DG, BS, thermal load controller (TLC).	Levelized cost of energy, net present cost and high renewable fraction.
Aykut Fatih Guven et al. [100]	PV, WT, BS	Optimal size, reliability improvement, minimization of annual system cost
Davide Fioriti et al. [101]	RESs	Levelized cost of energy, Net present cost, discounted payback period
Devansh Agarwal et al. [102]	RESs	The optimal operation is to minimize the operating cost, minimise power loss during local trade, and maximise total market gain.
Wenqiang zhu et al. [103]	WT, BS, Tidal turbine currents	Minimize the loss of power supply probability, the cost of energy and the sizing optimization problem

4.3. Different HRES with Multi-Objective Optimization Methods

Many objective approaches for solving problems in RES are discussed in various works and a few suggestions are that they are used in HRES. A GA is designed for issues with multiple objectives. According to this research, genetic algorithms are a popular meta-heuristic technique suited for these problems. In recent years, genetic algorithms have been a standard method for objective optimizations of several HRES. In [122], the authors designed the HRES over its lifetime by considering its operation. The sizing issue in HRES has received more attention in recent papers than other issues such as placement, cost, design, and control approach. In [123], the authors addressed how a hybrid model could improve the forward-feeding back-propagation model with a GA. A GA optimized the sizing and economic analysis of a WT–PV–battery hybrid system, reducing the annualized system cost. In this work, researchers used a MOGA to optimize the sizing of a hybrid solar–wind–battery system with two main goals: reducing the annualized cost of the system and decreasing the feasibility of losing power supply. Table 4 shows the performance of each MOO algorithm regarding different objectives, as mentioned. It can be concluded that the MOO algorithms are superior to the single objective optimization techniques.

Table 4. Performance evolution of each MOO algorithm.

Reference	MO Algorithms	Objectives	Description
[7]	MOPSO, pareto envelop-based selection algorithm-II (PESA-II), strength pareto evolutionary algorithm-II (SPEA-II)	NPC, COE and CO_2 emission	A SPEA-II algorithm is the best in terms of robustness and reliability. In general, the proposed hybrid microgrid system is cost-effective and reliable and ensures energy is available more than 98% of the time at a reasonable cost.
[8]	MOEA	Optimal size, NPC, COE and CO_2 emission	The multi-objective optimal design of hybrid PV-wind-diesel-battery system for the reliable power-supply.
[13]	MOPSO, MOWDO, MOGA	Operating cost, Carbon emission	The operating cost is reduced by 12% and 6% with and without hybrid DRPS and IBT using MOGA, 13% and 8% using MOWDO compared to MOPSO. Similarly, the availability of RES is maximized by 20% and 17% using MOGA and 25% and 19% using MOWDO as compared to MOPSO, respectively.
[14]	MOGOA	Voltage profiles, DG BESS costs, and maximize energy transfer	MOGOA is used to solve the formulated constrained optimization problem. The performance of the MOGOA algorithm is compared with the other heuristic optimization algorithms using two Pareto optimality indices.
[15]	MO model based on mixed-integer programming approach	Carbon emission, energy cost	The proposed system is designed with 100 photovoltaic modules and 94 wind turbines; the system can supply 18% of the plant's energy requirements while emitting the least amount of carbon dioxide (90,899 $kgCO_2$-eq/yr). Furthermore, the energy cost is 0.0557 \$/kWh, less than the cost of kWh purchased from the grid.
[18]	MO robust optimization (Monte Carlo simulation and simulated annealing algorithm)	Levelized COE	Compared with the deterministic optimal design, the standard deviation of LCOE of the multi-objective robust optimum is reduced by 17.22%, which is less sensitive to the uncertainties.
[19]	MOGA	Optimal size, the total cost of electricity	To size the developed system considering all storage dynamics. To achieve an optimal system configuration, different economic analysis cases were established.
[31]	MOPSO and technique for order preforence by similarity to ideal solution method (TOPSIS)	Cost of electricity, pollution emissions	The proposed method is compared with simulated annealing and genetic algorithm to show its faster computation speed and higher solution quality.
[32]	MOPSO	Reliability of the system, cost of electricity production	The optimization and the assessment of an HMGS in different cities to point out the potential of each location for HMGS investment. MOPSO is used to find the optimal system configuration and the optimal component size for each location
[42]	MOMVO	Voltage profile, Annual cost	The proposed formulation eliminated all the voltage magnitude violations and provided almost 50% loss reductions. Pareto fronts of the proposed method are be better than the non-dominated sorting genetic algorithm and multi-objective particle swarm optimization.

5. Optimization Techniques

The optimization algorithms focus on optimizing a problem and refer to strategies for finding the upper and lower bounds of a given function by computing the value of the process using inputs extensively chosen from within an acceptable set. The techniques which are widely used for microgrids are described in this section. Since the utility grid can be considered the reference distributed energy resource, several existing optimizers have been used in grid-connected MG. These algorithms are classified as traditional, heuristic/meta-heuristic, and hybrid optimization methods. The conventional techniques depend on linear and non-linear mixed-integer programming algorithms [124]. Since the 1940s, the problems in the power system can be solved by heuristic search techniques. These depend on the situation that uses trial and error to find solutions to challenging issues quickly. Furthermore, population-based heuristic approaches are thoroughly examined, and various hybrid methods relating to algorithms that combine multiple methods are presented.

In [125], the authors implemented a novel hierarchical two-tier optimization methodology for a network of HRESs. In the proposed method, the operational optimization of each HRES was carried out by minimizing the operating cost of various sub-units in the first layer. In the second layer, three cooperative optimization strategies inspired by concepts of double-auction e-marketing were applied where HRESs were assumed to operate under the grand coalition. In [126], the author provided an in-depth overview of the EMS optimization problem of islanded microgrids (IMGs) by systematically analyzing the most representative studies. Metaheuristic algorithms can be population- or trajectory-based and are available in many shapes and sizes. On the other hand, GAs work with a population of strings and are categorized as population-based algorithms, whereas hill-climbing algorithms work with a trajectory. Metaheuristic algorithms are divided into two groups: single-solution-based and population-based. The population-based metaheuristic algorithms are divided into two types 1. Evolutionary algorithms 2. Swarm-intelligence algorithms. The following Table 5 explains the difference between heuristic and metaheuristic algorithms.

Table 5. Comparisons between Heuristic and Metaheuristic Algorithms [127].

Heuristic Algorithm	Metaheuristic Algorithm
This technique depends on the problem	This technique does not depend on the problem
They are frequently adjusted to the issue at hand	However, to customize the approach to this issue, significant fine-tuning of its intrinsic properties is required.
They make every effort to take advantage of the problem's unique characteristics.	They do not take benefit of the problem's uniqueness.
They are frequently very greedy.	They are not avaricious
They frequently become locked in a local optimum and, as a result, fail to find the global optimum solution.	They may even be willing to put up with a temporary degradation of the solution.

By comparing both, it can be concluded that the heuristic algorithms have some disadvantages over the meta-heuristic algorithms.

5.1. Heuristic Optimization Techniques

Heuristic techniques popularly used for the EMS of islanded microgrids are GWO, AC, PSO, artificial bee colony (ABC), teaching learning based optimization (TLBO), EAs, GS, JAYA, and their advanced versions. According to the observation of all heuristic techniques, the most popular algorithms are PSO and EAs, the ant colony optimization (ACO), gravitational search algorithm (GSA), TLBO, and JAYA algorithms are also employed for a few applications [128].

5.1.1. Genetic Algorithms (GA)

GA was introduced by Holland in 1975 and is one of the most-used EA approaches. Generally, it is a population-based approach used to simulate the process of natural selection. The GA method consists of initialization, objective function (OF) assessment, selection, crossover for offspring production, and mutation. The OF in the offspring is analyzed, and the termination criterion is finally validated. The procedure is complete if the stopping requirement is fulfilled; otherwise, it must be repeated. Many papers have examined the efficacy of this approach for IMG energy management [129].

GA optimizes single and MO operations while keeping operational costs and emissions to a minimum. Furthermore, a non-dominated sorted genetic algorithm (NS-GA) is employed for the optimal design of an MG while considering the cost of power generation and the life-cycle cost of the battery. The optimization is carried out in a general IMG by investigating nine alternative situations and nine weighting factor combinations for the multi-objective problem formulation [130]. The outcomes are compared against two different standards, PSO and GA methods. The accuracies of the memory-based genetic algorithm (MGA) and PSO are identical but much superior to the others. However, the processing time in the PSO-based algorithms is nearly twice as long.

5.1.2. Ant Colony Optimization Algorithm

In 1992, Dorigo initially proposed this simple and fast heuristic optimizer. ACO is motivated by the activity of ants when looking for food. These little insects often leave pheromones behind them that their neighbors can identify. This pheromone-filled path, known as the favored path, is used by posterior ants by increasing the strength of the pheromone and finally converging on the shortest route, which is from the nest to the food source [131]. ACO is also used as an IMG for ED and emission reduction. Finally, compared to the gradient-based technique, the ACO method is more effective.

5.1.3. Particle Swarm Optimization Algorithm

Kennedy and Eberhart developed this technique in 1995. The behavior of social organisms such as birds, ants, and fish influences PSO. The algorithm replicates how members communicate information among themselves. The mathematical formulation includes two components to describe each group member's intellectual and social impact in determining the best response. The PSO algorithm has been successfully applied for ED to grid-connected IMGs with intense centralized distributed energy resources (CDER) penetration. PSO is used with a deep recurrent ANN to estimate solar energy supply and load demand.

The authors of [132] employed a supervised PSO method to restrict the velocity of the particles. They provided a variable cost function for recharging with a penalty term when the battery is not entirely restored by focusing on the grid-connected configuration. In [133], the authors concentrated on multi-layer energy management systems of multi-microgrid intelligent distribution networks. An evaluation of effectiveness in actual power losses for energy management within units was presented. The demand response technique was incorporated into the optimization procedure. In [134], the authors developed a multi-objective optimal dispatch model for a standalone MG composed of wind turbines, photovoltaics, diesel engine unit, load, and battery energy storage system. The economic cost, environmental concerns, and power supply consistency were expressed via sub-objectives with varying priorities. Then, the analytic hierarchy process algorithm was employed to specify the weight coefficients of the sub-objectives reasonably.

5.1.4. Simulated Annealing Algorithm (SA)

In 1983, Kirkpatrick, Gelatt, and Vecchi were the first to apply simulated annealing to optimization problems. It is a random search approach that simulates the metal annealing process. Metal is heated at extreme temperatures, then cooled and condensed to form a crystalline condition using the least amount of energy. As a response, the metal produces larger crystals with fewer defects within the metallic structure. The most important aspect of the entire operation is temperature control. SA is less prevalent in hybrid system scaling than GA or PSO. For a size problem in an HRES, the authors in [135] compared SA to another metaheuristic approach termed the tabu-search algorithm. According to the findings, SA was faster to converge but less efficient. In [136], the authors described the Levy flight and fitness distance balance (FDB)-based coyote optimization algorithm (LRFDBCOA) for improving the automated generation control (AGC) of three different interconnected PV-based power systems.

5.1.5. Artificial Bee Colony Algorithm

In 2005, Karaboga introduced this method. ABC attempts to replicate the hunting behavior of a bee colony. The bees are divided into three groups: (1) employed bees account for half of the whole population, searching for food and relaying this message to onlooker bees; (2) the other half of the population, the onlooker bees, is in charge of picking the finest food that the hired bees locate; and (3) the third type of bee is the scout, produced by a few working bees. These bees quit their usual food source in search of new sources. This method was used to manage the energy of an IMG. Unfortunately, this technique is sensitive to becoming trapped at a minimum and has poor stability in significant optimization problems such as MG energy management. As a result, two improvements to the conventional ABC optimization approach are presented to improve its performance, including using a different probability function for the exploitation process and a new search strategy [137].

5.1.6. Gravitational Search Algorithm

In 2009, Rashedi proposed this technique. GSA is based on the physical principles of motion and gravity, with each agent representing the object’s mass and determining the item’s performance. This procedure causes actual items to move, with a preference to move towards the direction of the agents with heavier weights. The algorithm does a comprehensive search since the more significant the mass, the slower the displacement. By simulation, this approach is used to control the energy of an IMG. GSA-based EMS is contrasted with PSO-based EMS. The results suggest that GSA is faster and saves a lot of money. Several enhancements to the classic GSA are proposed. In [138], the authors proposed that the starting estimations be compared against their opposite ones. As per statistical inference, a guess will reflect the ideal answer better 50% of the time than its equivalent opposing guess. Thus, applying this method using the best assumptions in each iteration is preferable. This procedure will accelerate the convergence. To enhance convergence characteristics and deal with energy availability, market rates, and load profile uncertainties. In [139], the authors proposed using probability functions for uncertainty modelling and a self-adaptive mutation technique for GSA to reduce the total operational expenses of a regular grid-connected MG.

5.1.7. Teaching–Learning-Based Optimization Algorithm

The effectiveness of heuristic optimization methods is mainly determined by parameter tuning. To address this issue, in [140], the authors presented the TLBO method in 2011, which does not require unique parameter tuning. The flow process of communication between a student and a teacher for sharing knowledge about a subject is the foundation of TLBO. Initialization is a step in the algorithm process in which each control variable is initialized with a vector of various values within the permissible limits. The average value of every variable was determined, and the best population member is identified as the teacher of a corresponding cycle. Each parameter was moved between its average value and the teacher's corresponding value. Considering that the control parameters interact with one another to strengthen their knowledge at this level [141]. Whenever a stopping requirement is reached, the algorithm terminates. The TLBO method was used in an MG for ED of CDERs and was compared to three gradient-based optimization techniques: regular false, bisection, and the golden section. Hence, the TLBO is similar to gradient-based algorithms, obtaining optimal operating points without complicated formulations. The longer processing time is a disadvantage. In [142], the authors recommended that the training phase of TLBO be modified to prevent obtaining trapped in a minimum and to investigate more broadly in the global optimization space. In terms of processing time and accuracy, the modified TLBO outperformed the others.

5.1.8. Grey Wolf Optimization Algorithm

Mirjalili initially reported this technique in 2013. GWO is influenced by grey wolf hunting rules and their responsibilities in the group, which typically includes 5 to 12 wolves. The group's leader is alpha, while the second command is beta, which helps strengthen the leader's orders and provides feedback to the leader. The wolf at the bottom of the hierarchy is known as the omega, and it is always required to remain submissive to all others. Other wolves that do not belong to these groups are known as deltas and are generally hunters. In [143,144] optimization issues, the best solution is commonly referred to as alpha, while the second and third best solutions are referred to as beta and gamma, respectively. When the outcomes are compared to other standard heuristic algorithms, such as PSO, it is feasible to observe that GWO outperforms them regarding the number of iterations needed to converge. Convergence is authorized under various test settings, including communication systems and system architecture changes. GWO was used to reduce the operating costs of a grid-connected MG. Furthermore, a grid-connected MG was optimized using MOGWO, performed similarly to MOPSO but with an outside archive to store dominant answers. In [145], the authors proposed the reconfiguration of DG of techno-economic analysis of hybrid micro grids using crow search-grey wolf optimization (CS-GWO) algorithms. In [146,147], the authors presented a novel expert fuzzy system-grey wolf optimization (FL-GWO)-based intelligent metaheuristic method for battery sizing and energy management. The proposed energy management operation was carried out by a grey wolf optimizer (GWO) that helped to set the membership functions and rules of the fuzzy logic expert system. The unit commitment issue, which is essential for the operation of the isolated microgrid, was also considered.

5.1.9. JAYA Algorithm

In 2016, Venkata introduced this population-based technique. In Sanskrit, the term JAYA signifies "victory". This technique, similar to teaching learning-based optimization, was recently developed for optimization without parameter adjustment (only the number of generations, stop criterion, and population size is required). However, unlike TLBO, which requires two stages in each cycle, JAYA requires one process. This heuristic approach facilitates the optimal solution while rejecting the worst solution. Each parameter is modified by inserting a term that leads to an optimal solution and eliminating another word that leads to the worst solution [148]. This technique was used to control the energy of grid-connected IMGs. Using the peak load pricing scheme in the load profile, JAYA achieves the lowest cost of production with the least amount of computing time.

When the MG employs ESSs, the results indicated that JAYA is superior in terms of overall energy cost and preparation time. However, reduced client satisfaction was reported regarding the load waiting period. JAYA, PSO, a gradient-based algorithm, and ACO are used in the MO economic load dispatch optimization. The results placed JAYA in first place. In [149], The authors have proposed several improvements to increase its efficiency and processing time. The traditional JAYA is modified in three ways: changeable population size, searchability enhancement, and three mutations. Furthermore, the changed JAYA algorithm behavior was compared with TLBO, PSO and JAYA in a deterministic scheme; the changed algorithm outperformed the others. So far, several heuristic methods and their use in IMG operation optimization have been discussed.

5.2. Hybrid Optimization Techniques

The hybridization of several optimization algorithms has been suggested to enhance the effectiveness of the EMS optimization issue. This mixture is dependent on the particular problem requirements. For example, FL and GWO were proposed [150]. The FL method was used to calculate the best battery size, while the GWO algorithm was used to calculate the optimal ED. FL-GWO exceeded an RB approach and regular GWO in terms of economic benefits. However, the percentage of renewable energy was limited, particularly during the winter season. Using the mutation approach of GA in ABC, a MABC algorithm was presented, which was applied to address a day-ahead ED challenge in an IMG in the RHC architecture. PSO, ABC and GA were compared with the algorithm. The results indicated that MABC is superior in terms of reliability but has the most significant processing time.

6. Discussions

Nowadays, the multi-objective optimization approach has become more popular than single-objective optimization. The research issues in MOO are huge and can be found in different areas of human life. Beyond this, there are many methods to determine MOO problems. These problems do not require complex mathematical equations to solve and produce compromise solutions. Reviewing all the papers shows that the main objectives of these studies are minimum energy cost, minimum net present cost, a high percentage of renewable fraction, low carbon emission and minimum operating cost. Multi-objective optimization techniques with evolutionary algorithms include MOGA, MOPSO, MOGWO, MOGOA etc. It can be seen that there is a possibility of using multi-objective hybrid evolutionary algorithms to improve reliability and reduce the operating cost of the hybrid AC/DC microgrid.

7. Conclusions

This article reviewed recent research articles on renewable energy sources with multi-optimization with evolutionary algorithms for the optimal design of a hybrid AC/DC microgrid. While numerous optimization methods of RESs exist with a single objective optimization, only a few studies have addressed the multi-objective optimization of a stand-alone HRES system. The multi-objective optimization algorithm provides a better optimal design compared to single-objective optimization. A specific evolutionary algorithm with multi-objective optimization was utilized for the specified region of the stand-alone HRES system, including MOGA, MOPSO, MOGWO, and MOGOA optimization. Furthermore, to enhance the performance of a hybrid AC/DC microgrid, there is a need to use hybrid MO optimization methods. In this context, MOGA and MOPSO are the most valuable and promising approaches in HRES design among the multiple MOEAs. Thus, employing other combinations of multi-objective optimization may be preferable to increase the performance of optimal stand-alone hybrid microgrid systems.

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Nomenclature

Symbols	
m^2	Meter Square
m/s	Meter per Second
V	Volts
%	Percentage
Abbreviations	
ABC	Artificial Bee Colony
AC	Alternating Current
ACS	Annualized Cost of the system
ACO	Ant Colony Optimization
AE	Applied Energy
AGC	Automatic Generation Control
Ah	Ampere hour
AJK	Azad Jammu and Kashmir
ANN	Artificial Neural Network
ASCJ	Applied Soft Computing Journal
BA	Bat Algorithm
BESS	Battery Energy Storage System
CDER	Centralized Distributed Energy Resources
CEE	Computers and Electrical Engineering
COE	Cost of Energy
CO_2	Carbon dioxide
DC	Direct Current
DG	Distributed Generation
DFIG	Double-Fed Induction Generators
EA	Evolutionary Algorithms
ECM	Energy Conversion and Management
ED	Energy Distribution
EMOGWA	Enhanced multi-objective grey wolf optimization algorithm
EMS	Energy Management System
EP	Energy Programme
ESS	Energy Storage System
EVs	Electrical Vehicles
FDB	Fitness Distance Balance
FL	Fuzzy Logic
FOPID	Fractional order frequency Proportional-Integral-Derivative
GA	Genetic Algorithm
GSA	Gravitational Search Algorithm
GWO	Gray Wolf Optimization
HEV	Hybrid Electric Vehicle
HMOMFO	Hybrid multi-objective moth flame optimization
HOMER	Hybrid Optimization Multiple Energy Resources
HPS	Hybrid Power System
HRES	Hybrid Renewable Energy Sources
hSA-GA	Hybrid Simulated Annealing-Genetic Algorithm
IBA	Improve Bat Algorithm
IBT	Incline Black Tariff
IMOWCA	Improved multi-objective water cycle algorithm
ISMODA	Immune selection multi-objective dragonfly optimization algorithm
IMGs	Islanded Micro Grid System
IABC	Improved the artificial bee colony algorithm
JCP	Journal of Cleaner Production
kV	kilo Volts
LCE	Life Cycle Emissions
LRFDBCOA	Levy flight and Fitness Distance Balance-based coyote optimization

Algorithm	
LPSP	Loss of power supply probability
MABC	Mutation-based Artificial Bee Colony
MAS	Multi-Agent System
MBA	Mine Blast Algorithm
MG	Micro Grid
MW	Mega Watt
MO	Multi-Objective
MOOP	Multi-Objective Optimization
MODE	Multi-objective differential evolution algorithm
MMODA	Modify multi-objective dragonfly algorithm
MOALO	Multi-objective ant lion optimization algorithm
MOFEPSO	Multi-objective feasible enhanced particle swarm optimization
MO-MFEA-II	Multi-objective multifactorial Evolutionary Algorithm.
MOCWCA	Multi-objective chaotic water cycle algorithm
MOICA	Multi-objective imperialist competitive algorithm
MOSCA	Multi-objective sine cosine algorithm
MOBSFPA	Multi-objective bat-search flower-pollination algorithm
MOMVO	Multi-objective multi-verse optimization algorithm
MOWOA	Multi-objective whale Optimization Algorithm
MOWDO	Multi-objective wind-driven optimization
MOPSO	Multi-objective particle swarm optimization
MOSBO	Multi-objective satin bowerbird optimizer
MOEA	Multi-Objective Evolutionary Algorithm
MOEA-DM	Multi-objective evolutionary algorithm with decision-making
MOGOA	Multi-objective grasshopper optimization algorithm
MOGWO	Multi-objective grey wolf optimization
MOFMO	Multi-objective moth-flame optimization
MSSA	Multi-Objective Salp Swarm Optimization
MOBA	Multi-Objective Bat Algorithm
MOGA	Multi-Objective Genetic Algorithm
MIMO	Multiple Input Multiple-Output
MPPT	Maximum Power Point Tracking System
NSGA-II	Non-Dominated Sorting Genetic Algorithm-II
NPC	Net present cost
OPF	Optimal Power Factor
PV	Photo Voltaic
PSO	Particle Swarm Optimization
PMSG	Permanent Magnet Synchronous Generators
RB	Risk-Based
R&D	Research and Development
RDNs	Radial Distribution Networks
RDS	Radial Distribution System
RE	Renewable Energy
RES	Renewable Energy Sources
RHC	Rural Health Clinic
SA	Simulated Annealing
SBA	Super Bat Algorithm
SCS	Sustainable Cities and Society
SOC	State of Charge
SPV	Solar Photo Voltaic
TEG	Thermoelectric generator
TLBO	Teaching Learning-Based Algorithm
TOPSIS	Technique for Order Preference by Similarity to Ideal Solution method
TS	Tabu Search
UPF	Unity Power Factor
WECS	Wind Energy Conversion System
WT	Wind Turbine

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