energies

MDPI

Review

Intelligent and Optimized Microgrids for Future Supply Power from Renewable Energy Resources: A Review

Mohammadali Kiehbadroudinezhad [1], Adel Merabet [1,*], Ahmed G. Abo-Khalil [2], Tareq Salameh [2] and Chaouki Ghenai [2]

[1] Division Engineering, Saint Mary's University, Halifax, NS B3H 3C3, Canada; mohammadali.kiehbadroudinezhad@smu.ca

[2] Sustainable and Renewable Energy Engineering Department, College of Engineering, University of Sharjah, Sharjah P.O. Box 27272, United Arab Emirates; aabokhalil@sharjah.ac.ae (A.G.A.-K.); tsalameh@sharjah.ac.ae (T.S.); cghenai@sharjah.ac.ae (C.G.)

* Correspondence: adel.merabet@smu.ca; Tel.: +1-902-420-5712

Abstract: Using renewable energy sources instead of fossil fuels is one of the best solutions to overcome greenhouse gas (GHG) emissions. However, in designing clean power generation microgrids, the economic aspects of using renewable energy technologies should be considered. Furthermore, due to the unpredictable nature of renewable energy sources, the reliability of renewable energy microgrids should also be evaluated. Optimized hybrid microgrids based on wind and solar energy can provide cost-effective power generation systems with high reliability. These microgrids can meet the power demands of the consuming units, especially in remote areas. Various techniques have been used to optimize the size of power generation systems based on renewable energy to improve efficiency, maintain reliability, improve the power grid's resilience, and reduce system costs. Each of these techniques has shown its advantages and disadvantages in optimizing the size of hybrid renewable energy systems. To increase the share of renewable energies in electricity supply in the future and develop these new technologies further, this paper reviews the latest and most efficient techniques used to optimize green microgrids from an economical and reliable perspective to achieve a clean, economical, and highly reliable microgrid.

Keywords: wind energy; solar energy; reliability; optimization; artificial intelligence; cost analysis; hybrid microgrid

check for updates

Citation: Kiehbadroudinezhad, M.; Merabet, A.; Abo-Khalil, A.G.; Salameh, T.; Ghenai, C. Intelligent and Optimized Microgrids for Future Supply Power from Renewable Energy Resources: A Review. *Energies* **2022**, *15*, 3359. https://doi.org/10.3390/en15093359

Academic Editor: Konstantin Suslov

Received: 22 February 2022
Accepted: 28 April 2022
Published: 5 May 2022

1. Introduction

Today, the need to generate electricity from clean and green resources has become a necessity. In fact, classic thermal power plants, due to the use of fossil fuels, have polluted the environment and destroyed many natural resources [1]. These serious concerns have led researchers, policymakers, and investors in energy to research and develop power generation microgrids that reduce dependence on fossil fuels and reduce the environmental impacts [2]. It is important to replace resources to minimize the unfavorable environmental impacts while meeting the growing electricity demand with a cost of power that is competitive. In line with this, focusing on renewable energy resources has been more prominent. Although these resources have many benefits and are sustainable, clean, and inexhaustible, they have low efficiency because they have significant limitations, such as variable solar irradiance and fluctuating wind speed [3]. A combination of more than one resource for power generation systems from renewable energy resources or hybrid renewable energy systems (HRES) is used to overcome this problem. Furthermore, in order to address this problem, it is necessary to develop appropriate energy storage systems for the HRES [4,5].

According to the location of an area, wind, solar and other renewable energy can be proper supplements to supply electricity to power consumption units in HRESs. Energy storage or support system units such as battery bank storage (BBS) are used in stand-alone

HRE microgrids to increase system reliability [5]. A wind power generation microgrid can be integrated with a solar or other renewable energy power generation system. Some studies have shown that wind and solar systems are complementary [5,6]. Thus, in the hours of the year when the potential for exploitation of wind resources is weak, the source of solar or other renewable energies power supply can compensate for this shortage and vice versa. As mentioned, an HRES consists of several renewable energy sources such as wind, solar, and tidal. The use of different renewable energy sources in supplying power to HRESs increases the reliability of the power generation system and, consequently, requires fewer support units; in other words, the ability to supply power to the consuming power system increases during the year. Nevertheless, due to the nature of these resources, most HRESs are equipped with support and energy storage units. The use of storage units such as batteries and fuel cells provide a clean power generation unit with higher reliability.

Although an HRES that uses various renewable energy resources for power generation is more economical and reliable in comparing a single hybrid renewable power generation system, the wrong size of system components can challenge system costs and system reliability [6]. Therefore, the system size needs to be optimized based on various perspectives before running the system. Different criteria can be considered to determine the size of each component of HRESs with different configurations, such as reliability, economic, environmental impacts, optimization approaches, life cycle assessment, and so on [7,8]. In recent years, valuable research and efforts have been made regarding the sizing methods for HRES microgrids. The research has focused on improving the economic and reliability performance of the HRESs and predicting the annual power generating capacity of these units with fewer negative environmental consequences. For example, Borowy et al. [8] used the concept of loss of load probability (LLP) to determine the optimal size of the wind turbine (WT)/photovoltaic (PV) panel microgrid for power generation and cost of energy (COE). Shrestha et al. [9] developed a new technique for simulating power generation from wind and solar energy sources and then optimized the HRE microgrid size. Kellogg et al. [10] analyzed the sizing of a hybrid renewable energy microgrid. Their research is based on the loss of power supply possibility (LPSP) and the levelized cost of energy (LCOE). Maleki [11] used mathematical modeling and optimization algorithms to optimize the size of various hybrid microgrid configurations. They also compared the performance of different optimization algorithms. In general, the review of studies shows that each of the methods used in optimization has different advantages and disadvantages, which can significantly help researchers improve existing methods and introduce new techniques. Accordingly, the current study discusses and reviews studies that have optimized the size of HRESs linked to photovoltaic panel/wind turbine hybrid microgrids (Figure 1) using different methods.

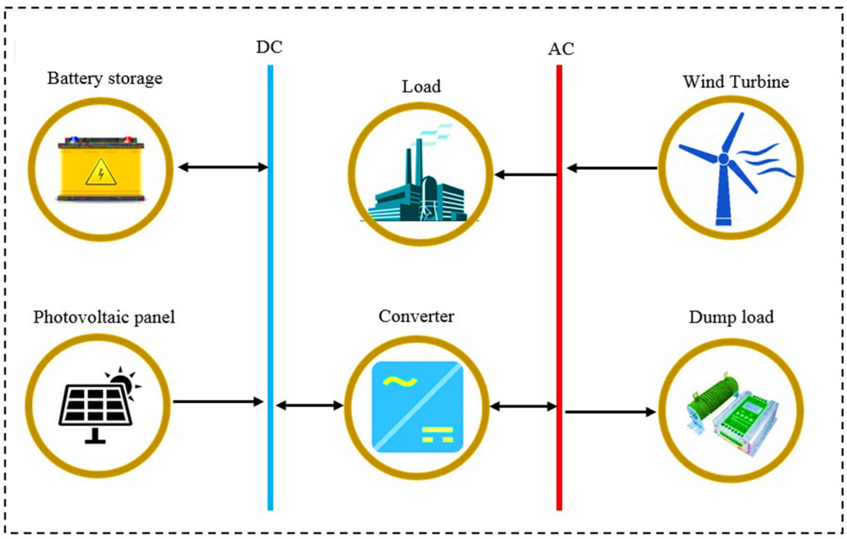

Figure 1. General schematic of the photovoltaic panel/wind turbine hybrid microgrid with direct current (DC) bus and alternating current (AC) bus.

After the Introduction section, the current study is structured as follows: a description of wind solar-based microgrid configuration; key points for designing and optimizing this hybrid microgrid; and applications of this power generation system are given in Section 2. The PV/WT hybrid microgrid components' mathematical modeling is presented in Section 3. The most important factors that should be considered to optimize the size of the power generation system are mentioned in Section 4. In Section 5, different methods to estimate the reliability of a microgrid hybrid system are studied. According to economic criteria, common and widely used methods to determine the optimal size of a hybrid system are studied in Section 6. Popular techniques and tools used to optimize a wind and solar-based hybrid system are reviewed in Section 7. In Section 8, various artificial intelligence (AI) techniques for sizing problems are studied. Finally, the conclusion and future works are mentioned in Section 9.

2. Solar PV/Wind Turbine Hybrid Microgrid

Due to the variable nature of the availability of renewable energy resources in hours of a year, many studies are focused on this issue. The following are the most important and major problems facing the development of renewable hybrid microgrid technology [12]:

(1) The potential of renewable energy sources depends on the conditions and environmental location.
(2) The capital, installation, and maintenance costs of these microgrids are high.
(3) These clean power generation systems are less reliable than traditional power generation systems.

The irregular or sometimes indeterminate pattern of these renewable resources makes it difficult to predict the amount of annual power generation by these sources. Researchers have suggested that several renewable resources be used to supply power to the consumption units to solve this problem. The design and implementation of a renewable hybrid system depend on various factors such as the potential of exploiting the natural resources of the considered place, access to the electricity network, and technical constraints (system efficiency, capacity factor, and power quality). Optimizing the size of these clean power generation units can optimize the cost of implementing these microgrids and increase system reliability [13]. A hybrid microgrid usually consists of parts such as a control and management unit, power generation units from renewable resources, energy storage units, support system units, and electric current converters.

As mentioned, wind and solar power generation systems need energy storage units such as batteries and fuel cells. In addition, these systems require a support unit such as diesel generators. Additionally, HRESs are categorized into stand-alone or grid-connected systems. Due to the high cost of developing transmission lines for remote areas, stand-alone or off-grid microgrids may be used to generate electricity [14]. Economic efficiency is very important for the development of power plants. Traditional power generation systems for remote areas often operate by fossil fuel. The research results show that using hybrid microgrids based on solar-wind energy for remote areas that have a good potential for exploiting renewable energy resources can meet the power requirements of the power-consuming units [14,15]. These renewable microgrids have shown their ability and competence in the field of power supply. The purpose of evaluating power generation systems from hybrid renewable energy sources is to achieve an HRE microgrid with optimal size and cost-effectiveness. To achieve this objective, first, the potential of renewable energy resources of the study area, such as wind speed, the intensity of irradiation sunlight, and ambient temperature, are estimated. Subsequently, each component of the hybrid microgrid, such as solar modules, wind turbine, converter, battery, and diesel generators, is modeled. The required load is also simulated; eventually, the objective function, variables decision, and objective function constraints are defined. Subsequently, each component size of the HRES is optimized by an optimization method [15]. The objective function, variables decision, and constraints should be defined so that the objectives such as reliability and economic aspects are completely met. To evaluate and optimize the performance of the wind-solar hybrid microgrid, each component is modeled, and then the entire configuration is evaluated and estimated to satisfy the requirements. Moreover, for better performance of the wind-solar microgrids, it is necessary to determine an accurate and efficient system for power control and management (Figure 2). Solar and wind energy are both inexhaustible and permanent renewable natural resources. These two sources can be excellent sources for power generation in hybrid microgrids. Additionally, they can complement each other; for example, there is a lot of sunlight on a sunny summer day, which can compensate for the lack of wind energy.

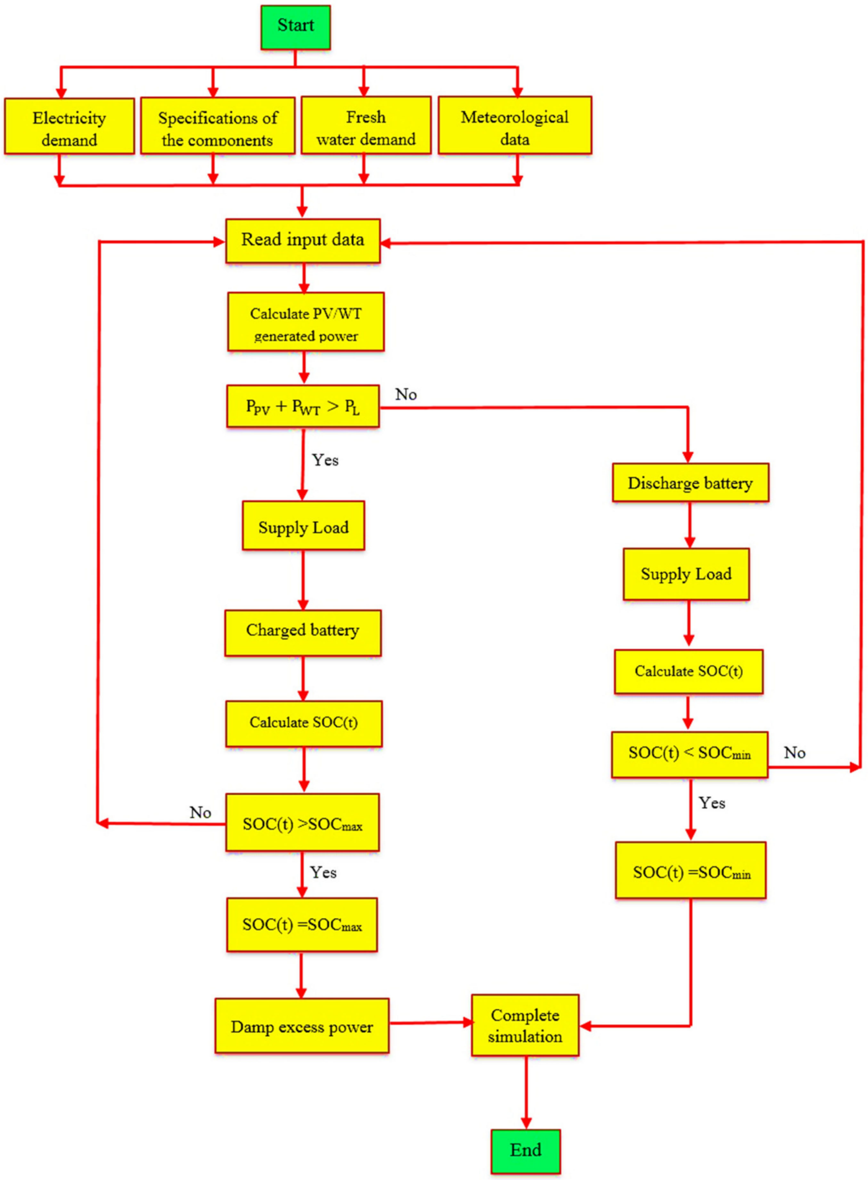

Figure 2. Schematic of a hybrid renewable energy microgrid's power control and management system from Kiehbadroudinezhad et al. [6]. With permission from John Wiley & Sons Ltd. Copyright © 2020; License Number: 5237281090835.

Simultaneously using these two inexhaustible and permanent sources is a good guarantee of achieving a stable HRE microgrid. The most common limitations considered for evaluating renewable energy microgrids are the technical–economic characteristics of microgrid components, such as wind turbines, solar panels, battery banks, electric converters, and diesel generators.

Ribeiro et al. [16] introduced an analytical method called multi-criteria decision analysis (MCDA). This tool focuses on economic and environmental issues. Some data have a very significant effect on estimating and optimizing the size of the HRE microgrid configuration. These data include meteorological data, the technical–economic data of each component, and power consumption. Meteorological data refers to hourly data on solar irradiation, wind speed, and ambient temperature throughout the year. Sometimes the average monthly data is also used. Additionally, the economic data of each component refers to the initial capital costs, operation, maintenance, and replacement of each component. Furthermore, technical data refer to the specifications and technical data of each component. It should be noted that since some hourly data, such as climate data, is hard to get in remote areas, for this purpose, usually monthly average data is used instead of hourly data in a year. Climate data can be obtained from reputable sites such as the National Aeronautics and Space Administration (NASA) or collected from local weather organizations [5]. If this data is collected in smaller intervals, such as hours, optimizing the size of the HRE microgrid configuration will be more accurate. Furthermore, a more appropriate estimate of the performance of this power generation unit can be made. Blanching et al. [17] designed and optimized a renewable hybrid microgrid using a horizontal axis wind turbine, solar panels, a diesel generator as the support unit, and batteries as the support and energy storage unit. In their study, they used a diesel generator to support the power generation system during peak load, and the results of their research showed that they could control and manage the peak load well. Load demand plays a vital role in designing and constructing solar and wind power generation systems, especially if this microgrid system is stand-alone. Meeting the power demand, especially at peak times, is also critical to the sustainability of stand-alone renewable-energy-based microgrids. Therefore, a support unit is often used to compensate for this lack of power generation from renewable sources.

3. Modeling of Solar–Wind Energy Microgrid

The availability of solar and wind energy for the site where the hybrid microgrid project is to be built depends on the location of the project's site. Environmental circumstances such as ambient temperature, wind speed, and solar irradiation are also different depending on each place. Hence, the renewable energy potential measurement of the project location plays a significant role in the design and size of green microgrids [18]. Bagul et al. [19] also presented an interesting and particular strategy for optimal photovoltaic cells and wind turbines. These researchers used battery bank storage as a support and storage unit. Kaabeche et al. [20], using a special algorithm, could determine the optimal number of wind generators and solar panels for a small-scale HRE microgrid. The researchers also used a battery bank as an energy storage unit. Cano et al. [21] developed a method for determining the appropriate number of wind turbines, photovoltaic modules, and battery banks. They used climate data such as solar radiation and average wind speed to quantify each component of the hybrid renewable energy microgrid; these researchers also obtained solar data from the PVGIS and wind data from the Wind finder. Zhang et al. [22] considered a hybrid microgrid consisting of a wind generator, a photovoltaic panel, a battery, and a diesel generator. They estimated the occupied area and size of the photovoltaic panels, the battery banks' storage, the height of the wind generators, and the hours that the diesel generator should be running. In the first step to achieving an optimized wind-solar-based microgrid, all components of it must be mathematically modeled (Table 1). Then, the optimal size of each component can be obtained using different types of optimization methods. The objectives and constraints intended to optimize these hybrid green power generation units can be economical and reliable. In general, after modeling and optimization of the HRES, a cost-effective and reliable hybrid system should be provided. This power generation system can fully and continuously meet the needs of power consumption units throughout the year [23].

Table 1. A summary of the PV/WT hybrid microgrid components' mathematical modeling.

HRES Components	Remarks	Mathematical Equations	Ref.
Wind Turbine	Power-law exponent	$\frac{V}{V_0} = \left[\frac{h}{h_0}\right]^{\alpha}$	[6,7]
	Power generated	$P_{WT} = \begin{cases} 0, & V(t) \leq Vci \ \ or \ \ V(t) \geq Vco \\ a \times V^3 - b \times P_r, & Vci \leq V(t) \leq Vr \\ P_r, & Vr \leq V(t) \leq Vco \end{cases}$	
	Total power generated	$P_T = N_{WT} \times P_{WT}$	
	Rated power	$P_r = 1/2 \times A_{WT} \times C_p \times \rho_a \times \eta_r \times \eta_{WT} \times V_r^3$	
Photovoltaic Panel	Power generated	$P_{PV}(t) = R_t \times \eta_{PV} \times A_{PV}$	[5]
	Panel efficiency	$\eta_{PV} = \eta_r \times \eta_{PC} \left[1 - \beta \times \left(\left(T_{air} + \left[\frac{NOCT-20}{800}\right] \times R_t\right) - T_{ref}\right)\right]$	
Battery Storage	Charging mode	$SOC(t) = SOC(t-1) \times (1-\sigma) + [P_G(t) - \frac{P_L(t)}{\eta_{Inv}}] \times \eta_{BC}$	[11]
	Discharge mode	$SOC(t) = SOC(t-1) \times (1-\sigma) - \left[\frac{P_L(t)}{\eta_{Inv}} - P_G(t)\right] / \eta_{BF}$	
	Loss of power supply	$LPS(t) = \frac{P_L(t)}{\eta_{Inv}} - P_G(t) - [SOC(t-1) \times (1-\sigma) - SOC_{min}(t)\,] \times \eta_{BF}$	
	Minimum of charge	$SOC_{min} = (1 - DOD) \times S_{BBS}$	

3.1. Solar Energy Modeling

As indicated in Table 1, the output power per PV panel depends on solar insolation, the area occupied by PV panels, and the efficiency of PV panels. Maghraby et al. [24] suggested that to optimize the size of the clean power generation units, the area occupied by the solar panels and the number of battery banks should be estimated by the probable load. Terra et al. [25] could extract the maximum possible power from a hybrid renewable energy system based on photovoltaic panels and wind generators using fuzzy optimization techniques. In this study, the decision variables were the total cost of photovoltaic panels, the angle of the surface of these panels, and the continuous and stable power generated by this HRE microgrid. Habib et al. [26] also designed and simulated a renewable energy-based microgrid. These researchers optimized factors such as the angle of inclination and latitude of the solar panel's surface, the maximum power point of the solar panels, and the lifespan and efficiency of the battery bank and inverters. Koutroulis et al. [27] provided an optimal renewable power generation system in which the size of the photovoltaic panel and its inclination surface angle were optimized. They considered the energy storage source's battery charge level and capacity as decision variables and optimized it using hourly climate data for one year. Using ambient temperature and solar radiation data, Borowy et al. [8] introduced an efficient model that can model and estimate the maximum output power of the photovoltaic module. Zhou et al. [28] presented a model that can predict the performance of a photovoltaic module concerning ambient temperature and solar irradiation. Yang et al. [29] developed an efficient model for achieving maximum output power from photovoltaic panels. Their proposed model also considered the maximum power point tracking (MPPT) controller. The amount of snow shade or cover and the loss of wiring in this study were other considered factors.

3.2. Wind Energy Modeling

Some data are essential to model the power generation unit from wind energy. These data include meteorology data such as solar irradiation, technical data such as wind turbine height from the ground and its nominal power, the amount of load required by consuming electricity units, and economic data such as capital and maintenance cost of wind generators. As shown in Table 1, the WT's power output is also affected by two factors: the height of the WT hub and the speed of the wind. The higher accuracy of the relevant data leads to a more accurate model for the power generation unit. The use of hourly weather data increases the accuracy of the modeling results [6]. However, this hourly data is not available for every location. Hence, sometimes predictive algorithms or simulation programs are used. Carpentiero et al. [30] developed an efficient model using weather data, load consumption, and the techno-economic data of diesel generators, wind turbines, and energy storage units. Then, they used different wind speed data to evaluate the output of wind and diesel generators (the amount of power generated). Elbaset [31] also suggested a probabilistic model that is a simple model for predicting the output power of a large-scale microgrid. In the proposed microgrid, lead-acid batteries were used to store extra energy, and these batteries provide the required power for times when the wind energy was insufficient to meet the load. Proper and accurate modeling is an important factor in getting the maximum power from the wind power generation system. This modeling usually considers turbine hub height, wind speed, and nominal wind turbine power. The variable nature of wind energy causes the variable power generation from this renewable energy source throughout the year. This problem has caused researchers to present new and efficient models, such as Weibull, to determine power from a wind source. Some researchers have also developed a model based on the wind's cut-in, cut-out, and rated speed [6].

3.3. Battery Bank Storage Modeling

Since the output of renewable energy sources is variable and has a slow response, energy and power storage units such as batteries and fuel cells are used to store excess energy produced by these natural energy resources. An optimal energy storage system should have a maximum capacity for storing electrical power, long life, high response speed, and low cost. Due to recent advances in the energy storage industry, various models have been produced to store electrical power with a high life cycle and efficiency. The supercapacitor, superconducting magnetic storage, flywheel storage, sodium-sulfur (NaS), flow batteries, and compressed air are examples of this advanced technology. As demonstrated in Table 1, the energy demand, the amount of power generated by wind and solar energy, and the initial state of charge (SOC) are three critical factors that play prominent roles in the battery state of charge as energy storage [5,32].

In an interesting study, Yang et al. [32] showed that the ampere-hour counting method for lead batteries is the best approach to modeling batteries, with two factors of voltage floating charge and state of charge. In another research, Zhou et al. [28], to evaluate the relationship between temperature and efficiency and performance of battery bank storage in the HRE microgrid, replaced the concept of the state of charge with the concept of voltage state. The size of the batteries as the power storage unit of a hybrid renewable power generation system depends on the depth of discharge (DOD) of the batteries, the cost of the battery bank and the potential of renewable energy to generate power and supply the needed power. To optimize the size of the battery bank storage, factors such as the depth of discharge of the batteries, changes in the temperature of the battery bank, the cost of the batteries, and their lifespan are the most important factors that must be considered. Bayram et al. [33] also optimized an on-grid microgrid storage unit in terms of size. These researchers used a battery bank for the power storage unit. Their method was based on a stochastic sizing approach. The task of this storage and support system was to meet part of the required microgrid power.

In another study, Ghiassi et al. [34] optimized a solar microgrid's battery bank storage size. They presented the method of stochastic calculus. In their research, these researchers also considered the concept of loss of power supply probability (power system reliability assessment). Yuan et al. [35] also proposed an optimization method that reduces fuel consumption and increases the use of renewable energy resources. They used Homer software to validate the optimization results of their research. Nagara et al. [36] studied the optimization method, namely, convex-optimization. This method was focused on the charge and discharge rate of lithium-ion batteries. The purpose of these researchers was to investigate the impact of this factor on the life cycle cost (LCC). Since the output of HRE microgrids is usually not uniform, Lee et al. [37] introduced a power management and control system for the power generation unit from wind and solar sources. Their research used two techniques, namely, real-time power distribution and state of charge (SOC) feedback control, to regulate and control the battery bank power distribution. Li et al. [38] developed a scheduling strategy to overcome the problem of battery power distribution as a unit of energy storage at peak times. This strategy made the output of the solar microgrid uniform.

4. Sizing of the Solar–Wind Energy Microgrid

In order to determine the optimal size of a hybrid green microgrid, it is necessary to consider several important factors, including the cost of capital, maintenance, operation, and replacement. The purpose of optimizing the size of a hybrid renewable energy microgrid is to estimate the size of each component of this system so that in addition to providing the load required of the unit consuming electricity, the HRES also has the lowest cost. Various methods are used to optimize the size of the power generation system, such as artificial intelligence (AI), the analytical method, the probabilistic approach, and the software-based approach. The classical method generally uses analytical, graphical, and probabilistic techniques for optimization; it also uses mathematical methods and differential calculus to obtain the optimal results of an objective function. The modern method, which is also widely used today, uses artificial intelligence techniques. The reason for the high usage of this method is the high accuracy and speed of the results obtained by this method. Additionally, the last method is software-based, used to optimize hybrid renewable energy systems such as wind-solar microgrids, including the hybrid optimization model for electric renewable (HOMER) and the transient systems simulation program (TRNSYS).

Shrestha et al. [9] suggested a hybrid renewable power generation system to optimize the size of photovoltaic panels. The researchers also estimated the number of battery banks in the power generation system. To reduce the annual cost of the microgrid hybrid system, Kellogg et al. [10] set restrictions on configuring the power generation unit from the renewable energy source and the storage and support unit of this microgrid. Kiehbadroudinezhad et al. [5], in their research, concluded that the reliability, total annual cost, and gas emissions' volume of the HRES are the most important factors that should be considered for the modeling, optimization, and evaluation of wind and solar-based power generation microgrids. Habib et al. [26] also found that the cost of the total power generation system increases in a renewable energy system if the size of the renewable resources is considered too large; if it is too small, then the system's reliability decreases. Gupta [39] introduced an optimization algorithm to optimize the size of an HRE microgrid based on wind and solar and used the requested load hourly data to model and optimize the HRE microgrid. This study also used hourly climate data for one year. Yang et al. [32] operated the variables of reliability, total cost, and greenhouse gas emissions to obtain the optimal results of the HRE power generation system from wind and solar energies. Zhang et al. [22] also utilized an improved genetic algorithm to optimize the power generation system from renewable resources. These researchers showed that the introduced optimization algorithm was not only faster than the standard genetic algorithm in terms of obtaining optimization results but the results obtained by this algorithm were also more accurate. Elbaset [31] optimized the cost of the total life cycle of an HRE microgrid unit. The optimal power generation system was able to meet all the required load needs per year without a shortage of power generation. The researchers [7,40] optimized a desalination plant driven by wind and solar energy. They used an annealing-chaotic search algorithm for the optimization of this system.

5. Estimating HRE Microgrid Reliability

Generally, there are many different methods to estimate the reliability of a microgrid hybrid system (Table 2). The methods like loss of power supply probability (LPSP), loss of energy expected (LOEE), loss of energy probability (LOEP), deficiency of power supply probability (DPSP), loss of load expected (LOLE), loss of load risk (LOLR), and loss of load probability (LOLP) are the most widely used methods that can be mentioned.

Yang et al. [40] also used the levelized cost of energy (LCOE) method to optimize the cost of a renewable hybrid system. This researcher also used the DPSP method to determine the reliability of the HRES. Belmilia et al. [41] used the LPSP method to determine the reliability of their hybrid system.

Table 2. The most important reliability indicators used for HRESs.

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	$LOLE = \sum_{h=1}^{H} \sum_{i \in S} P_i \times T_i$
7	LOCE	Levelized cost of energy	$LOCE(t) = \frac{\sum_{t=1}^{n} \frac{I_t + M_t + F_t}{(1+r)^t}}{\sum_{t=1}^{n} \frac{E_t}{(1+r)^t}}$

Bajpai et al. [42] determined the number of photovoltaic panels and the battery bank storage (energy storage) using the LPSP method. Al-ashwal et al. [43] optimized an HRE microgrid and operated the loss of load hours method to determine the reliability of their optimized system. Nelson et al. [44] used the LPSP method to determine the reliability of their renewable energy power generation system, which hoped to meet the power requirements of energy-consuming units. They also defined the optimal size of the electrical power storage (battery bank). Gupta et al. [39] conducted a study to determine the amount of power generation from a renewable wind source for a year. They used the LPSP method in their study to specify the reliability capacity of an HRE microgrid. Kaabeche et al. [20] proposed an innovative model for the hybrid microgrid based on the DPSP. Diaf et al. [45] utilized the LPSP method to characterize the reliability of a hybrid solar and wind-based power generation system. Al-Ashwal et al. [43] used the LOLR method to determine the reliability of a renewable power generation system. Negi et al. [46] examined different reliability methods and declared that the LPSP method is the best way to determine the reliability of a hybrid renewable energy renewable system.

6. Cost Investigation

Researchers have proposed various methods to determine the optimal size of a hybrid system according to economic criteria [47]. Often the cost function of an HRES consists of a combination of factors such as capital, installation, maintenance, and replacement costs (Table 3). The cost function modeled in the research of Kellogg et al. [10] included annual production cost and system maintenance cost. Koutroulis et al. [18] also specified the size of an HRE unit based on the amount of load demand and the system's total cost. The lifespan considered in this study was twenty years. Zhang et al. [22] optimized the costs of installing and maintaining a hybrid renewable energy system. Nowdeh et al. [48] also optimized the cost of an off-grid renewable hybrid system. The system consisted of a wind generator, solar module, and fuel cell as the energy storage unit and support system. The total cost function considered in this study consisted of factors such as capital and maintenance–operation costs.

In another study, Perera [49] operated the system LCC method to determine the optimal cost of an HRE microgrid. The cost function of this researcher included the costs of each component of this power generation system. In this total cost function, the lifespan of each component of this system was considered. In another study, Hakimi et al. [50] also proposed a new way to improve the performance of standard cost functions. These researchers proposed constraints for the three known cost functions of net present cost (NPC), LCC, and LCOE so that the final cost of a hybrid renewable energy system could be estimated more accurately. Belmilia et al. [41] estimated an HRE microgrid's total LCC for one year to optimize their study's renewable generation power system. They named this innovative method the annual LCC (ALCC). The cost function used in the research of Gupta et al. [39] also included the cost of LCC and the initial and maintenance–operation costs.

Table 3. A summary of some key HRES indicators based on mathematical modeling.

Indices	Remarks	Mathematical Equations	Ref.
CRF	Capital recovery factor	$CRF(i,n) = \frac{i(1+i)^n}{(1+i)^n - 1}$	[6]
PW	Factor of payment present worth	$PW = C \times \sum_{k=0}^{n} \frac{1}{(1+i)^k}$	[51]
TLCC	Total life cycle cost	$TLCC(A_{WT}, A_{PV}, N_{BBS}) = \sum_{m = PV,WT,BBS} LCC_m$	[52]
LCC	Life cycle cost	$LCC = CC + MC$	[11]
LCC_{PV}	Life cycle cost of photovoltaic	$LCC_{PV} = CC_{PV} + MC_{PV}$ $CC_{PV} = A_{PV} \times C_{PV} \times CRF$ $MC_{PV} = C_{Mnt-PV} \times A_{PV}$	
LCC_{WT}	Life cycle cost of wind turbine	$LCC_{WT} = CC_{WT} + MC_{WT}$ $CC_{WT} = A_{WT} \times C_{WT} \times CRF$ $MC_{WT} = C_{Mnt-WT} \times A_{WT} \times \sum_{k=0}^{19} \frac{1}{(1+i)^k} \times CRF$	[5]
LCC_{BAT}	Life cycle cost of battery	$LCC_{BAT} = CC_{BAT} + MC_{BAT}$ $CC_{BAT} = N_{BAT} \times PW_{BAT} \times CRF$ $MC_{BAT} = N_{BAT} \times C_{Mnt-BAT}$	[53]
LCC_{INV}	Life cycle cost of inverter	$LCC_{INV} = CC_{INV} + MC_{INV}$ $CC_{Conv/inv} = N_{Inv} \times PW_{Inv} \times CRF$ $MC_{Conv/Inv} = N_{Inv} \times C_{Inv}$	[54]

The initial cost consists of capital cost and installation cost. Lagorsea et al. [55] introduced two new concepts of system initial equipment cost (SIEC) and system total investment cost (STIC) to estimate the cost of a hybrid green power generation microgrid. In an interesting study, Belmili et al. [41] also explored an HRES from an economic perspective. He considered essential factors such as capital, replacement, and maintenance–operation costs in his research. Yazdanpanah [56] considered the system's annual cost (ACOS) method, including the capital, replacement, maintenance, and operation costs.

7. Optimization Methods of HRE Microgrid

There are a variety of techniques and tools used to optimize a wind and solar-based hybrid system for power generation (Table 4). Sometimes, these techniques are justified by conflicting objectives, such as simultaneously increasing the reliability of an HRE microgrid and reducing the total cost of this system. Koutroulis et al. [18] concluded that the genetic algorithm (GA) obtains optimization results faster than other optimization algorithms. Their study was focused on a microgrid based on wind and solar energy. These researchers also utilized hourly weather data such as wind speed, average ambient temperature, and solar irradiation to optimize the hybrid power generation system. Habib et al. [57] optimized the size of a wind–solar microgrid. They used an optimization method based on numerical techniques. Palabazer [58] established a fuzzy quadratic model to express the relationship between the power curve of the wind turbines and wind speed, which is the basis for optimizing the power and size of wind turbines in many research papers. Yazdanpanah [56] introduced a multi-objective function to optimize a microgrid based on wind and solar energy. This researcher optimized the size of this hybrid microgrid using the particle swarm optimization (PSO) algorithm, i.e., the number of photovoltaic panels and wind generators. This clean power generation system could meet all load demands without shortage. Today, software such as HOMER, TRNSYS, and HOGA allow users to simulate and find their ideal and optimal configuration. These software are widely used today among energy analysts and other researchers. Using optimization algorithms such as genetic algorithms and PSO, important parameters such as the reliability of the power generation system and the total cost of the power generation system can be optimized. Nasiraghdam et al. [59] also designed a green power generation system that consisted of wind generators, photovoltaic panels, and fuel cells as energy storage and support units. The researchers optimized the size of this hybrid microgrid using the PSO optimization algorithm. Hakimi et al. [50] obtained the optimal size of each component of the wind generator and fuel cell configuration using the PSO algorithm. Maleki et al. [53] developed and introduced a new hybrid optimization method. They used genetic algorithms and fuzzy logic in combination to optimize the renewable power generation system. Carpentiero et al. [30] also concluded that the two most widely used optimization algorithms, i.e., GA and PSO, are the most appropriate algorithms for optimizing a hybrid power generation unit.

Table 4. A recent literature review on optimization techniques for hybrid renewable energy microgrids.

Authors	Renewable Components		Support Units		Operating Methods		Objectives	Optimization Methods	Year	Ref.
	PV	WT	DG	Battery	Off-Grid	Grid-Connected				
Suman et al.	✓ *	✓	✓	✓	✓	-	COE	PSO, GWO	2021	[60]
Mokhtara et al.	✓	✓	✓	✓	✓	-	COE	PSO	2021	[61]
Hassan et al.	✓	-	-	✓	✓	✓	COE	GA	2021	[62]
Das et al.	✓	✓	✓	✓	✓	✓	TNPC	HOMER	2021	[63]
Hong et al.	-	✓	-	-	✓	-	Production efficiency	ABC	2021	[64]
Kumar et al.	✓	-	-	-	✓	-	Power stability	PSO, BFOA	2021	[65]
Naderipour et al.	✓	✓	-	✓	✓	-	TNPC, COE	GOA	2021	[66]
Kiehbadroudinezhad et al.	✓	✓	✓	✓	✓	-	Sizing, TLCC	DA	2021	[5]
Emad et al.	✓	✓	-	✓	✓	-	Sizing, COE	GWO	2021	[67]
Çetinbaş et al.	✓	✓	✓	✓	✓	-	Sizing, TNPC	HHO	2021	[68]
Fares et al.	✓	✓	-	✓	✓	-	Sizing, TNPC	FPA	2022	[69]
Emrani et al.	✓	✓	-	-	-	✓	GES	GA	2022	[70]
Makhloufi et al.	✓	✓	-	-	✓	-	LCOE	Cuckoo	2022	[71]
Maheri et al.	✓	✓	✓	✓	✓	-	Sizing	GA, NSGA	2022	[72]
Nuvvula et al.	✓	✓	-	✓	✓	-	Sizing	PSO	2022	[73]
Hemeida et al.	✓	✓	✓	✓	✓	-	COE	MOMVO	2022	[74]

* It means selecting or using renewable components, support units, and operating methods.

8. Artificial Intelligence (AI) Technique for HRE Microgrid Sizing

As mentioned in the previous sections of this study, there are a variety of optimization algorithms for optimizing the size of hybrid renewable systems, such as the genetic algorithm (GA), the artificial bee colony algorithm (ABC), particle swarm optimization (PSO), the ant colony algorithm (ACA), the grey wolf optimizer (GWO), Harris hawks optimization (HHO), the flower pollination algorithm (FPA), the grasshopper optimization algorithm (GOA), multi-objective multi-verse optimization (MOMVO), spotted hyena optimization (SHO), or a combination of these algorithms. Some researchers combine several intelligent optimization algorithms to create a new algorithm that has the advantages of both algorithms and overcomes the disadvantages of each of the combined optimization algorithms [75]. In general, combined intelligent optimization algorithms have a higher computational speed than traditional optimization methods. In other words, the convergence speed of these algorithms is faster than previous and traditional methods. The researchers also showed that the optimal results obtained by these types of optimization algorithms are more accurate. Many of these optimization algorithms are used for the size of the hybrid power generation system, consisting of wind turbines and photovoltaic panels [76]. In the continuation of this study, some widely used and efficient optimization algorithms will be introduced.

8.1. Genetic Algorithm (GA)

The genetic optimization algorithm was developed in 1960 by John Holland. This optimization algorithm solves optimization problems with techniques inspired by the phenomenon of evolution and nature (Figure 3). Like the phenomenon of evolution, this optimization method consists of four parts (a) inheritance, (b) mutation, (c) selection, and (d) crossover. This algorithm is well known and has many advantages, such as (a) solving multiple problems, (b) being easy to understand, (c) high accuracy, and (d) convenient flexibility with other software such as MATLAB. Genetic algorithms, despite their many advantages, also have limitations. These disadvantages are (a) stuck in local optimum points and (b) slow response time. In recent years, many kinds of research have been done by researchers using genetic algorithms to optimize the size of an off-grid HRE microgrid based on wind and solar energy. For example, the size of a solar wind stand-alone power generation system was estimated by Koutroulis et al. [18] using the genetic algorithm. Achieving a low-cost hybrid renewable energy system was one of the main goals of this power generation system. Additionally, this optimized clean power generation system could fully meet the required load needs. In an interesting study, researchers used a solar wind microgrid to meet the power demand of a desalination unit. The researchers optimized the size of all components of this microgrid, including wind generators and photovoltaic panels [32].

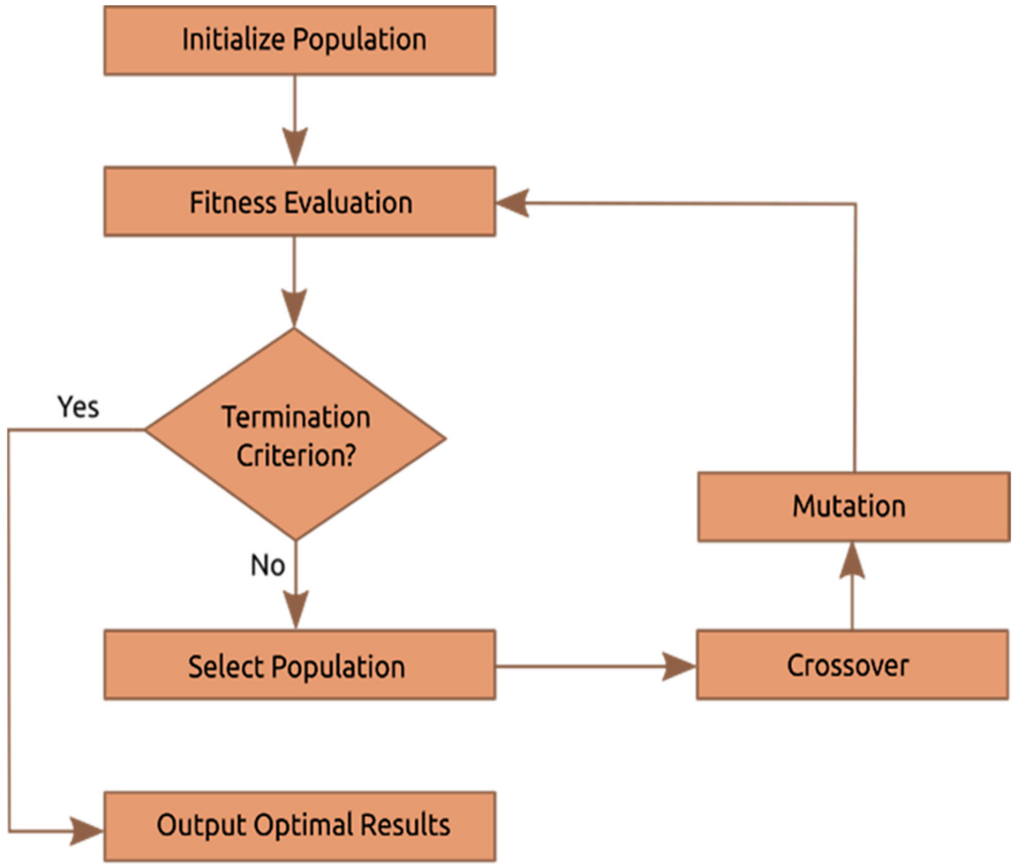

Figure 3. The implementation process of the genetic algorithm.

Some researchers designed a power generation system consisting of wind turbines, photovoltaic panels, and batteries [29,40]. Using genetic optimization algorithm, the researchers determined the number of photovoltaic panels, wind generators, and battery banks. Operating this algorithm, they also optimized and determined two other decision variables, namely, the slope angle of the panels and the height of the wind turbine hub. This system was responsible for supplying electricity to a telecommunication unit. Bilal et al. [77] used a genetic optimization algorithm to optimize the green power generation system from wind and solar energy sources. They set two constants for their objective function: LPSP and the minimum annual cost. The researchers used a battery bank to store the excess energy produced. In another study using a genetic algorithm, Nafeh [78] optimized the power output of wind turbines and photovoltaic panels units. This system was cost-effective and highly reliable. Merei et al. [79] designed and simulated a stand-alone hybrid renewable system that included a wind turbine–photovoltaic panel, a battery, and a diesel generator. This power generation system was optimized using a genetic algorithm. Researchers have also optimized the LCC of wind and solar power generation systems using GA. Another goal of this research was to increase the reliability of the system. The researchers also considered the system embodied energy (EE) constraint [48].

8.2. Particle Swarm Optimization (PSO)

The particle swarm optimization (PSO) algorithm is another widely used optimization algorithm. This algorithm is also inspired by nature. PSO is a meta-heuristic algorithm developed using the cumulative motion of animals (Figure 4). This algorithm was invented and introduced by a researcher named Kennedy [80]. He succeeded in finding the idea of developing this optimization algorithm by studying and assessing the group movement of animals. PSO has a high search speed among a collection of the possible answers to an objective function. The simple calculation method is another advantage of this algorithm. However, this algorithm has a limitation; it does not work properly in non-coordinated systems. Today, this method is widely used by researchers.

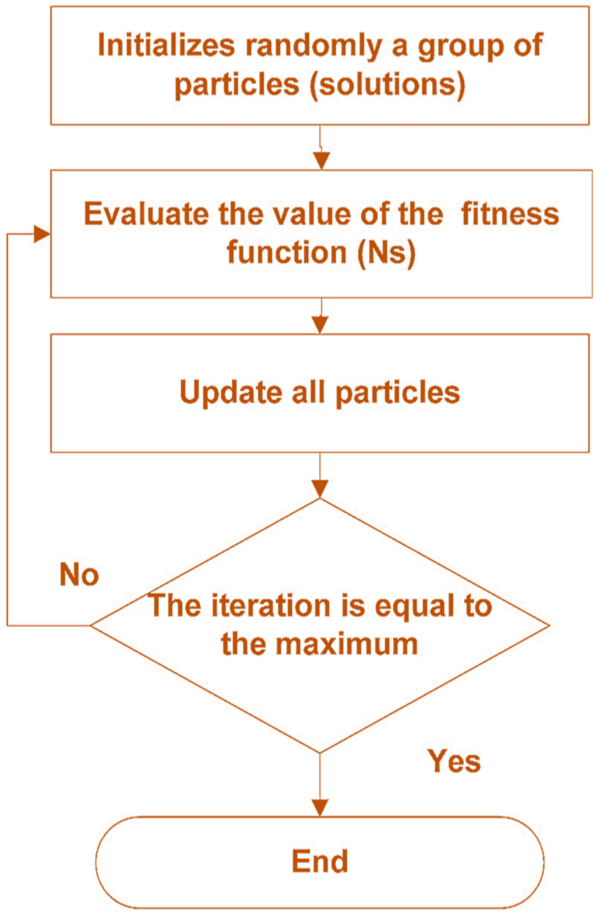

Figure 4. The implementation process of the particle swarm optimization algorithm.

Lee et al. [81] used this optimization algorithm to optimize the capacity of wind and solar energy resources in a hybrid renewable power generation system. The objective function of these researchers was to achieve a cost-effective power generation system. In an interesting study, researchers simulated and optimized a power generation system consisting of a wind generator and a photovoltaic panel with a lifespan of 20 years [82]. This study used a fuel cell as the energy storage unit and system support. The purpose of this study was to reduce the annual cost of this HRE microgrid by considering the system's reliability so that this green power generation system could meet all the demand power. Bansal et al. [83] utilized the Meta PSO algorithm. This new technique is named MPSO. They optimized the power generation system based on wind and solar energy with the MPSO algorithm. It should be noted that in this study, batteries served as an energy storage unit and system support.

In another study, the PSO optimization algorithm was used to solve the optimization problem [84]. The hybrid renewable energy microgrid of this study consisted of a wind generator and a photovoltaic panel as power generation units. Batteries and fuel cells were also used as energy storage and system support. The diesel generator was also considered another system support unit in this research. Borhanazad et al. [85] also operated the PSO multi-objective algorithm to optimize the size of a microgrid based on wind and solar energy. Batteries and diesel generators were also utilized in this power generation unit.

8.3. Artificial Bee Colony Algorithm (ABC)

The artificial bee colony algorithm (ABC) is an optimization algorithm based on a metaheuristic optimization algorithm. Karaboga and Basturk [86] suggested this method. In this algorithm, a food source's location relates to a feasible optimization problem solution, and the quality of the related solution relates to the quantity of a nectar food source. Some researchers proposed a novel multi-objective ABC method for sizing a hybrid microgrid that included PV, wind turbines, and fuel cells [87]. In addition, the total loss of power, the total cost of the power, the total gas emissions produced by this hybrid microgrid, and the index of voltage stability system were also discovered in this paper. Maleki and Askarzadeh [53] have suggested an artificial bee swarm optimization (ABSO) method for sizing a hybrid renewable energy microgrid based on the photovoltaic panel, wind turbine, fuel cell, and hydrogen tank for the eastern area of Iran, intending to achieve the best possible energy efficiency.

8.4. Division Algorithm (DA)

In recent years, a new optimization algorithm was developed to overcome the weaknesses of the widely used GA [51]. This improved optimization algorithm is called the division algorithm (DA). DA keeps the advantages of GA, such as finding the optimal solutions to an optimization problem simultaneously. Additionally, DA does not have the disadvantages of GA, such as the slow process of finding the optimal solutions to the objective function and complexity. The DA can find the optimal solution without the operators available in the genetic algorithm, such as crossover and mutation, making it faster, more straightforward, and more accurate than GA [52].

8.5. Ant Colony Algorithms (ACA)

Ant colony algorithms were first presented in the research published by Dorigo [89,90]. The algorithm's goal is to find the most efficient path across a graph. Some researchers have developed an ant system based on graphs to reduce the total cost of off-grid hybrid wind-PV microgrids while still adhering to the LPSP's limitation on system size [91]. Figure 5 shows the general implementation process of this algorithm.

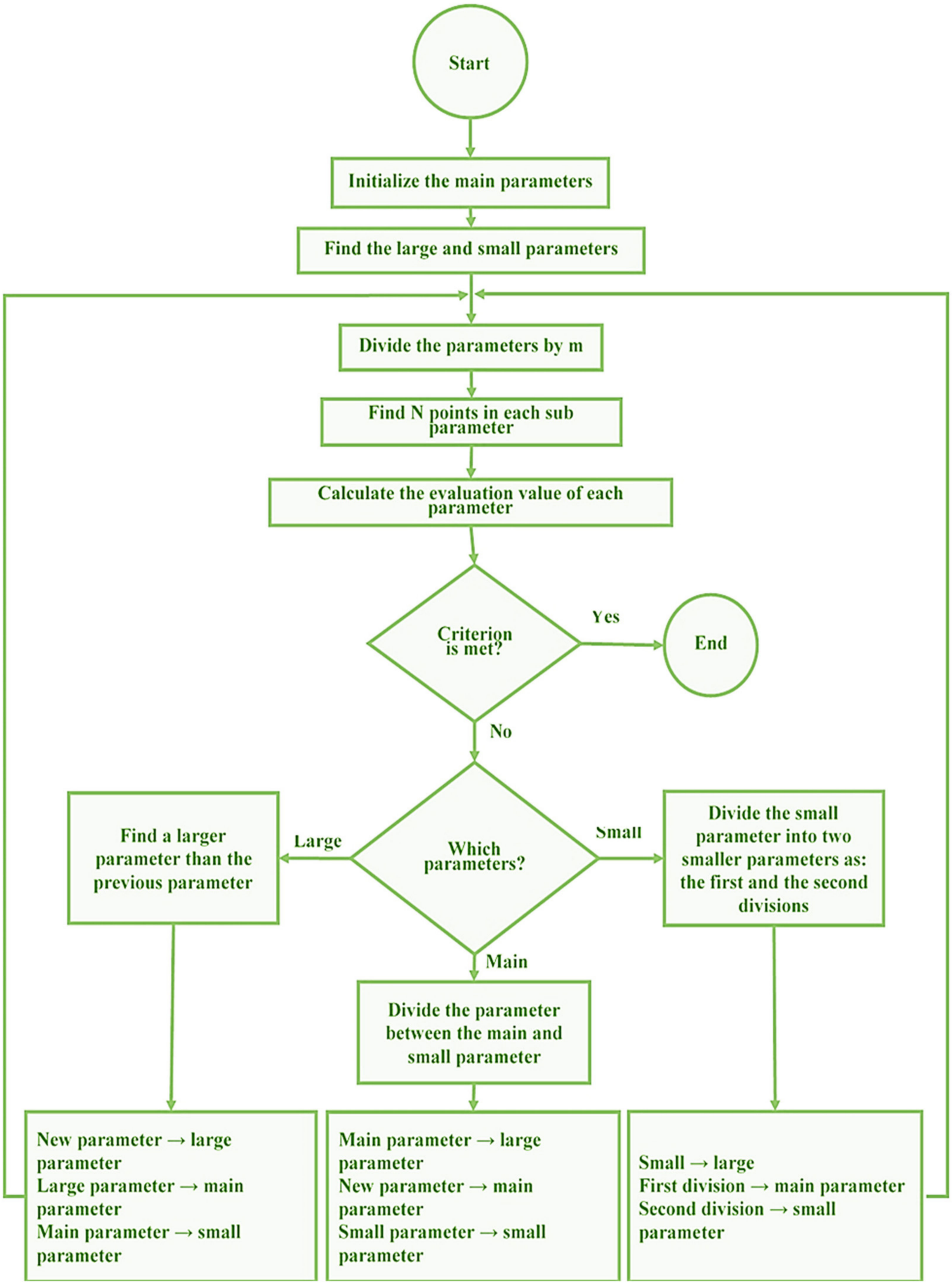

Figure 5. The division algorithm's implementation procedure, from Kiehbadroudinezhad et al. [6] (cited in Kiehbadroudinezhad et al. [88]). With permission from John Wiley & Sons Ltd. Copyright © 2020; License Number: 5237280843956.

9. Conclusions and Future Works

This review article has shown that renewable hybrid microgrids are the best and most important alternative to fossil fuel sources. However, due to the unpredictable nature of these clean sources, the use of renewable energy sources has low reliability. Additionally, this clean technology is not economically viable compared to traditional technology. However, recent advances in science and clean energy technologies have made the cost of construction and implementing power generation systems from clean sources lower and more economical than in previous years. Studies have also shown that using more than one renewable energy source to generate power also increases the reliability of the power generation system. Wind and solar are two suitable renewable resources in terms of availability; if the size of wind turbines and photovoltaic panels used in the hybrid microgrid is optimized, it will be an economical hybrid power generation system. Today, many methods that calculate and determine the size of a system based on cost criteria while considering the system's reliability are used to optimize hybrid renewable systems. Nature-inspired algorithms or hybrid optimization algorithms are the best-advanced tools for optimizing hybrid renewable microgrids. Recent studies have also shown that energy storage units such as batteries and fuel cells can be an efficient source of power and a suitable support unit for the power generation system when the renewable power generation system is short of power.

In addition, for future work, Environmental analyzes such as life cycle assessment (LCA) should be more attention [92]. Also, meta-heuristic optimization algorithms should be developed with greater speed and accuracy. As recent studies have shown, hybrid meta-heuristic algorithms should be more widely used because these algorithms perform better and more efficiently than individual optimization algorithms. Additionally, more precise mathematical models must be provided to describe the performance and efficiency of each component of the hybrid renewable energy microgrid. Nowadays, most of the objective functions studied focus on the economic aspects of hybrid renewable energy microgrids, which should also pay attention to other aspects such as reliability and the life cycle assessment of this system. Other renewable resources should also be investigated, especially geothermal energy, hydro energy, nuclear energy, and tidal energy. Comprehensive studies should also be performed on new energy storage devices such as fuel cells and clean fuels such as low carbon fuels (biodiesel, biogas, syngas) and zero-carbon fuels (green hydrogen H_2 and ammonia NH_3) [93,94].

Author Contributions: Conceptualization, M.K. and A.M.; formal analysis, M.K., A.M., A.G.A.-K., T.S. and C.G.; resources, M.K., A.M., A.G.A.-K., T.S. and C.G.; writing—original draft preparation, M.K.; writing—review and editing, A.M., A.G.A.-K., T.S. and C.G.; supervision, A.M.; project administration, A.M.; funding acquisition, A.M. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded in part by the Natural Sciences and Engineering Research Council of Canada (NSERC), discovery grant number Rgpin-2018-05381.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available inside the article.

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

Nomenclature

A_{PV}	Total area occupied by the PV panels (m^2)
A_{WT}	Total area swept by the WT generator blades (m^2)
C_{BAT}	Battery bank cost (CAD)
CC	Capital cost (CAD)
C_{Inv}	Converter/inverter price (CAD)
$C_{Mnt\text{-}BAT}$	Annual maintenance cost of battery (CAD/year)
$C_{Mnt\text{-}Inv}$	Annual maintenance cost of converter/inverter (CAD/year)
$C_{Mnt\text{-}PV}$	Annual maintenance cost of PV system (CAD/m^2/year)
$C_{Mnt\text{-}WT}$	Annual maintenance costs of wind turbine (CAD/year)
C_P	Wind power coefficient
C_{PV}	Unit cost of PV panel system (CAD/m^2)
CRF	Capital recovery factor
C_{WT}	Wind turbine price (CAD)
DOD	Depth of discharge (%)

E_t	Electrical energy generated in the year t
E_j	The energy not supplied
GA	Genetic algorithm
F_t	fuel expenditures in the year t
GHG	Greenhouse gases
$HRES$	Hybrid renewable energy systems
i	Interest rate (%)
I_t	Investment expenditures in the year t
MC	Maintenance cost (CAD)
M_t	Maintenance and operations expenditures in the year t
n	Project lifetime (year)
η_{bc}	Charge efficiency of battery bank (%)
η_{bf}	Discharging efficiency of battery bank (%)
η_{Inv}	Converter/inverter efficiency (%)
η_{PV}	PV panel efficiency (%)
N_{WT}	Number of wind turbine
$NOCT$	Normal operating cell temperature
η_{WT}	Wind turbine reference efficiency (%)
P_{BAT}	Output power of battery bank storage (kW)
P_{def}	Power shortage of the system at time t (kW)
$\mathrm{p_j}$	Probability of capacity outage
P_{inv}	Nominal inverter power (kw)
P_L	Annual load demand (kW)
P_{PV}	Output power of PV panels (kW)
P_r	Rated power of the wind turbine (kW)
P_T	Overall generated power by wind turbine (kW)
PW	Factor of payment present worth
P_{WT}	Output power of wind turbine (kW)
r	Discount rate
R_t	Solar irradiance (kW/m^2)
S_{BAT}	Nominal capacity of battery bank (kWh)
$SOC(t)$	State of the battery charge at the time t (%)
$SOC(t-1)$	State of the battery charge at the time $t-1$ (%)
SOC_{max}	Maximum charge of the battery bank (%)
SOC_{min}	Minimum charge of the battery bank (%)
T_{air}	Ambient temperature (°C)
t_j	Percentage of time when the load exceeds
$TLCC$	Total life cycle cost (CAD)
T_{ref}	Cell temperature at reference conditions (°C)
V_{ci}	Cut-in wind speed (m/s)
V_{co}	Cut-out wind speed (m/s)
V_r	Nominal wind speed (m/s)
β	Temperature coefficient of PV panel (°C^{-1})
η_{PC}	Power conditioning efficiency (%)
η_r	Reducer efficiency (%)
ρ_a	Air density (kg/m^3)
σ	Hourly self-discharge rate (%)

References

1. Atilgan, B.; Azapagic, A. Life cycle environmental impacts of electricity from fossil fuels in Turkey. *J. Clean. Prod.* **2015**, *106*, 555–564. [CrossRef]
2. Adefarati, T.; Bansal, R.C. Application of renewable energy resources in a microgrid power system. *J. Eng.* **2019**, *2019*, 5308–5313. [CrossRef]
3. Bosisio, A.; Moncecchi, M.; Cassetti, G.; Merlo, M. Microgrid design and operation for sensible loads: Lacor hospital case study in Uganda. *Sustain. Energy Technol. Assess.* **2019**, *36*, 100535. [CrossRef]

4. Maleki, A.; Ameri, M.; Keynia, F. Scrutiny of multifarious particle swarm optimization for finding the optimal size of a PV/wind/battery hybrid system. *Renew. Energy* **2015**, *80*, 552–563. [CrossRef]
5. Kiehbadroudinezhad, M.; Merabet, A.; Rajabipour, A.; Cada, M.; Kiehbadroudinezhad, S.; Khanali, M.; Hosseinzadeh-Bandbafha, H. Optimization of wind/solar energy microgrid by division algorithm considering human health and environmental impacts for power-water cogeneration. *Energy Convers. Manag.* **2021**, *252*, 115064. [CrossRef]
6. Kiehbadroudinezhad, M.; Rajabipour, A.; Cada, M.; Khanali, M. Modeling, design, and optimization of a cost effective and reliable hybrid renewable energy system integrated with desalination using the division algorithm. *Int. J. Energy Res.* **2021**, *45*, 429–452. [CrossRef]
7. Zhang, G.; Wu, B.; Maleki, A.; Zhang, W. Simulated annealing-chaotic search algorithm based optimization of reverse osmosis hybrid desalination system driven by wind and solar energies. *Sol. Energy* **2018**, *173*, 964–975. [CrossRef]
8. Borowy, B.S.; Salameh, Z.M. Methodology for optimally sizing the combination of a battery bank and PV array in a wind/PV hybrid system. *IEEE Trans. Energy Convers.* **1996**, *11*, 367–375. [CrossRef]
9. Shrestha, G.B.; Goel, L. A study on optimal sizing of stand-alone photovoltaic stations. *IEEE Trans. Energy Convers.* **1998**, *13*, 373–378. [CrossRef]
10. Kellogg, W.D.; Nehrir, M.H.; Venkataramanan, G.; Gerez, V. Generation unit sizing and cost analysis for stand-alone wind, photovoltaic, and hybrid wind/PV systems. *IEEE Trans. Energy Convers.* **1998**, *13*, 70–75. [CrossRef]
11. Maleki, A.; Pourfayaz, F. Optimal sizing of autonomous hybrid photovoltaic/wind/battery power system with LPSP technology by using evolutionary algorithms. *Sol. Energy* **2015**, *115*, 471–483. [CrossRef]
12. Shiva, C.K.; Mukherjee, V. A novel quasi-oppositional harmony search algorithm for automatic generation control of power system. *Appl. Soft Comput.* **2015**, *35*, 749–765. [CrossRef]
13. Ekren, O.; Ekren, B.Y. Size optimization of a PV/wind hybrid energy conversion system with battery storage using simulated annealing. *Appl. Energy* **2010**, *87*, 592–598. [CrossRef]
14. Sanajaoba, S.; Fernandez, E. Maiden application of Cuckoo Search algorithm for optimal sizing of a remote hybrid renewable energy System. *Renew. Energy* **2016**, *96*, 1–10. [CrossRef]
15. Castañeda, M.; Fernández, L.M.; Sánchez, H.; Cano, A.; Jurado, F. Sizing methods for stand-alone hybrid systems based on renewable energies and hydrogen. In Proceedings of the 2012 16th IEEE Mediterranean Electrotechnical Conference, Yasmine Hammamet, Tunisia, 25–28 March 2012; pp. 832–835.
16. Ribeiro, F.; Ferreira, P.; Araújo, M. Evaluating future scenarios for the power generation sector using a Multi-Criteria Decision Analysis (MCDA) tool: The Portuguese case. *Energy* **2013**, *52*, 126–136. [CrossRef]
17. Ados Santos, H.F.; Duarte, G.A.S.; da Costa Rachid, C.T.; Chaloub, R.M.; Calderon, E.N.; de Barros Marangoni, L.F.; Bianchini, A.; Nudi, A.H.; Do Carmo, F.L.; Van Elsas, J.D. Impact of oil spills on coral reefs can be reduced by bioremediation using probiotic microbiota. *Sci. Rep.* **2015**, *5*, 18268. [CrossRef]
18. Koutroulis, E.; Kolokotsa, D.; Potirakis, A.; Kalaitzakis, K. Methodology for optimal sizing of stand-alone photovoltaic/wind-generator systems using genetic algorithms. *Sol. Energy* **2006**, *80*, 1072–1088. [CrossRef]
19. Bagul, A.D.; Salameh, Z.M.; Borowy, B. Sizing of a stand-alone hybrid wind-photovoltaic system using a three-event probability density approximation. *Sol. Energy* **1996**, *56*, 323–335. [CrossRef]
20. Kaabeche, A.; Belhamel, M.; Ibtiouen, R. Optimal sizing method for stand-alone hybrid PV/wind power generation system. *Rev. Energ. Renouvelables Bou Ismail Tipaza* **2010**, *1*, 205–213.
21. Cano, A.; Jurado, F.; Sánchez, H.; Fernández, L.M.; Castañeda, M. Optimal sizing of stand-alone hybrid systems based on PV/WT/FC by using several methodologies. *J. Energy Inst.* **2014**, *87*, 330–340. [CrossRef]
22. Zhang, L.; Barakat, G.; Yassine, A. Deterministic optimization and cost analysis of hybrid PV/wind/battery/diesel power system. *Int. J. Renew. Energy Res.* **2012**, *2*, 686–696.
23. Li, J.; Wei, W.; Xiang, J. A simple sizing algorithm for stand-alone PV/wind/battery hybrid microgrids. *Energies* **2012**, *5*, 5307–5323. [CrossRef]
24. Maghraby, H.A.M.; Shwehdi, M.H.; Al-Bassam, G.K. Probabilistic assessment of photovoltaic (PV) generation systems. *IEEE Trans. Power Syst.* **2002**, *17*, 205–208. [CrossRef]
25. La Terra, G.; Salvina, G.; Tina, G.M. Optimal sizing procedure for hybrid solar wind power systems by fuzzy logic. In Proceedings of the MELECON 2006—2006 IEEE Mediterranean Electrotechnical Conference, Benalmadena, Spain, 16–19 May 2006; pp. 865–868.
26. Habib, A.H.; Disfani, V.R.; Kleissl, J.; de Callafon, R.A. Optimal switchable load sizing and scheduling for standalone renewable energy systems. *Sol. Energy* **2017**, *144*, 707–720. [CrossRef]
27. Koutroulis, E.; Kolokotsa, D. Design optimization of desalination systems power-supplied by PV and W/G energy sources. *Desalination* **2010**, *258*, 171–181. [CrossRef]
28. Zhou, W.; Yang, H.; Fang, Z. A novel model for photovoltaic array performance prediction. *Appl. Energy* **2007**, *84*, 1187–1198. [CrossRef]
29. Yang, H.; Wei, Z.; Chengzhi, L. Optimal design and techno-economic analysis of a hybrid solar-wind power generation system. *Appl. Energy* **2009**, *86*, 163–169. [CrossRef]

30. Carpentiero, V.; Langella, R.; Manco, T.; Testa, A. A markovian approach to size a hybrid wind-diesel stand alone system. In Proceedings of the 10th International Conference on Probablistic Methods Applied to Power Systems, Rincon, PR, USA, 25–29 May 2008; pp. 1–8.
31. Elbaset, A.A. Smoothing of Grid-connected Wind-Diesel Power Output Using Energy Capacitor System. *J. Eng. Sci. Technol. Rev.* **2014**, *7*, 47–52. [CrossRef]
32. Yang, H.; Zhou, W.; Lu, L.; Fang, Z. Optimal sizing method for stand-alone hybrid solar-wind system with LPSP technology by using genetic algorithm. *Sol. Energy* **2008**, *82*, 354–367. [CrossRef]
33. Bayram, I.S.; Abdallah, M.; Tajer, A.; Qaraqe, K.A. A stochastic sizing approach for sharing-based energy storage applications. *IEEE Trans. Smart Grid* **2015**, *8*, 1075–1084. [CrossRef]
34. Ghiassi-Farrokhfal, Y.; Keshav, S.; Rosenberg, C.; Ciucu, F. Solar power shaping: An analytical approach. *IEEE Trans. Sustain. Energy* **2014**, *6*, 162–170. [CrossRef]
35. Yuan, C.; Illindala, M.S.; Khalsa, A.S. Co-optimization scheme for distributed energy resource planning in community microgrids. *IEEE Trans. Sustain. Energy* **2017**, *8*, 1351–1360. [CrossRef]
36. Nagarajan, A.; Ayyanar, R. Design and strategy for the deployment of energy storage systems in a distribution feeder with penetration of renewable resources. *IEEE Trans. Sustain. Energy* **2014**, *6*, 1085–1092. [CrossRef]
37. Lee, K.Y.; El-Sharkawi, M.A. *Modern Heuristic Optimization Techniques: Theory and Applications to Power Systems*; John Wiley & Sons: Hoboken, NJ, USA, 2008; Volume 39, ISBN 0471457116.
38. Li, P.; Dargaville, R.; Cao, Y.; Li, D.-Y.; Xia, J. Storage aided system property enhancing and hybrid robust smoothing for large-scale PV systems. *IEEE Trans. Smart Grid* **2016**, *8*, 2871–2879. [CrossRef]
39. Gupta, S.K.; Purohit, P. Renewable energy certificate mechanism in India: A preliminary assessment. *Renew. Sustain. Energy Rev.* **2013**, *22*, 380–392. [CrossRef]
40. Yang, H.; Lu, L.; Zhou, W. A novel optimization sizing model for hybrid solar-wind power generation system. *Sol. Energy* **2007**, *81*, 76–84. [CrossRef]
41. Belmili, H.; Almi, M.F.; Bendib, B.; Bolouma, S. A computer program development for sizing stand-alone Photovoltaic-Wind hybrid systems. *Energy Procedia* **2013**, *36*, 546–557. [CrossRef]
42. Bajpai, P.; Dash, V. Hybrid renewable energy systems for power generation in stand-alone applications: A review. *Renew. Sustain. Energy Rev.* **2012**, *16*, 2926–2939. [CrossRef]
43. Al-Ashwal, A.M.; Moghram, I.S. Proportion assessment of combined PV-wind generating systems. *Renew. Energy* **1997**, *10*, 43–51. [CrossRef]
44. Nelson, D.B.; Nehrir, M.H.; Wang, C. Unit sizing of stand-alone hybrid wind/PV/fuel cell power generation systems. In Proceedings of the IEEE Power Engineering Society General Meeting, San Francisco, CA, USA, 12–16 June 2005; pp. 2116–2122.
45. Diaf, S.; Notton, G.; Belhamel, M.; Haddadi, M.; Louche, A. Design and techno-economical optimization for hybrid PV/wind system under various meteorological conditions. *Appl. Energy* **2008**, *85*, 968–987. [CrossRef]
46. Negi, S.; Mathew, L. Hybrid renewable energy system: A review. *Int. J. Electron. Electr. Eng.* **2014**, *7*, 535–542.
47. Daud, A.-K.; Ismail, M.S. Design of isolated hybrid systems minimizing costs and pollutant emissions. *Renew. Energy* **2012**, *44*, 215–224. [CrossRef]
48. Nowdeh, S.A.; Hajibeigy, M. Economic designing of pv/fc/wind hybrid system considering components availability. *Int. J. Mod. Educ. Comput. Sci.* **2013**, *5*, 69. [CrossRef]
49. Perera, A.T.D.; Attalage, R.A.; Perera, K.; Dassanayake, V.P.C. A hybrid tool to combine multi-objective optimization and multi-criterion decision making in designing standalone hybrid energy systems. *Appl. Energy* **2013**, *107*, 412–425. [CrossRef]
50. Hakimi, S.M.; Moghaddas-Tafreshi, S.M. Optimal sizing of a stand-alone hybrid power system via particle swarm optimization for Kahnouj area in south-east of Iran. *Renew. Energy* **2009**, *34*, 1855–1862. [CrossRef]
51. Kiehbadroudinezhad, S.; Bousquet, J.-F.; Cada, M.; Short, C.I.; Shahabi, A.; Kiehbadroudinezhad, S. Expansion of a Y-Shaped Antenna Array and Optimization of the Future Antenna Array in Malaysia for Astronomical Applications. *J. Mod. Phys.* **2019**, *10*, 888–908. [CrossRef]
52. Kiehbadroudinezhad, M.; Merabet, A.; Hosseinzadeh-Bandbafha, H. Optimization of wind energy battery storage microgrid by division algorithm considering cumulative exergy demand for power-water cogeneration. *Energies* **2021**, *14*, 3777. [CrossRef]
53. Maleki, A.; Askarzadeh, A. Comparative study of artificial intelligence techniques for sizing of a hydrogen-based stand-alone photovoltaic/wind hybrid system. *Int. J. Hydrogen Energy* **2014**, *39*, 9973–9984. [CrossRef]
54. Maleki, A.; Pourfayaz, F.; Ahmadi, M.H. Design of a cost-effective wind/photovoltaic/hydrogen energy system for supplying a desalination unit by a heuristic approach. *Sol. Energy* **2016**, *139*, 666–675. [CrossRef]
55. Lagorse, J.; Simoes, M.G.; Miraoui, A.; Costerg, P. Energy cost analysis of a solar-hydrogen hybrid energy system for stand-alone applications. *Int. J. Hydrogen Energy* **2008**, *33*, 2871–2879. [CrossRef]
56. Yazdanpanah, M.-A. Modeling and sizing optimization of hybrid photovoltaic/wind power generation system. *J. Ind. Eng. Int.* **2014**, *10*, 1–14. [CrossRef]
57. Habib, M.A.; Said, S.A.M.; El-Hadidy, M.A.; Al-Zaharna, I. Optimization procedure of a hybrid photovoltaic wind energy system. *Energy* **1999**, *24*, 919–929. [CrossRef]
58. Pallabazzer, R. Evaluation of wind-generator potentiality. *Sol. Energy* **1995**, *55*, 49–59. [CrossRef]

59. Nasiraghdam, H.; Jadid, S. Optimal hybrid PV/WT/FC sizing and distribution system reconfiguration using multi-objective artificial bee colony (MOABC) algorithm. *Sol. Energy* **2012**, *86*, 3057–3071. [CrossRef]
60. Suman, G.K.; Guerrero, J.M.; Roy, O.P. Optimisation of solar/wind/bio-generator/diesel/battery based microgrids for rural areas: A PSO-GWO approach. *Sustain. Cities Soc.* **2021**, *67*, 102723. [CrossRef]
61. Mokhtara, C.; Negrou, B.; Settou, N.; Settou, B.; Samy, M.M. Design optimization of off-grid Hybrid Renewable Energy Systems considering the effects of building energy performance and climate change: Case study of Algeria. *Energy* **2021**, *219*, 119605. [CrossRef]
62. Hassan, A.; Al-Abdeli, Y.M.; Masek, M.; Bass, O. Optimal sizing and energy scheduling of grid-supplemented solar PV systems with battery storage: Sensitivity of reliability and financial constraints. *Energy* **2022**, *238*, 121780. [CrossRef]
63. Das, B.K.; Alotaibi, M.A.; Das, P.; Islam, M.S.; Das, S.K.; Hossain, M.A. Feasibility and techno-economic analysis of stand-alone and grid-connected PV/Wind/Diesel/Batt hybrid energy system: A case study. *Energy Strateg. Rev.* **2021**, *37*, 100673. [CrossRef]
64. Hong, Z.; Wei, Z.; Han, X. Optimization scheduling control strategy of wind-hydrogen system considering hydrogen production efficiency. *J. Energy Storage* **2021**, *47*, 103609. [CrossRef]
65. Kumar, R.; Diwania, S.; Khetrapal, P.; Singh, S.; Badoni, M. Multimachine stability enhancement with hybrid PSO-BFOA based PV-STATCOM. *Sustain. Comput. Inform. Syst.* **2021**, *32*, 100615. [CrossRef]
66. Naderipour, A.; Ramtin, A.R.; Abdullah, A.; Marzbali, M.H.; Nowdeh, S.A.; Kamyab, H. Hybrid energy system optimization with battery storage for remote area application considering loss of energy probability and economic analysis. *Energy* **2022**, *239*, 122303. [CrossRef]
67. Emad, D.; El-Hameed, M.A.; El-Fergany, A.A. Optimal techno-economic design of hybrid PV/wind system comprising battery energy storage: Case study for a remote area. *Energy Convers. Manag.* **2021**, *249*, 114847. [CrossRef]
68. Çetinbaş, P.; Tamyürek, B.; Demirta, M. Sizing optimization and design of an autonomous AC microgrid for commercial loads using Harris Hawks Optimization algorithm. *Energy Convers. Manag.* **2021**, *245*, 114562. [CrossRef]
69. Fares, D.; Fathi, M.; Mekhilef, S. Performance evaluation of metaheuristic techniques for optimal sizing of a stand-alone hybrid PV/wind/battery system. *Appl. Energy* **2022**, *305*, 117823. [CrossRef]
70. Emrani, A.; Berrada, A.; Bakhouya, M. Optimal sizing and deployment of gravity energy storage system in hybrid PV-Wind power plant. *Renew. Energy* **2022**, *183*, 12–27. [CrossRef]
71. Makhloufi, S.; Khennas, S.; Bouchaib, S.; Arab, A.H. Multi-objective cuckoo search algorithm for optimized pathways for 75% renewable electricity mix by 2050 in Algeria. *Renew. Energy* **2022**, *185*, 1410–1424. [CrossRef]
72. Maheri, A.; Unsal, I.; Mahian, O. Multiobjective optimisation of hybrid wind-PV-battery-fuel cell-electrolyser-diesel systems: An integrated configuration-size formulation approach. *Energy* **2022**, *241*, 122825. [CrossRef]
73. Nuvvula, R.S.S.; Devaraj, E.; Elavarasan, R.M.; Taheri, S.I.; Irfan, M.; Teegala, K.S. Multi-objective mutation-enabled adaptive local attractor quantum behaved particle swarm optimisation based optimal sizing of hybrid renewable energy system for smart cities in India. *Sustain. Energy Technol. Assess.* **2022**, *49*, 101689. [CrossRef]
74. Hemeida, A.M.; Omer, A.S.; Bahaa-Eldin, A.M.; Alkhalaf, S.; Ahmed, M.; Senjyu, T.; El-Saady, G. Multi-objective multi-verse optimization of renewable energy sources-based micro-grid system: Real case. *Ain Shams Eng. J.* **2022**, *13*, 101543. [CrossRef]
75. Lujano-Rojas, J.M.; Dufo-López, R.; Bernal-Agustín, J.L. Probabilistic modelling and analysis of stand-alone hybrid power systems. *Energy* **2013**, *63*, 19–27. [CrossRef]
76. Sinha, S.; Chandel, S.S. Review of recent trends in optimization techniques for solar photovoltaic-wind based hybrid energy systems. *Renew. Sustain. Energy Rev.* **2015**, *50*, 755–769. [CrossRef]
77. Bilal, B.O.; Sambou, V.; Ndiaye, P.A.; Kébé, C.M.F.; Ndongo, M. Optimal design of a hybrid solar-wind-battery system using the minimization of the annualized cost system and the minimization of the loss of power supply probability (LPSP). *Renew. Energy* **2010**, *35*, 2388–2390. [CrossRef]
78. Nafeh, A.E.-S.A. Optimal economical sizing of a PV-wind hybrid energy system using genetic algorithm. *Int. J. Green Energy* **2011**, *8*, 25–43. [CrossRef]
79. Merei, G.; Berger, C.; Sauer, D.U. Optimization of an off-grid hybrid PV-Wind-Diesel system with different battery technologies using genetic algorithm. *Sol. Energy* **2013**, *97*, 460–473. [CrossRef]
80. Kennedy, J.; Eberhart, R. Particle swarm optimization. In Proceedings of the ICNN'95—International Conference on Neural Networks, Perth, Australia, 27 November–1 December 1995; Volume 4, pp. 1942–1948.
81. Lee, T.-Y.; Chen, C.-L. Wind-photovoltaic capacity coordination for a time-of-use rate industrial user. *IET Renew. Power Gener.* **2009**, *3*, 152–167. [CrossRef]
82. Kaviani, A.K.; Riahy, G.H.; Kouhsari, S.H.M. Optimal design of a reliable hydrogen-based stand-alone wind/PV generating system, considering component outages. *Renew. Energy* **2009**, *34*, 2380–2390. [CrossRef]
83. Bansal, A.K.; Gupta, R.A.; Kumar, R. Optimization of hybrid PV/wind energy system using Meta Particle Swarm Optimization (MPSO). In Proceedings of the India International Conference on Power Electronics 2010 (IICPE2010), New Delhi, India, 28–30 January 2011; pp. 1–7.
84. Sharafi, M.; ELMekkawy, T.Y. Multi-objective optimal design of hybrid renewable energy systems using PSO-simulation based approach. *Renew. Energy* **2014**, *68*, 67–79. [CrossRef]
85. Borhanazad, H.; Mekhilef, S.; Ganapathy, V.G.; Modiri-Delshad, M.; Mirtaheri, A. Optimization of micro-grid system using MOPSO. *Renew. Energy* **2014**, *71*, 295–306. [CrossRef]

86. Karaboga, D.; Basturk, B. A powerful and efficient algorithm for numerical function optimization: Artificial bee colony (ABC) algorithm. *J. Glob. Optim.* **2007**, *39*, 459–471. [CrossRef]
87. Karaboga, D.; Basturk, B. Artificial bee colony (ABC) optimization algorithm for solving constrained optimization problems. In Proceedings of the International Fuzzy Systems Association World Congress, Cancun, Mexico, 18–21 June 2007; Springer: Berlin/Heidelberg, Germany, 2007; pp. 789–798.
88. Kiehbadroudinezhad, S.; Valente, D.; Cada, M.; Noordin, N.K.; Shahabi, A. Optimization of Positioning of Interferometric Array Antennas Using Division Algorithm for Radio Astronomy Applications. *Astron. J.* **2017**, *154*, 167. [CrossRef]
89. Dorigo, M.; Gambardella, L.M. Ant colony system: A cooperative learning approach to the traveling salesman problem. *IEEE Trans. Evol. Comput.* **1997**, *1*, 53–66. [CrossRef]
90. Dorigo, M.; Birattari, M.; Stutzle, T. Ant colony optimization. *IEEE Comput. Intell. Mag.* **2006**, *1*, 28–39. [CrossRef]
91. Xu, D.; Kang, L.; Chang, L.; Cao, B. Optimal sizing of standalone hybrid wind/PV power systems using genetic algorithms. In Proceedings of the Canadian Conference on Electrical and Computer Engineering, Saskatoon, SK, Canada, 1–4 May 2005; pp. 1722–1725.
92. Hosseinzadeh-Bandbafha, H.; Kiehbadroudinezhad, M. Environmental Impacts of Chocolate Production and Consumption. In *Trends in Sustainable Chocolate Production*, 1st ed.; Galanakis, C.M., Ed.; Springer: New York, NY, USA, 2022; Volume 1, pp. 229–258. [CrossRef]
93. Chuanyu, S.; Enrico, N.; Keti, V.; Gioele, P.; Gianni, C.; Angeloclaudio, N.; Yannick, B.; Vito, N. Hybrid inorganic-organic proton-conducting membranes based on SPEEK doped with WO3 nanoparticles for application in vanadium redox flow batteries. *Electrochim. Acta* **2019**, *309*, 311–325.
94. Huan, Z.; Chuanyu, S. Cost-effective iron-based aqueous redox flow batteries for large-scale energy storage application: A review. *J. Power Sources* **2021**, *493*, 229445.