sustainability

Review

Role of Metaheuristics in Optimizing Microgrids Operating and Management Issues: A Comprehensive Review

Hegazy Rezk [1,*], A. G. Olabi [2,3], Enas Taha Sayed [4] and Tabbi Wilberforce [5]

1 Department of Electrical Engineering, College of Engineering in Wadi Alddawasir, Prince Sattam bin Abdulaziz University, Al-Kharj 11942, Saudi Arabia
2 Sustainable Energy & Power Systems Research Centre, RISE, University of Sharjah, Sharjah P.O. Box 27272, United Arab Emirates
3 Department of Sustainable and Renewable Energy Engineering, University of Sharjah, Sharjah P.O. Box 27272, United Arab Emirates
4 Department of Chemical Engineering, Faculty of Engineering, Minia University, Minya 61519, Egypt
5 Mechanical Engineering and Design, School of Engineering and Applied Science, Aston University, Aston Triangle, Birmingham B4 7ET, UK
* Correspondence: hr.hussien@psau.edu.sa

Abstract: The increased interest in renewable-based microgrids imposes several challenges, such as source integration, power quality, and operating cost. Dealing with these problems requires solving nonlinear optimization problems that include multiple linear or nonlinear constraints and continuous variables or discrete ones that require large dimensionality search space to find the optimal or sub-optimal solution. These problems may include the optimal power flow in the microgrid, the best possible configurations, and the accuracy of the models within the microgrid. Metaheuristic optimization algorithms are getting more suggested in the literature contributions for microgrid applications to solve these optimization problems. This paper intends to thoroughly review some significant issues surrounding microgrid operation and solve them using metaheuristic optimization algorithms. This study provides a collection of fundamental principles and concepts that describe metaheuristic optimization algorithms. Then, the most significant metaheuristic optimization algorithms that have been published in the last years in the context of microgrid applications are investigated and analyzed. Finally, the employment of metaheuristic optimization algorithms to specific microgrid issue applications is reviewed, including examples of some used algorithms. These issues include unit commitment, economic dispatch, optimal power flow, distribution system reconfiguration, transmission network expansion and distribution system planning, load and generation forecasting, maintenance schedules, and renewable sources max power tracking.

Keywords: metaheuristics; optimization; electrical engineering; renewable energy; microgrid operation; performance enhancement

check for updates

Citation: Rezk, H.; Olabi, A.G.; Sayed, E.T.; Wilberforce, T. Role of Metaheuristics in Optimizing Microgrids Operating and Management Issues: A Comprehensive Review. *Sustainability* **2023**, *15*, 4982. https://doi.org/10.3390/su15064982

Academic Editors: Marc A. Rosen, Pablo García Triviño and Maxim A. Dulebenets

Received: 9 February 2023
Revised: 6 March 2023
Accepted: 8 March 2023
Published: 10 March 2023

1. Introduction

Because of the excessive use of fossil fuels for energy generation, global interest is going to the environmental crisis. As a result, a transformation to clean alternative energy is necessary to avert economic and environmental problems. Thus, the transition from the current power system's dependency on conventional fossil-based energy resources to an energy mix that includes renewable energy resources (RESs) is required [1]. These RESs (wind, solar, water, biomass, geothermal, and other non-fossil energies) are characterized as cleaner and more sustainable power sources [2]. The development and usage of RESs have increasingly become the sole solution to assure social and sustainable development [3]. Renewable energy often necessitates the utilization of distributed generating technologies (DG) [4]. DG technology, as opposed to the traditional centralized power network, is designed and used in accordance with the geographical distribution features of RESs and loads. Nonetheless, an increase in grid permeability can damage the distribution network in terms of loss in active power, harmonic, power flow, short circuit current, voltage flicker, and dynamic and transient stabilities [5]. Hence, the traditional power system is not built to accommodate new generating sources, posing technical and economic hurdles in maintaining stability, extending durability, and maximizing economic viability. To accommodate these problems, microgrids (MGs) are suggested by the Consortium for Electric Reliability Technology Solutions (CERTS) [6]. According to the (CERTS), the microgrid paradigm involves the interconnection of loads and micro-sources working as a single system delivering electricity and heat. Most of these sources must be combined with power electronic converters to give the flexibility necessary to operate correctly with enhanced reliability and security. MGs based on RESs are installed near end consumers to help reduce greenhouse gas emissions, eliminate transportation losses, enhance economic benefits, enhance power quality and safety, flexibly operate in grid or island mode, and ensure power supply in the event of a primary grid outage [7]. Furthermore, this technology is suitable for electrifying islands and rural and isolated zones [8]. However, the complexity of MG operation might make assuring a safe and economic power supply more difficult [9]. A microgrid may function as a controlled unit for large power grid systems since it has variable operating modes and schedulable performance. It can function autonomously in case of grid black-out, or the power quality does not satisfy the criteria. To summarize, microgrids tackle the challenge of large-scale access, maximize their benefits, and achieve an efficient, safe, clean, and stable energy supply.

Energy management must optimize the combination and integration of RESs, hybrid energy storage systems (ESSs), and controlled and non-controlled loads while taking into account energy and market projections, user demands, and operational restrictions [10]. In addition, the demand response has to be fulfilled by the implemented management strategy [11]. Other options can be included, such as minimizing the oscillations in the produced renewable power, controlling power resources to accommodate microgrid restrictions in near real-time, optimizing power flows, and providing ancillary services [12]. With the continued expansion of microgrid technologies, research on optimizing microgrid energy management has theoretical value and importance [13]. As a result, various studies and review papers have been published recently. Cagnano et al. [14] outlined the major design aspects of current microgrids, partly based on their experience with the Prince Lab microgrid in Italy. Shuai et al. [15] conducted a thorough study on power system stability while taking into account the microgrid operating states, induced disturbance, and operating time. A study of demand response (DR) modeling in MG operation has been proposed by Hosseini et al. [16], focusing on time-based DR applications. Rebollal et al. [17] examined 23 DGs for microgrid standards, concentrating on grid connection and operating technical criteria. Carpintero-Rentera et al. [18] conducted a study of the literature on microgrids concerning several issues like economic performance, standards, emissions, infrastructure, control plans, and operation. A review that highlights the advancements in DC microgrids planning, operation, and control has been suggested by Saleh Al-Ismail [19].

Adequately addressing these fundamental tasks depends upon solving nonlinear optimization problems that include multiple linear or nonlinear restrictions and continuous or discrete variables that may involve a large dimensionality search space to achieve the optimal or sub-optimal solution. Metaheuristic optimization algorithms (MOAs) are getting more suggested in the literature contributions for microgrid applications to solve these optimization problems satisfactorily [20,21]. Using metaheuristic optimization algorithms to solve these problems seems an excellent solution [22]. Despite MOAs' success in addressing larger problems, they cannot handle all optimization problems, and on average, all MOAs perform equally (no free lunch theorems [23]). In other words, no algorithm can be regarded as the best one. Then, the NFL theorem encourages the development of new, effective optimizers. This study depicts and analyzes the recently developed MOAs and examines how they might be used to improve renewable-based microgrids. This paper began with an overview of MOAs, concentrating on the principal steps for their application:

framing the optimization problem within the heuristics, the definition of the search space, constraints, initial positions generation, best individuals' selection, and whole individuals' movement based on iterative process according to the inspiration behavior. Then, the following section review several published works in the context of microgrids. Unfortunately, there is a limited number of comprehensive review papers that covers microgrid optimization approaches and strategies. As a result, this study analyzes existing works on microgrid operation optimization in several aspects.

This paper reviews the optimization of microgrid issues that can be considered in the electrical engineering field. This paper provides multiple contributions. First and foremost, this paper includes the basics of MOAs and the presentation and explanation of several most used MOAs. Second, a detailed review concentrating on microgrid operating optimization is provided in the paper. Last, this paper includes the deployment of MOAs on other related MG applications. Compared to the other published review papers, this paper presents a complete review between the metaheuristic optimization algorithms and several microgrid issues that the metaheuristic optimizers will resolve. This paper include recently published sources that reflect the current tendency in the studied topic.

2. Metaheuristic Optimization Algorithms

2.1. Overview

Metaheuristics are approximation techniques that integrate fundamental heuristic approaches to provide a more effective exploration of the search space [24]. A metaheuristic is described by Voßet al. [25] as a repetitive process that leads and changes the tasks using subordinate heuristics to simplify generating high-quality optimal or near-optimal solutions. At each iteration, the MA can operate with single or multiple solutions with a minimization or maximization procedure. The essential features of metaheuristics, according to [26], can be listed as

1. They are algorithms used to "guide" the search phase.
2. They aim to efficiently explore the search space in order to achieve the optimal or sub-optimal solution.
3. The methods employed to encompass various algorithms, from basic searches to complicated learning technics.
4. Mechanisms to prevent the local optimum may be included.
5. They are not limited to specific issues.
6. They may employ domain-specific information via local heuristics.

In terms of the phrase "metaheuristic," the term "heuristic" refers to a tool that aids in discovery, while "meta" is often included to denote the existence of higher-level technics that helps in the tracking of optimal solutions [27]. The foundation of many metaheuristics is converting an inspiring phenomenon into algorithms [28]. The coordination of exploration and exploitation search schemas enables the metaheuristics' robust searching mechanism. While exploitation (intensification) tends to explore new regions, exploration (diversification) is accountable for looking at the locations closest to the best solutions.

Technically, each MOA employs unique mechanisms. The availability of several algorithms presents an important question: are all of the MOAs utilized truly distinct from each other? A set of common fundamental conceptions were raised to respond to this question [29]. These conceptions, on the other hand, contain structural distinctions across methods.

- Parallelism: This concept is used in population-based algorithms, where various individuals are dispatched at the same time to execute one function, and the outcomes are compared. Further concepts are used based on the comparison to determine individuals' evolution in the swarm (population) or to generate new individuals.
- Acceptance: It appears in three cases: 1. Accept temporary solutions that impair objective function because of search space extension, 2. handling of the cost function's restrictions (objective function). The restrictions can be dealt with in 2 methods. The

first method rejects any solutions that include any violation. This method is employed when the initial conditions match any feasible solution. The second method is applied if a numerical value can be assigned to any solution. All solutions are automatically enrolled in this scenario, and the initial conditions may match infeasible solutions, 3. Adding limits to the accepted solutions that enhance the existing best solution by at least the limiting threshold. This method helps avoid numerical problems when comparing numbers derived from earlier calculations.
- Elitism: In repetitive population-based algorithms, the best solution must be preserved from one iteration to another. The elitism principle is used to do this by keeping the individual with the best-discovered solution and using it as a reference for the next iteration or updating it if another best solution is discovered. The concept of elitism may also be used for multiple individuals, forwarding an élite set of individuals to the following iteration.
- Selection: It is a probability-based mechanism that allows generating of new random individuals from the available individuals. This mechanism may include weights to the probabilistic selection where random individuals are selected to generate new individuals.
- Decay (or Reinforcement): It enables larger initial flexibility, followed by progressive flexibility restrictions. This concept is based on a multiplicative factor of less than one that is performed at each iteration. In certain circumstances, Reinforcement is used similarly by employing a multiplicative factor greater than one.
- Immunity: it is used by discovering some aspects of the solutions that lead to suitable configurations. Immunity prioritizes solutions with features comparable to those traits.
- Self-Adaptation: it is a mechanism that allows updating the algorithms' parameters according to the optimization evolution.
- Topology: it is used if the analyzed problem must be submitted to specific constraints.

These concepts are summarized in Figure 1. This figure presents the characteristics of each concept, which makes understanding them easier.

The MOAs can be classified as follows:

- Source of inspiration.
- The number of solutions used in the algorithm's iterations.
- Type of objective functions used.

The MOAs algorithms are classified according to the number of solutions into two types [30]:

- Single solution-based type: a series of solutions is calculated, and only if each new one meets a set of criteria is the solution updated. These algorithms are also named trajectory algorithms.
- Population-based type: many individuals work at the same time to address one task. These collective actions are simulated to connect the whole population, and the best individual is selected for the next search step.

According to the source of inspiration, the population-based algorithms may be classified based on their inspiration into four categories [31,32]: evolutionary (EA), Physics-based (PA), Human-based (HA), and swarm intelligence-based MAs (SIA).

- EAs like Genetic Algorithm (GA) [33], Differential Evolution (DE) [34], and Biogeography-Based Optimizer (BBO) [35] mimic biological evolutionary processes such as recombination, mutation, and selection. These methodologies efficiently deal with a wide range of issues by combining prior knowledge into an evolutionary search-yielding process that quickly examines a search space. Individuals who are weak and inactive are disregarded and replaced by superior ones. Nonetheless, EAs cannot develop a global solution to various problems. Numerous academics have merged these algorithms with other optimizers to improve their results.

- PAs such as Central Force Optimization (CFO) [36], Big-Bang Big-Crunch (BBBC) [37], Gravitational Search Algorithm (GSA) [38], and Gradient-based optimizer [39] are inspired by physical laws such as gravity, magnetic force.
- HAs, including Socio Evolution and Learning Optimization (SELO) [40], Social Network Search (SNS) [41], and Human Felicity Algorithm (HFA) [42], are inspired by human activities and behaviors.
- SIAs like Particle Swarm Optimization (PSO) [43], Salp Swarm Algorithm (SSA) [44], and COOT algorithm [45] mimic the social behaviors of animals or organisms living in swarms, communities, or packs [46]. Each individual can improve their fitness by moving from one position to another. The swarm is continually investigating new positions inside the search space to discover the global solution rapidly. On the other hand, collective movement may induce a mass collapse in a local solution, and the difficulty of leaving this zone may result in the expedition being ended early.

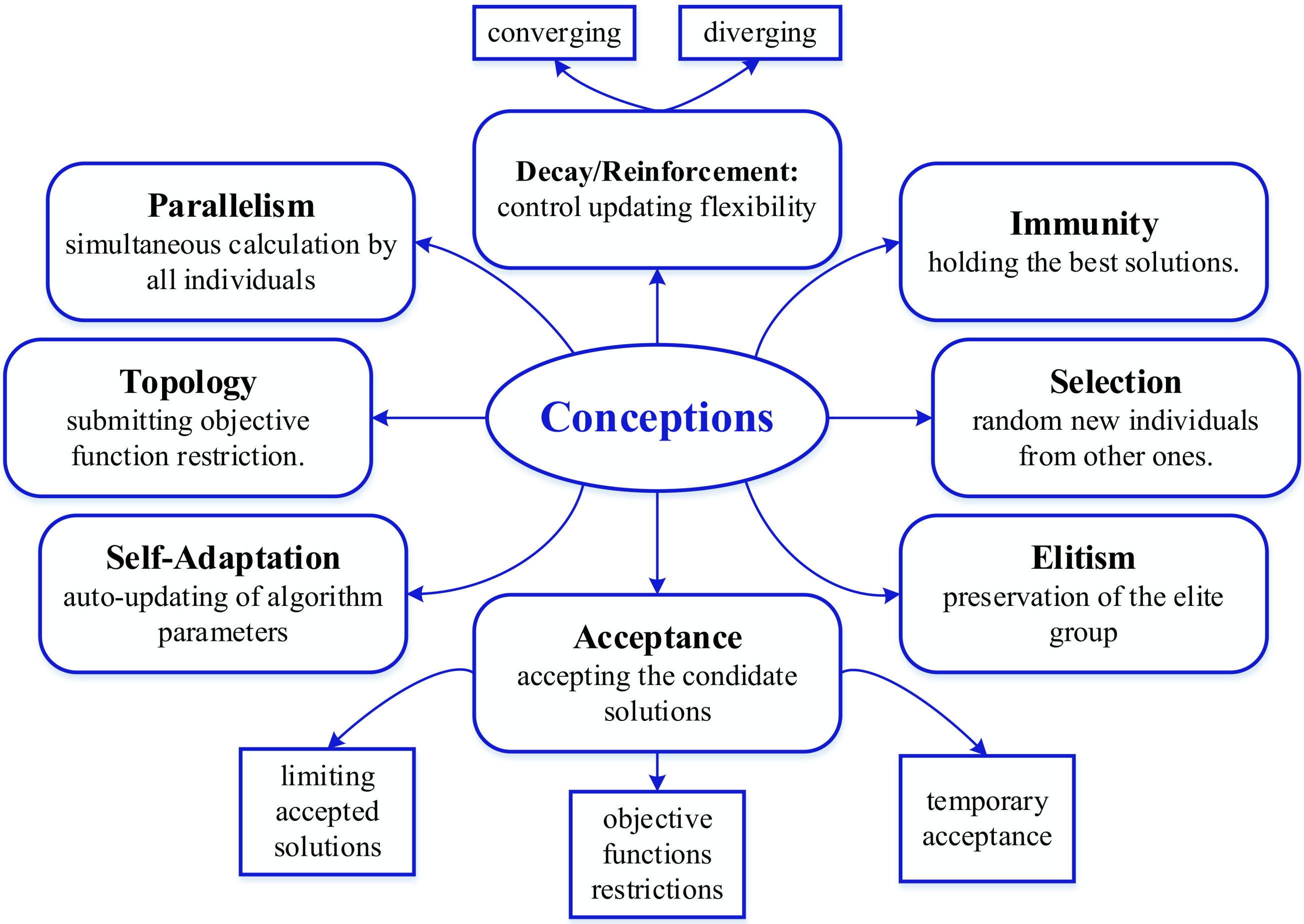

Figure 1. MOAs common fundamental conceptions.

In addition, when evaluating the number of optimization objectives, MAs can be classified following the type of objective function:

- A single objective: only one objective function is considered for minimization or maximization.
- Multi-objective: the algorithm includes two or more functions for minimization or maximization. When objectives conflict with one another, decision-making processes benefit significantly from using optimization techniques based on Pareto-dominance. If no other solution does exist that is superior for each of the distinct goal functions, that solution is said to be non-dominated. The Pareto front comprises the compromise

of a set of non-dominated alternative solutions from which the decision-maker can select the best one.

The MAs classification is presented in Figure 2. The number of OF means the number of the objective function, where the single OF includes only one objective function to handle. The multi OF reflects the multi-objective optimization algorithms that involve multiple problems. The solution type reflects the algorithm nature population or single point optimizer. The last case presents the classification according to the inspiration type.

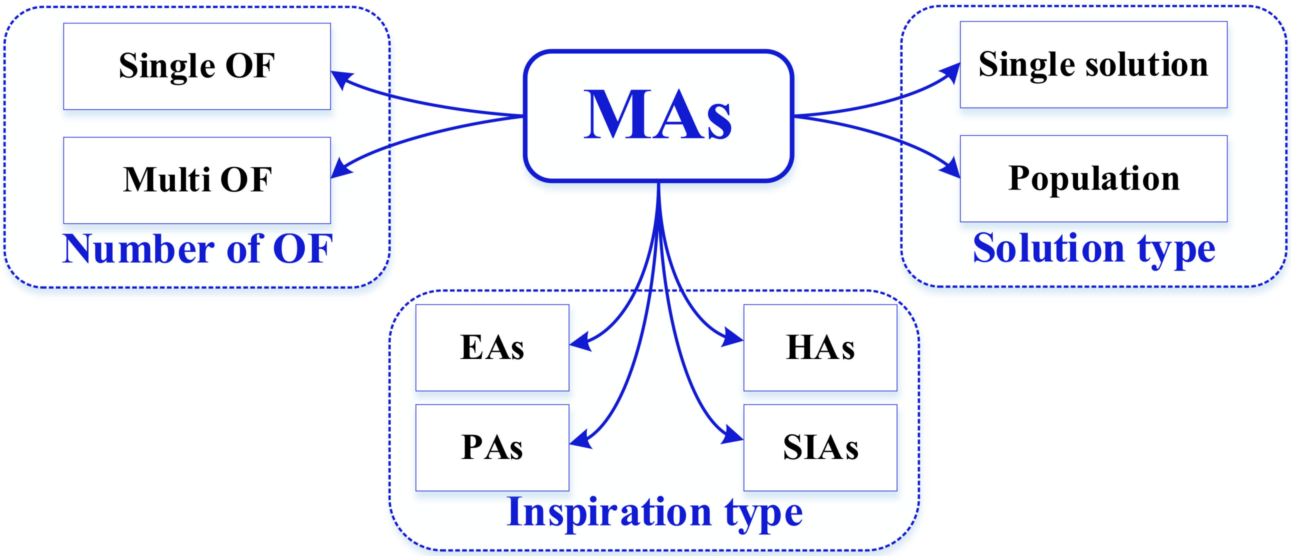

Figure 2. MAs classification according to solution type, number of objective functions, and inspiration type.

2.2. Examples of Recent Optimization Algorithms

2.2.1. Marine Predator Algorithm (MPA)

The Marine Predators Algorithm (MPA) is a newly created nature-inspired metaheuristic optimization algorithm by laws that govern a marine creature's ideal foraging behavior and encounter rate policy [47]. MPA mimics the behavior of aquatic predators in their hunt for food. Three phases are used in this process. Phase 1 is involved if the iteration t is in the first third of t_{Max}. It can be modeled as:

$$\begin{gathered} D_i = R_B \otimes (\mathrm{Elite}_i - R_B \otimes Prey_i) \\ Prey_{i+1} = Prey_i + 0.5 \cdot R \otimes D_i \end{gathered} \tag{1}$$

where D_i is the step size of the ith predator, R_B is a vector generated using Brownian motion's distribution, R represents random numbers [0, 1], and. The notation $\otimes$ shows entry-wise multiplications. If t is in the second third of t_{Max}, phase 2 is involved. This phase is separated into two subphases. If t is less than half of t_{Max}, this phase can be expressed as:

$$\begin{gathered} D_i = R_L \otimes (\mathrm{Elite}_i - R_L \otimes Prey_i) \\ Prey_{i+1} = Prey_i + 0.5 \cdot R \otimes D_i \end{gathered} \tag{2}$$

where R_L is a vector generated using Lévy motion's distribution; if t is greater than half of t_{Max}, this phase can be expressed as:

$$\begin{gathered} D_i = R_L \otimes (R_L \otimes \mathrm{Elite}_i - Prey_i) \\ Prey_{i+1} = \mathrm{Elite}_i + 0.5 \cdot CF \otimes D_i \\ CF = [1 - (t/t_{Max})]^{2t/t_{Max}} \end{gathered} \tag{3}$$

The last phase can be modeled as:

$$\begin{aligned} D_i &= R_L \otimes (\text{Elitee}_i - R_L \otimes Prey_i) \\ Prey_{i+1} &= Prey_i + 0.5 \cdot R \otimes D_i \end{aligned} \tag{4}$$

The MPA flowchart is presented in Figure 3.

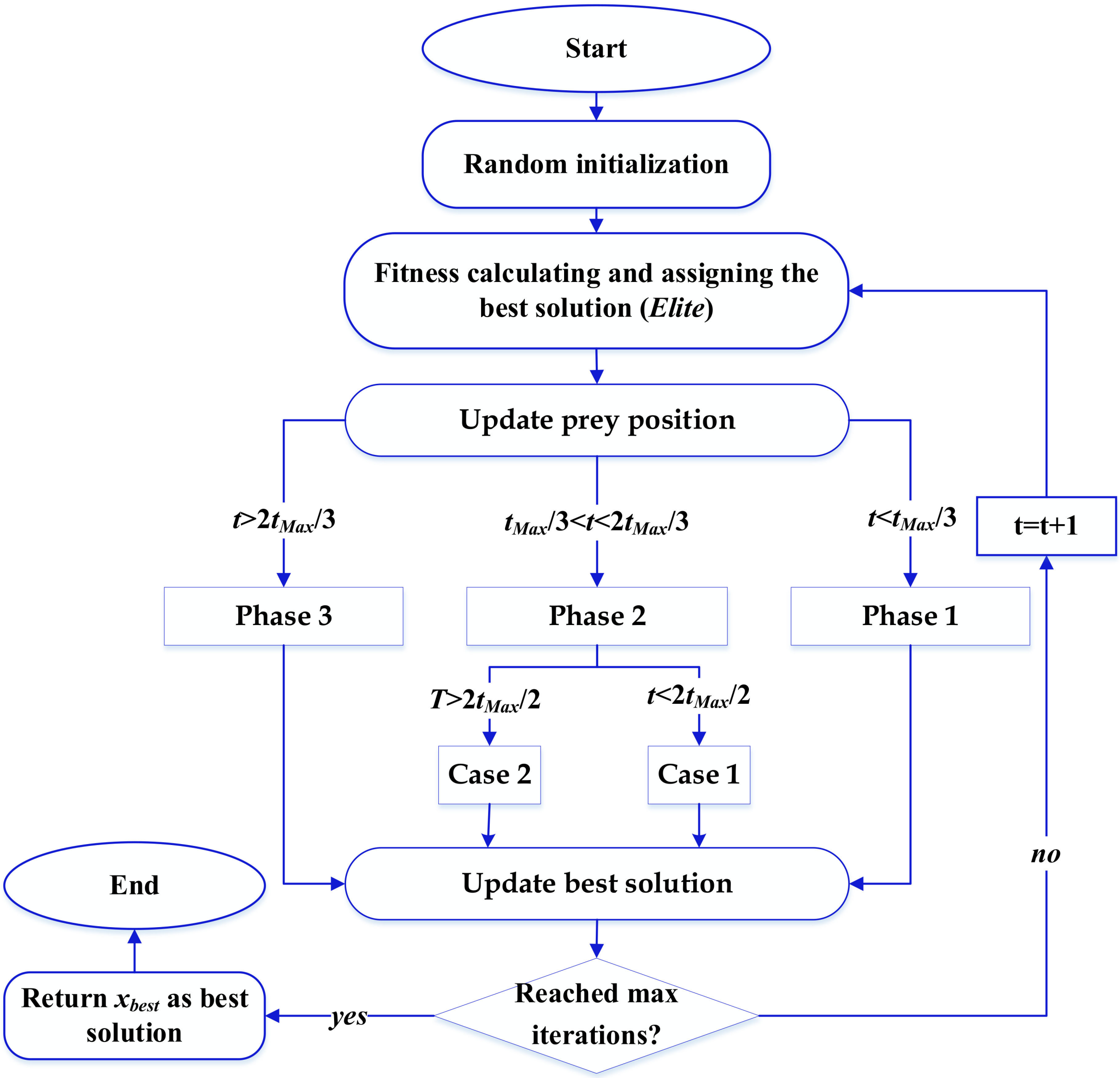

Figure 3. MPA flowchart.

2.2.2. Bald Eagle Search Algorithm (BES)

The bald eagle search (BES) algorithm is a modern, nature-inspired MOA that simulates bald eagles' hunting strategy or intelligent social behavior when looking for fish [48]. This algorithm has approved its efficiency for a large number of applications. BES hunting is separated into three stages. An eagle chooses the space with the most outstanding amount of prey in the first step (selecting space). The eagle goes inside the designated space to look for prey in the second stage (searching in space). The eagle swings from the best position discovered in the second stage to choose the optimum spot to hunt in the third stage (swooping). Swooping begins at the best place, and all subsequent motions are geared toward it. The first stage is modeled as:

$$x(t+1) = x_{best} + \alpha \cdot r \cdot (x_{mean} - x(t)) \tag{5}$$

where α is a constant [1.5,2], and r is random. The second stage can be modeled as follows:

$$x_i(t+1) = x_i(t) + Y_i(x_i(t) - x_{i+1}(t)) + X_i.(x_i(t) - x_{mean}) \tag{6}$$

where X and Y are directional coordinates calculated as follows:

$$\begin{aligned} X_i &= \frac{r_x(i)}{\max(|r_x|)};\ r_x(i) = r(i)\cdot\sin(\theta(i)) \\ Y_i &= \frac{r_y(i)}{\max(|r_y|)};\ r_y(i) = r(i)\cdot\cos(\theta(i)) \\ \theta(i) &= \beta_1\cdot\pi\cdot r;\ r(i) = \theta(i)\cdot R\cdot r \end{aligned} \tag{7}$$

where β_1 is a constant [5, 10], and R is a constant gain [0.5, 2]. The last stage can be expressed as follows:

$$\begin{aligned} x_i(t+1) &= r\cdot x_{best} + X_{1i}(x_i(t) - r_1\cdot x_{mean}) + Y_{1i}(x_i(t) - r_2\cdot x_{best}) \\ X_{1i} &= \frac{r_x(i)}{\max(|r_x|)};\ r_x(i) = r(i)\cdot\sinh(\theta(i)) \\ Y_{1i} &= \frac{r_y(i)}{\max(|r_y|)};\ r_y(i) = r(i)\cdot\cosh(\theta(i)) \\ \theta(i) &= \beta_2\cdot\pi\cdot r;\ r(i) = \theta(i) \end{aligned} \tag{8}$$

The BES flowchart is illustrated in Figure 4.

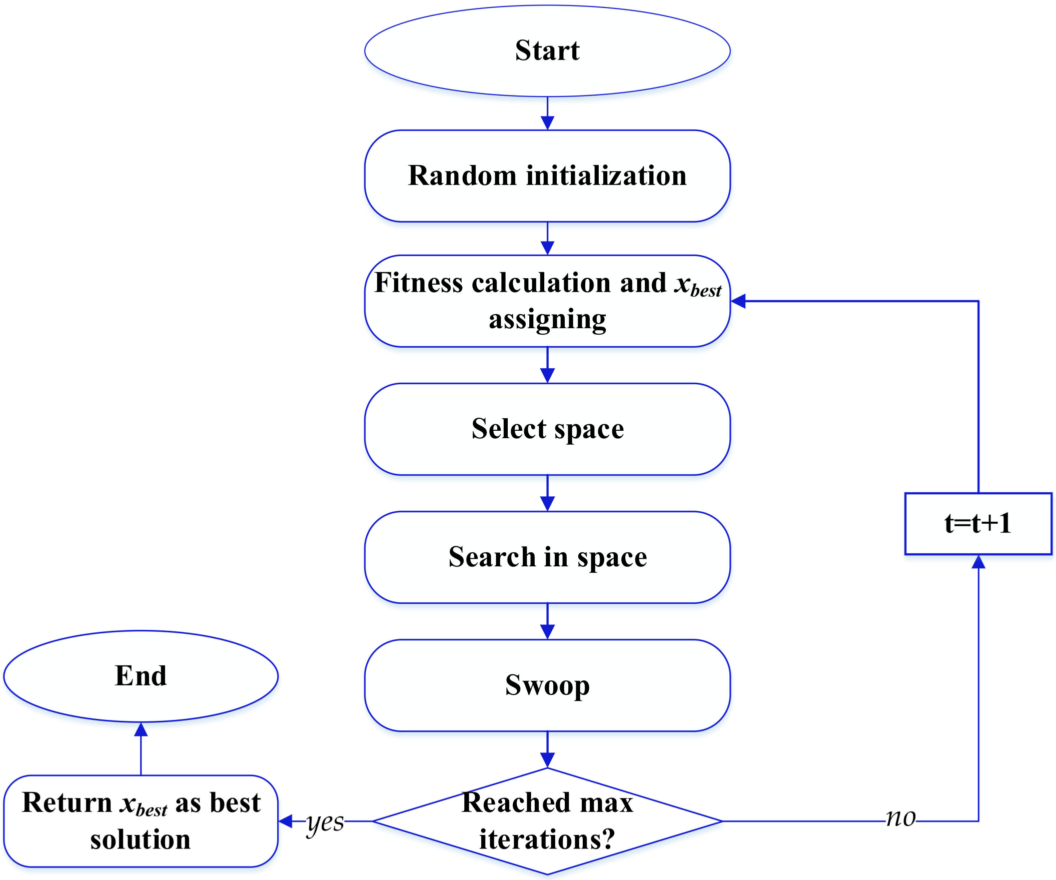

Figure 4. BES flowchart.

Table 1 presents a comparison of the characteristics of some reported MOAs. This table includes the advantages and drawbacks of each optimizer.

Table 1. MOAs characteristics.

MOA	Advantages	Drawback
PSO [43]	Simple Reduced number of parameters Simple updating mechanism	Limited performance for a large number of optimization issues Weak escaping ability
SSA [44]	Simple and small size of the code Reduced number of parameters Simple updating mechanism Easy to implement	Low accuracy in several applications due to the leaders' stochastic movement.
GWO [49]	High performance due to the three leading points.	The dependency of the whole population on the three leading wolves.
AEO [50]	Good performance with enhanced accuracy.	Reduced performance with a low number of iterations. Large size of code.
MPA [47]	Enhanced accuracy. Good escaping mechanization due to the implementation of Brownian and Levey stochastic distributions.	Reduced performance with a low number of iterations. Large size of code.
JSO [51]	Enhanced code size, which accelerates the computation time. Stochastic escaping mechanism which prevents it from falling into local solutions	Achieving the optimal value is challenging due to the increased stochastic behavior.
BES [48]	Complexed of three sub-algorithms which significantly improve the performance.	Large code size. Large computing time. Difficult to implement, especially for online applications.

2.3. MOA Summary

This section presents a summary of recent and most well-known MOAs. Table 2 presents the most well-known algorithms. This table includes the publication year and the inspiration source.

Table 2. Most well-known MOAs.

MOA	Abbrev	Year	Inspiration Source
Evolutionary MOAs			
Genetic algorithm [33]	GA	1992	Bio-inspired by chromosome representation
Differential Evolution [34]	DE	1997	Darwin's theory of evolution
Harmony Search [52]	HS	2001	The observation that music aims to search for a perfect state of harmony
Biogeography-based optimizer [35]	BBO	2008	Bio-inspired by the geographical distribution of biological organisms
Monkey king evolution [53]	MKE	2016	Nature-inspired by the actions of the Monkey King, a character in the well-known Chinese legendary tale Journey to the West.
Corona virus optimization [54]	CVO	2020	Bio-inspired by Coronavirus vulnerable infectious elimination model
Coronavirus herd immunity optimizer [55]	CHIO	2021	Bio-inspired by the herd immunity notion as a strategy to combat COVID-19.
Carnivorous plant algorithm	CPA	2021	

Table 2. *Cont.*

MOA	Abbrev	Year	Inspiration Source
Swarm intelligence MOAs			
Particle swarm optimization [43]	PSO	1995	Nature-inspired by particle swarm behavior
Ant colony optimization [56]	ACO	1999	Nature-inspired by the collective behavior of ants
Artificial bee colony [57]	ABC	2007	Nature-inspired by social behavior of bees
Grey wolf optimizer [49]	GWO	2014	Nature-inspired by grey wolf's hunting behavior
Whale optimization algorithm [31]	WOA	2016	Nature-inspired by Humpback whale hunting behavior
Salp swarm algorithm [44]	SSA	2017	Nature-inspired by collective behavior during navigating and foraging of salps
Spotted hyena optimizer [58]	SHO	2017	Nature-inspired by collaboration and social relationships among spotted hyenas
Coyote optimization algorithm [59]	COA	2018	The social organization of coyotes and their adaptability to their environment
Butterfly optimization algorithm [60]	BOA	2018	Bio-inspired by butterfly foraging and mating behavior
Harris hawks optimization [61]	HHO	2019	Nature-inspired by Harris hawks hunting behavior
Marine predators algorithm [47]	MPA	2020	Nature-inspired by predators' foraging strategies in maritime habitats
Bald eagle search optimisation algorithm [48]	BES	2020	Nature-inspired by bald eagles hunting behavior
Jellyfish search optimizer [62]	JSO	2021	Nature-inspired by collective behavior during the foraging of jellyfish
Physic based MOAs			
Big-Bang Big-Crunch [37]	BBBC	2006	Inspired by the Big Bang-Big Crunch theory, it creates arbitrary points in the Big Bang stage and compresses them to a unique representative point
Gravitational search algorithm [38]	GSA	2009	Inspired by Newton's gravity law
Charged system search [63]	CSS	2010	Inspired by the controlling Coulomb law of electrostatics and Newtonian principals
Water cycle algorithm [64]	WCA	2012	Inspired by real-world observations of the water cycle and how rivers and streams flow to the sea
Ray optimization algorithm [65]	ROA	2012	Inspired by Snell's light refraction law. When light moves from a lighter to a darker space, it refracts, and its direction changes.
Black hole [66]	BH	2013	Inspired by the black hole phenomenon during pulling stars and galaxies.
Electromagnetic field optimization [67]	EFO	2016	inspired by the behavior of various polarity electromagnets (positive, negative, and neutral)
Sine cosine algorithm [68]	SCA	2016	Inspired by the mathematical models of sine and cosine functions.
Central force optimization [36]	CFO	2017	Inspired by the gravitational kinematics metaphor
Chemical reaction optimization algorithm [69]	CRO	2017	Inspired by the transformation of reactants (or molecules) into products through a series of reactions
Artificial electric field algorithm [70]	AEFA	2020	Inspired by Coulomb's law of electrical force and Newton's equation of motion

Table 2. *Cont.*

MOA	Abbrev	Year	Inspiration Source
Gradient-based optimizer [39]	GBO	2021	Inspired by Newton's gradient-based technique
Human based MOAs			
Social cognitive optimization [71]	SCO	2002	Inspired by human intelligence with the social cognitive theory (SCT).
Teaching–learning-based optimization [72]	TLBO	2011	Inspired by the influence of a teacher on his learners
Soccer league competition algorithm [73]	SLO	2013	Inspired by soccer leagues and centered on team and player tournaments.
Social group optimization [74]	SGO	2016	Inspired by the notion of human social interaction in order to solve a challenging problem
Socio evolution and learning optimization [40]	SELO	2018	Inspired by human social learning behavior structured as families in a social setting
Group teaching optimization algorithm [75]	GTO	2020	Inspired by the group teaching mechanism based on four simple rules (the teacher allocation phase, ability grouping phase, teacher phase, and student phase)
Social Network Search [41]	SNS	2021	Inspired by social network users to achieve popularity by mimicking users' moods (imitation, conversation, disputation, and innovation).
Human Felicity Algorithm [42]	HFA	2022	Inspired by human society's aspirations to achieve happiness via a shift in human mentality

3. Microgrid Structure

A microgrid (MG) is a multisource system that incorporates several distributed generators (DGs), such as RESs, ESSs, loads (both controllable and non-controllable), and grid equipment, such as control and protection systems [76,77].

1. DGs: they can include new-generation technologies like combined heat and power systems (CHP) [78], fuel cell systems (FCs) [79], and photovoltaic generators (PVGs) [80]. DGs also include classic generators like induction and synchronous generators. Because of its great efficiency, adaptability, scalability, and lack of polluting emissions, fuel cell technology is one of the most promising fields of study. Proton exchange membrane FC (PEMFC), alkaline FC (AFC), phosphoric acid FC (PAFC), molten carbonate FC (MCFC), solid oxide FC (SOFC), and direct methanol FC are some of the forms of FC technologies (DMFC).
2. ESSs: their primary role is maintaining the power balance and energy demand within the MG [81]. In addition, they have to improve power quality against demand variations or intermittent RES and provide the necessary power for a smooth transition from grid-connected to island-based MG operation. Existing energy storage technologies suitable for MG applications include batteries, flywheels, and supercapacitors [82]. Batteries, because of their high energy density, can give excellent performance for this application.
3. MG loads: A MG may power a wide range of load types, including residential, commercial, and industrial. Commercial and industrial loads, in general, are critical that demand power quality and stability. As a result, the MG must control the loads by performing the following activities [83]:
    - Load shedding for non-critical loads optimizes the imported/exported power in grid-connected mode.
    - Voltage and frequency in off-grid mode by enabling load shedding.
    - Reduces the peak load.

4. DG interfacing systems: Most DGs need power electronic converters to adapt their output power to a common bus-compatible power (AC or DC). Filters, measuring components, and protective systems will be included in the power electronic interface [24].

DC and AC typical microgrids are illustrated in Figure 5. As described in this figure, all the sources are connected in parallel to the common bus through the power electronic converter. The microgrid is connected to the primary grid through the point of common coupling (PCC).

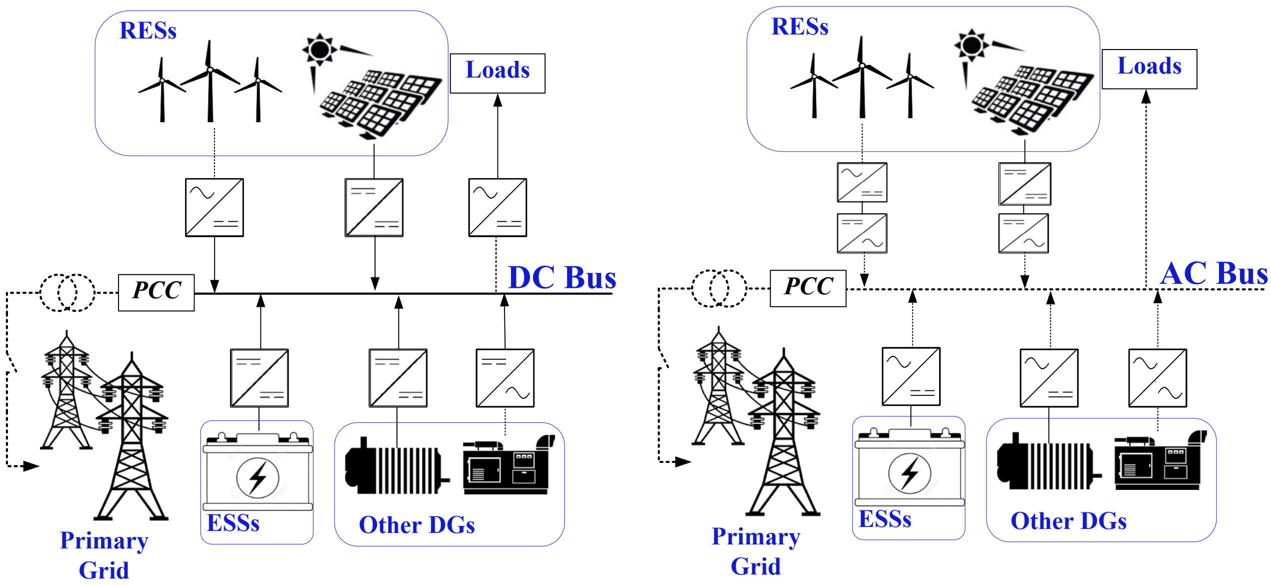

Figure 5. Typical DC and AC microgrid architectures.

4. Microgrid Operation and Management Optimization

Metaheuristic optimization algorithms are widely utilized in the microgrid domain to tackle numerous problems related to operating, planning, forecasting, controlling, durability, safety, identification, and demand response. A group of issues solved with MOAs has been taken into account in the literature. These issues include unit commitment, economic dispatch, system reconfiguration, optimal power flow, planning, forecasting, system identification, and maintenance schedule [84]. Below are some instances of how MOAs can be a feasible solver (or a more practical choice than) available mathematical solving tools for tackling a lot of optimization issues in the microgrid and power domain.

1. Unit Commitment: This issue entails arranging generation units to meet predicted demand in the future (e.g., from a single day to a week) while reducing overall generation costs. The output is a timetable for starting and stopping these units [22]. The issue involves integer and continuous variables, as well as a complicated set of restrictions for the units, including minimum up and down timings and start-up dynamics. This issue has typically been addressed using mathematical and stochastic programming approaches [85,86]. Using MOAs, such as GA [87], can provide better performance in binary coding that represents the on/off switching states for each unit. Evolutionary optimization algorithms are used to solve this issue better, as reported in [88]. PSO gained large popularity for this application [89]. Multiple versions of PSO, such as Binary PSO, Improved binary PSO, PSO with Lagrangian relaxation, and hybrid PSO–GWO [90], have used this problem. The ACO is also used for this application [91,92].
2. Economic Dispatch: The ED issue aims to reduce the operating costs of the microgrid. This issue is handled one step at a time considering system constraints such as power-generating boundaries and transmission line capacity. Classical programming tools

such as dynamic programming [93] and the interior point method [94] have been used. MOAs such as GA [95,96] and PSO [97] have been utilized to tackle the ED issue in recent decades, addressing special issues caused by the domain non-convexity of the definition of the variables. More recent solutions have been developed, such as interior point and DE [98] or hybrid versions based on PSO with other approaches [97]. Recent MOAs such as MPA [99] and BES [100] are also used.

3. Optimal Power Flow: It is a nonlinear and non-convex mixed-integer problem. Depending on which attributes are taken into account, the OPF problem can be expressed in a variety of ways (e.g., including reactive power-related aspects). There are a variety of constraints connected to the network and the DGs, as well as constraints related to contingencies. Many tools are used to solve the OPF problem, including a full set of mathematical programming tools that are also utilized to address difficult real-time OPF problems [101]. Interior point approaches [102] have emerged as the most efficient solutions. The nature of the OPF problem, on the other hand, makes MOAs suitable for giving effective solutions. GA, PSO, and DE are the most used MOAs [103]. The differential evolutionary particle swarm optimization (DEEPSO) [104], SSA [79], and African Vulture Optimization Algorithm (AVOA) [105] are other examples of the practical application of MOAs in this kind of application.
4. Distribution System Reconfiguration: This issue is about deciding which network branches to maintain open to produce a radial network and optimize a preset objective function. The principal limitations include the requirement to run a radial network, the equality restriction on power balancing, and inequality constraints involving node voltages, branch currents, short circuit currents, and others [106]. The problem's nature makes identifying a neighborhood of solutions and other regularities that may drive mathematical programming techniques challenging. As a result, MOAs can provide a suitable solution to this problem. GA [107], Plant Growth Simulation Algorithm (PGSA) [108], Bacterial Foraging Optimization Algorithm (BFOA) [109], and TLBO [110] are some examples of employing MOAs for solving this problem.
5. Transmission Network Expansion Planning: Resolving this issue aims to reduce the costs associated with transmission infrastructure and enhance its reliability considering load loss. Installing new lines, repowering the generator (or inserting new generators), and incorporating new technologies like FACTS are all possible activities. During cost optimization, modern solutions must consider uncertainties in the generation, load, market, and technology developments. The ideal set of investments is decided by considering the power balance (equality constraint), the maximum number of lines to be installed, their capacity, and the capacities of the various generators (inequality constraints). Optimizing this task is much easier using MOAs [111]. GA [112], ACO [113], PSO [114], HS [115], SFLA [116], and Multi-Verse Optimizer (MVO) [117] are some MOAs that are used in this application.
6. Distribution System Planning: This issue encompasses both expansion and operational planning strategies. The distinction between them is the number of system nodes, which remains constant when the operational planning strategy is used but can change in case of expansion. Different time horizons can be considered for expansion planning: short-term (1–4 years), long-term (5–20 years), and horizon-year planning (>20 years) [118]. The DSP is a nonlinear mixed-integer problem where binary optimization variables express either the installation of a new device or the upgrade of the existing one [119]. The principal objective of the DPS is to reduce the installation and operational costs, considering the technical and operational constraints. The MOAs are simple to employ and are especially beneficial for multi-objective DSP solving. Due to their binary coding of the information that permits the handling of potential on/off states of the components that are thought to be potential candidates to be included in the distribution network, GA is particularly suitable [120]. PSO can also provide competitive performance for this application [121].

7. Load and Generation Forecasting: forecasting the electrical loads and renewable generation is a long-standing issue that has been addressed using a variety of techniques, from statistical techniques to artificial intelligence-based techniques, particularly artificial neural network (ANN) and support vector machine (SVM), or more recently, techniques based on deep learning (DL) [122,123]. The growth in energy production from RESs has brought even more significant unpredictability, depending on the weather and energy costs. As a result, techniques that address the uncertainties in generation forecasting are required. Hybrid techniques have been developed by incorporating a MOA that enhances the parameter adjustment during the training stage into ANN technics. These hybridizations have taken into account MOAs such as GA, PSO, and SA [124]. These hybrid forecasting techniques are rising as effective tools, combining several forecasting methodologies to get higher accuracy in the outputs [125].
8. Maintenance Scheduling: The MS issue seeks to determine the appropriate time interval between maintenance interventions on DGs and microgrid components in order to retain their performance while minimizing the system's operational costs [126]. Two maintenance types are existed: DGs maintenance scheduling (DGMS) and transmission maintenance scheduling (TMS). GMS determines the length of DG outage in terms of time and duration, taking into account the reliability of the system where the DGs are located, human availability, and the dynamic restrictions of the DGs to return to ordinary operation. The TMS objective is to ensure that network component maintenance does not interfere with system functionality. Hence, the limitations are typically the same as in DGMS. After reconstructing the power system, the two issues may conflict since generators prefer to intervene when electricity prices are low. Thus, an iterative procedure is necessary to adjust scheduling periods while considering the generators' and network operators' requests [22]. MOAs have been used to solve this problem. To solve this mathematically, dynamic programming, mixed-integer programming, branch-and-bound, Benders decomposition, and Lagrangian relaxation have been employed [126]. Nevertheless, the nonlinearity of the system reduces their performance. MOAs have been introduced to provide better performance. GA, PSO, SA, and tabu search (TS) are the most common ones [127].
9. RESs MPPT: Due to the weather conditions dependency of RESs, their outputs are subjected to fluctuations which may decrease their performance. Resolving this problem using MPPT has been discussed widely in the literature. There are mainly three common types of MPPT: classical such as P&O and IC, intelligent-based fuzzy logic, and optimal MPPT strategies. The last type strategies have provided excellent performance using MOAs for wind [128] and PV systems [129]. The most promising MOAs are listed in Table 3. This table includes the authors, the publication year, and the used MOA.

Table 3. A set of MOA for MPPT applications.

Reference	Year	Used MOA
PV MPPT		
S. Kinattingal et al. [130]	2014	Artificial Bee Colony Algorithm (ABC)
C. Kumar et al. [131]	2016	Whale Optimization Algorithm (WOA)
S. Mohanty et al. [132]	2016	Grey Wolf Optimizer (GWO)
S. Titric et al. [133]	2017	Ant Colony Optimization (ACO)
D. Teshome et al. [134]	2017	Modified Firefly Algorithm (mFFA)
H. Li et al. [135]	2019	Particle Swarm Optimization (PSO)

Table 3. *Cont.*

Reference	Year	Used MOA
A. Mirza et al. [136]	2019	Particle Swarm Optimization (PSO), Cuckoo Search Optimization (CS), Artificial Bee Colony Algorithm (ABC), Hybrid PSO and Gravitational Search Optimization (PSOGS)
J. Shi et al. [137]	2019	Moth Flame Optimization (MFO)
M. Eltamaly et al. [138]	2020	Improved Cuckoo Search Algorithm (ICSA)
A. Mirza et al. [139]	2020	Salp Swarm Algorithm (SSA)
WT MPPT		
B. Yang et al. [140]	2018	Democratic Joint Operations Algorithm (DJOA)
Y. Mokhtari et al. [141]	2018	Ant Colony Optimization (ACO)
M. Qais et al. [142]	2018	Grey Wolf Optimizer (GWO)
A. Fathy, O. El-baksawi [143]	2019	Grasshopper Optimization Algorithm (GOA)
O. Maroufi et al. [144]	2020	Bat Algorithm (BA)
M. Qais et al. [145]	2020	Enhanced Whale Optimization Algorithm (IWOA)
M. Qais et al. [146]	2020	Salp Swarm Algorithm (SSA)
T. Anh Nguyenet al. [147]	2021	Equilibrum Optimizer (EO)
M. Hannachi et al. [148]	2021	Particle Swarm Optimization (PSO)
P. Rajesh et al. [149]	2021	Tunicate Swarm Algorithm (TSA)

10. DG parameters identification: Several elements are exposed to degradation, which may reduce the overall performance of the microgrid. The ESS is one of the elements that alternate continually due to its electrochemical aspect. The bidirectional migration of the ions between the cathode and the anode generates electricity. However, some of these ions sometimes stack in deep discharge or overcharge, forming a solid layer. This will lead to capacity degradation [150]. Fuel cells also are exposed to degradation. Several factors, such as the membrane degradation for the PEMFC type, cause this [151]. Photovoltaic panels also can degrade due to operating conditions and manufacturing materials [152]. To ensure the proper operation of the microgrid, the management system may require an exact DG model. Hence, identifying the actual parameters for each system is required. MOAs are excellent choices to address this task. Table 4 presents some of the MOAs used to extract the parameters of a Lithium-ion battery. Table 5 offers some of the MOAs used to extract the parameters of a PEM fuel cell, and a set of MOAs used to extract the parameters of a PV panel are presented in Table 6. These tables include the authors, the publication year, the used model, and the used MOA.

Table 4. A set of MOA for Li-ion battery identification.

Reference	Year	Used Model	Used MOA
Li-ion battery identification			
J. Forman et al. [153]	2012	Doyle-Fuller-Newman (DFN) model	Genetic Algorithm (GA)
V. Sangwan et al. [154]	2016		Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Ageist Spider Monkey Optimization (ASMO)

Table 4. *Cont.*

Reference	Year	Used Model	Used MOA
M. Rahman et al. [155]	2016	Electrochemical model	Particle Swarm Optimization (PSO)
X. Lai et al. [156]	2019	Equivalent circuit models	Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Grey Wolf Optimizer (GWO), Ant Colony Optimization (ACO), Firefly Algorithm (FFA), Multi-Verse Optimization (MVO) Whale Optimization Algorithm (WOA)
H. Chun et al. [157]	2019	Electrochemical model	Harmony Search (HS)
S. Zhou et al. [158]	2020	Equivalent circuit models	Hybrid Simulated Annealing Particle Swarm Optimization (PSO-SA)
M. Jusoh et al. [159]	2020	Tremblay's model	Particle Swarm Optimization (PSO), Gravity Search Algorithm (GSA), Genetic Algorithm (GA)
A. Lorestani et al. [160]	2020	Equivalent circuit models	evolutionary-particle swarm optimization (E-PSO)
S. Ferahtia et al. [161]	2021	Shepherd model	Particle Swarm Optimization (PSO), Salp Swarm Algorithm (SSA), Political Optimizer (PO), Artificial Eco-system Optimization (AEO), Equilibrium optimizer (EO)
S. Ferahtia et al. [162]	2021	Shepherd model	Salp Swarm Algorithm (SSA)
J. Kim et al. [163]	2022	Electrochemical model	Artificial Neural Network with Genetic Algorithm (ANN-GA)
E. Houssein et al. [164]	2022	Shepherd model	modified Coot Algorithm (mCOOT)
A. Fathi et al. [165]	2022	Shepherd model	Balde Eagle Search Algorithm (BES)
S. Ferahtia et al. [166]	2022	Shepherd model	modified Balde Eagle Search Algorithm (mBES)
T. Pan et al. [167]	2022	Electrochemical model	WOA
Y. Cheng [168]	2022	Equivalent circuit models	Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO), Harmony Search (HS), Golden Eagle Optimization (GEO)
R. Rizk-Allah et al. [169]	2022	Tremblay's model	hybrid Manta ray foraging optimization and PSO (MRFO-PSO)

Table 5. A set of MOA for PEM fuel cell identification.

Reference	Year	Used MOA
A. Askarzadeh et al. [170]	2011	modified Particle Swarm Optimization (mPSO)
Z. Sun et al. [171]	2015	hybrid Adaptive Differential Evolution Algorithm (ADA)
M. Ali et al. [172]	2017	Grey Wolf Optimizer (GWO)
A. El-Fergany [173]	2018	Salp Swarm Algorithm (SSA)
A. Fathi et al. [174]	2018	Multi-Verse Optimization (MVO)
G. Zhang et al. [175]	2020	Chaos Owl Search Algorithm (COSA), Bat Algorithm (BA), Firefly Algorithm (FFA), Multi-Verse Optimization (MVO)

Table 5. *Cont.*

Reference	Year	Used MOA
A. Diab et al. [176]	2020	Marin predator Algorithm (MPA), Political optimizer (PO)
F. Qin et al. [177]	2020	improved Fluid Search Optimization Algorithm (IFSO)
S. Menesy et al. [178]	2020	modified Artificial Eco-system Optimization (mAEO)
Y. Cao et al. [179]		improved Whale Optimization Algorithm (IWOA)
E. Houssein et al. [180]	2021	enhanced Archimedes Optimization Algorithm (eAOA), Archimedes Optimization Algorithm (AOA), Whale Optimization Algorithm (WOA), Moth Flame Optimization (MFO), Sin Cosin Algorithm (SCA), Particle Swarm Optimization (PSO), Harris Hawks Optimization (HHO), Tree-Seed Algorithm (TSA),
A. Fathi et al. [181]	2021	LSHADE-EpSin
Y. Zhu et al. [182]	2021	Adaptive Sparrow Search Algorithm (ASSA)
E. Houssein et al. [183]	2022	modified Artificial Electric Field Algorithm (mAEFA)
H. Rezk et al. [184]	2022	Gradient-Based Optimizer (GBO), Salp Swarm Algorithm (SSA), Heap-Based Optimizer (HBO), Differential Evolution (DE), Whale Optimization Algorithm (WOA), Moth Flame Optimization (MFO), Sin Cosin Algorithm (SCA), Harris Hawks Optimization (HHO)
T. Wilberforce et al. [185]	2022	Grey Wolf Optimizer (GWO), Particle Swarm Optimization (PSO), Slime Mould Algorithm(SMA), Harris Hawks Optimization (HHO), Artificial Eco-system Optimization (AEO)
H. Rezk et al. [186]		Balde Eagle Search Algorithm (BES)

Table 6. A set of MOA for PV identification.

PV Identification			
Q. Zhang et al. [187]	2016	Single diode model (SDM), Double diode model (DDM)	Fireworks Explosion Optimization (FEO)
Z. Wu et al. [188]	2019	Single diode model (SDM), Double diode model (DDM)	improved Lion Swarm Optimization (ILSO)
S. Ebrahimi et al. [189]	2019	Single diode model (SDM), Double diode model (DDM)	flexible Particle Swarm Optimization (FPSO)
H. Chen et al. [190]	2020	Single diode model (SDM), Double diode model (DDM)	Harris Hawks Optimization (HHO)
H. Zhang et al. [191]	2020	Single diode model (SDM), Double diode model (DDM)	Moth Flame Optimization (MFO)
I. Ahmadianfar et al. [192]	2021	Single diode model (SDM), Double diode model (DDM)	Gradient-Based Optimization (GBO)
D. Yousri et al. [193]	2021	Single diode model (SDM), Double diode model (DDM), Triple diode model (TDM)	Artificial Eco-system Optimization, Harris hawks Optimizer (HHO), Gray Wolf Optimizer (GWO), Salp Swarm Algorithm (SSA)

Table 6. *Cont.*

PV Identification			
X. Ye et al. [194]	2021	Single diode model (SDM), Double diode model (DDM)	modified Whale Optimization Algorithm (mWOA)
L. Sun et al. [195]	2021	Single diode model (SDM), Double diode model (DDM), Triple diode model (TDM)	Grouped Beetle Antennae Search (GBAS)
M. Abdel-Basset et al. [196]	2021	Single diode model (SDM), Double diode model (DDM)	Teaching-Learning-Based Optimization (TLBO)
M. Naeijian et al. [197]	2021	Single diode model (SDM), Double diode model (DDM), Triple diode model (TDM)	Whippy Harris Hawks Optimization Algorithm (WHHO)
W. Lei et al. [198]	2022	Single diode model (SDM), Double diode model (DDM), Triple diode model (TDM)	Improved Honey Badger Algorithm (IHBA)
M. El-Dabah et al. [199]	2023	Single diode model (SDM), Double diode model (DDM), Triple diode model (TDM)	Northern Goshawk Optimization (NGO)
A. Beşkirli, I. Dağ [200]	2023	Single diode model (SDM), Double diode model (DDM), Triple diode model (TDM)	Tunicate Swarm Algorithm (TSA)

5. Discussion

Integration and monitoring of RES present important problems for microgrids in terms of safe and efficient operation, as well as enhancing technical and economic efficiency and sustainability. Moreover, uncertainty in renewable generation, microgrid islanding, local energy community adoption, or demand-side management complicates decision-making.

The microgrid management system must align with current communication and optimization trends to handle the big data, discrete and continuous limits of any added equipment, and the requirement to integrate it to respond and make optimization choices more quickly. MOAs can address them effectively. Additionally, the scheduling of DGs, microgrid reconfiguration, planning, and forecasting can help to achieve certain operational goals that are frequently handled utilizing MOAs. Figure 6 summarizes the main tasks that are handled by employing optimization approaches. This figure includes the microgrid issues to be resolved and the most used MOA for each one.

A large number of new MOA is due to the necessity to discover excellent answers to tough optimization problems involving complicated systems and search areas with limited time and computing cost. Comparing them is a complex undertaking, as confirmed by the No Free Lunch (NFL) theorem(s) [23]. The NFL theorems basically argue that no MOA produces the optimum performance for all issues. In other words, if one algorithm outperforms another on a specific number of issues, the other algorithm should exceed the first on a corresponding number of problems. This encourages using more MOAs for resolving the microgrid problems.

Hover, there are critical limitations and difficulties in the existing studies that must be overcome in order to expand the acceptance and application of MOAs to microgrid applications:

- A wide range of MOAs makes selecting suitable algorithms for specific microgrid optimization issues challenging. The MOAs model the individuals and search space while taking into account the application limitations, the initialization of the optimization variables, and updating them towards the target based on its mathematical model that explains the inspiratory behavior. As a result, determining their benefits and drawbacks when examining their application in specific circumstances connected to microgrids is challenging.

- There are no standard testing procedures or benchmarks. Benchmarks are required to assess the performance and outcomes of each MOA used for microgrid operating and management optimization. These benchmarks must include microgrid configurations, the testing data, and the study kinds that must be carried out, including analysis and statistics about convergence, sensitivity, flexibility, exploitation, and exploration performances.
- The balance between exploring and exploiting phases in the optimization process considering the operational constraints of the microgrid. The challenging task here is efficiently managing the exploration and exploitation of the search space.
- The increased size of some MOA codes can be a drawback for real word applications, where the calculator's physical limits should be taken into consideration. In addition, reducing the code size for some algorithms can affect their performance.
- The utilization of new advanced analyzing tools, such as Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) group guidelines [201], to better help in describing the identification, screening, eligibility, and inclusion criteria. PRISMA is designed to improve the reporting of systematic reviews and meta-analyses. This will assist in analyzing the performance of the metaheuristic optimization algorithms for such applications.

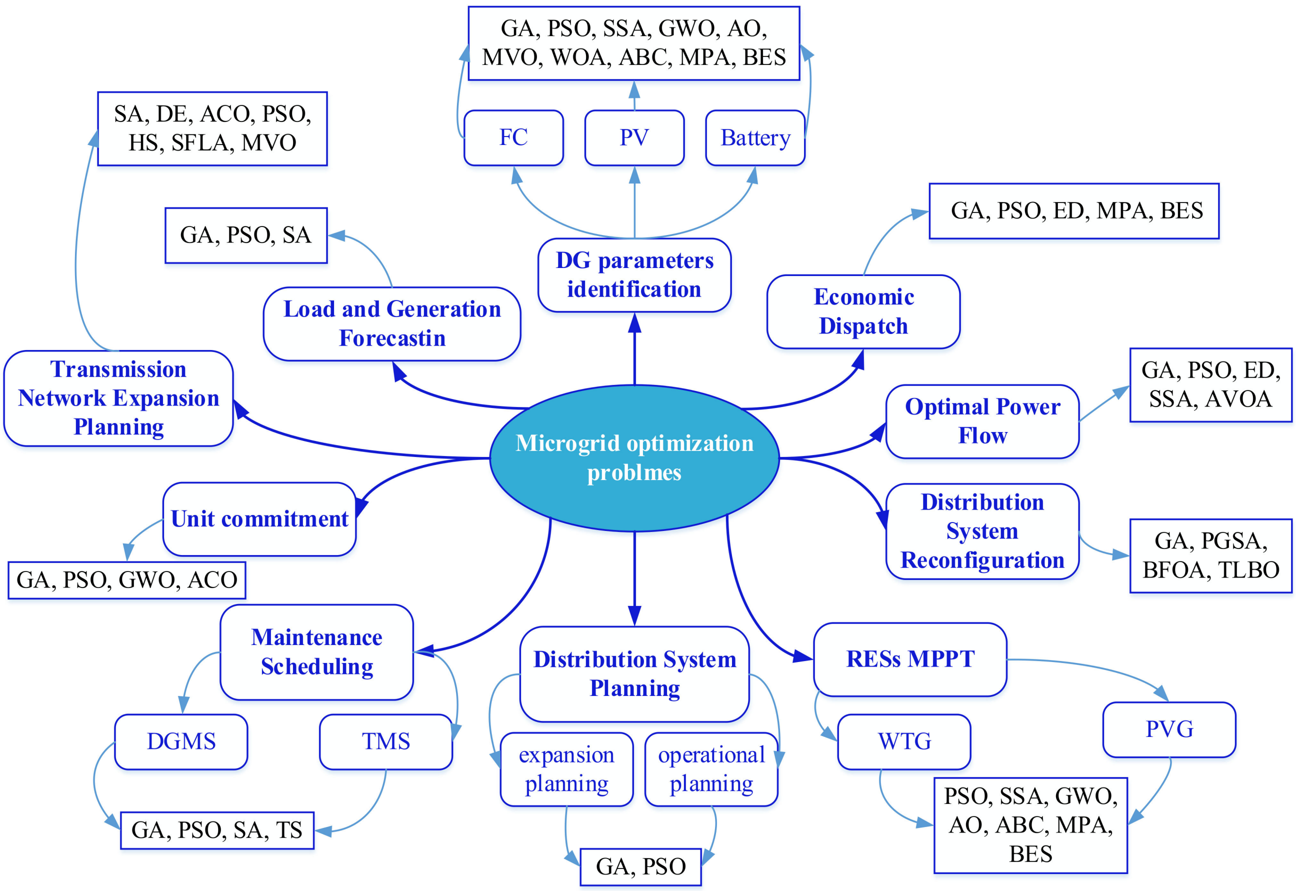

Figure 6. Microgrid optimization tasks and the main used MOAs.

The future works may focus on two parts: the creation of specified benchmark testing functions that can be used to assess the performance of the MOA for solving the microgrid issues. In the second part, the researchers may focus on profiting from some current MOAs to make them more suitable for microgrid applications. They may benefit from the abilities of the actual algorithms to create new ones or enhance the current ones by customizing heuristics [202], hybridization [203], adaptive and self-adaptive algorithms, learning-based algorithms, modified algorithms [166], reduced code size algorithms, etc.

6. Conclusions

This paper has contributed to the discussion on using a metaheuristic optimization algorithm to solve global optimization problems related to renewable-based microgrids. This paper gives a general overview of how to provide optimum microgrid solutions to accomplish several goals while taking operational restrictions into account. Starting from reviewing the metaheuristic fundamentals, concepts, and classifications. Then, a review of several published articles on metaheuristic algorithms was presented. These algorithms include the most well-known and recent ones. Microgrid basic structure has been revised as well as its main optimization problems such as power flow optimization and planning. The primary literature concerning microgrid optimization with metaheuristic optimization algorithms has been reviewed. Deciding on an algorithm's superiority over another method is challenging, as the no-free-lunch theory explains. On the other hand, a set of fundamental principles has been presented and discussed to systematically describe the properties of the metaheuristic optimization algorithms and find potential connections between the numerous algorithms suggested. The deployment of the metaheuristic optimization algorithms can be more emphasized by responding to several challenging tasks, such as the ones presented at the end of this paper.

Author Contributions: Conceptualization, H.R. and A.G.O.; methodology, H.R. and T.W.; formal analysis, E.S., H.R. and A.G.O.; investigation, H.R.; resources, H.R., T.W. and A.G.O.; writing—original draft preparation, H.R., T.W., E.S. and A.G.O.; writing—review and editing, H.R., T.W., E.S. and A.G.O.; supervision, A.G.O.; project administration, H.R.; funding acquisition, H.R. All authors have read and agreed to the published version of the manuscript.

Funding: This study was supported by the Prince Sattam bin Abdulaziz University through the Project Number 2023/RV/13.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Acknowledgments: This study was supported by the Prince Sattam bin Abdulaziz University through the Project Number 2023/RV/13.

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

References

1. Mohabat Doost, D.; Buffa, A.; Brunetta, G.; Salata, S.; Mutani, G. Mainstreaming Energetic Resilience by Morphological Assessment in Ordinary Land Use Planning. The Case Study of Moncalieri, Turin (Italy). *Sustainability* **2020**, *12*, 4443. [CrossRef]
2. Cergibozan, R. Renewable energy sources as a solution for energy security risk: Empirical evidence from OECD countries. *Renew. Energy* **2022**, *183*, 617–626. [CrossRef]
3. Śleszyński, P.; Nowak, M.; Brelik, A.; Mickiewicz, B.; Oleszczyk, N. Planning and Settlement Conditions for the Development of Renewable Energy Sources in Poland: Conclusions for Local and Regional Policy. *Energies* **2021**, *14*, 1935. [CrossRef]
4. Karunarathne, E.; Pasupuleti, J.; Ekanayake, J.; Almeida, D. The Optimal Placement and Sizing of Distributed Generation in an Active Distribution Network with Several Soft Open Points. *Energies* **2021**, *14*, 1084. [CrossRef]
5. Saleem, M.; Choi, K.-Y.; Kim, R.-Y. Resonance damping for an LCL filter type grid-connected inverter with active disturbance rejection control under grid impedance uncertainty. *Int. J. Electr. Power Energy Syst.* **2019**, *109*, 444–454. [CrossRef]
6. Lasseter, R.; Akhil, A.; Marnay, C.; Stephens, J.; Dagle, J.; Guttromsom, R.; Meliopoulous, A.S.; Yinger, R.; Eto, J. *Integration of Distributed Energy Resources: The CERTS Microgrid Concept*; Lawrence Berkeley National Lab.(LBNL): Berkeley, CA, USA, 2003.
7. Jayaram, J.; Srinivasan, M.; Prabaharan, N.; Senjyu, T. Design of Decentralized Hybrid Microgrid Integrating Multiple Renewable Energy Sources with Power Quality Improvement. *Sustainability* **2022**, *14*, 7777. [CrossRef]
8. Parag, Y.; Ainspan, M. Sustainable microgrids: Economic, environmental and social costs and benefits of microgrid deployment. *Energy Sustain. Dev.* **2019**, *52*, 72–81. [CrossRef]
9. Seshu Kumar, R.; Phani Raghav, L.; Koteswara Raju, D.; Singh, A.R. Impact of multiple demand side management programs on the optimal operation of grid-connected microgrids. *Appl. Energy* **2021**, *301*, 117466. [CrossRef]

10. Kharrich, M.; Mohammed, O.H.; Kamel, S.; Selim, A.; Sultan, H.M.; Akherraz, M.; Jurado, F. Development and Implementation of a Novel Optimization Algorithm for Reliable and Economic Grid-Independent Hybrid Power System. *Appl. Sci.* **2020**, *10*, 6604. [CrossRef]
11. Judge, M.A.; Manzoor, A.; Maple, C.; Rodrigues, J.J.P.C.; Islam, S. ul Price-based demand response for household load management with interval uncertainty. *Energy Rep.* **2021**, *7*, 8493–8504. [CrossRef]
12. Cioara, T.; Antal, M.; Mihailescu, V.T.; Antal, C.D.; Anghel, I.M.; Mitrea, D. Blockchain-Based Decentralized Virtual Power Plants of Small Prosumers. *IEEE Access* **2021**, *9*, 29490–29504. [CrossRef]
13. Yang, X.; Su, J.; Lü, Z.; Liu, H.; Li, R. Overview on micro-grid technology. *Proc. CSEE* **2014**, *34*, 57–70. [CrossRef]
14. Cagnano, A.; De Tuglie, E.; Mancarella, P. Microgrids: Overview and guidelines for practical implementations and operation. *Appl. Energy* **2020**, *258*, 114039. [CrossRef]
15. Shuai, Z.; Sun, Y.; Shen, Z.J.; Tian, W.; Tu, C.; Li, Y.; Yin, X. Microgrid stability: Classification and a review. *Renew. Sustain. Energy Rev.* **2016**, *58*, 167–179. [CrossRef]
16. Imani, M.H.; Ghadi, M.J.; Ghavidel, S.; Li, L. Demand Response Modeling in Microgrid Operation: A Review and Application for Incentive-Based and Time-Based Programs. *Renew. Sustain. Energy Rev.* **2018**, *94*, 486–499. [CrossRef]
17. Rebollal, D.; Carpintero-Rentería, M.; Santos-Martín, D.; Chinchilla, M. Microgrid and Distributed Energy Resources Standards and Guidelines Review: Grid Connection and Operation Technical Requirements. *Energies* **2021**, *14*, 523. [CrossRef]
18. Carpintero-Rentería, M.; Santos-Martín, D.; Guerrero, J.M. Microgrids Literature Review through a Layers Structure. *Energies* **2019**, *12*, 4381. [CrossRef]
19. Al-Ismail, F.S. DC Microgrid Planning, Operation, and Control: A Comprehensive Review. *IEEE Access* **2021**, *9*, 36154–36172. [CrossRef]
20. Dawoud, S.M.; Lin, X.; Okba, M.I. Hybrid renewable microgrid optimization techniques: A review. *Renew. Sustain. Energy Rev.* **2018**, *82*, 2039–2052. [CrossRef]
21. Chicco, G.; Mazza, A. Heuristic optimization of electrical energy systems: Refined metrics to compare the solutions. *Sustain. Energy Grids Netw.* **2019**, *17*, 100197. [CrossRef]
22. Chicco, G.; Mazza, A. Metaheuristic optimization of power and energy systems: Underlying principles and main issues of the 'rush to heuristics'. *Energies* **2020**, *13*, 5097. [CrossRef]
23. Wolpert, D.H.; Macready, W.G. No Free Lunch Theorems for Optimization. *IEEE Trans. Evol. Comput.* **1995**, *1*, 67–82. [CrossRef]
24. Yang, X. *Nature-Inspired Metaheuristic Algorithms*, 2nd ed.; Luniver Press: Frome, UK, 2010; p. 115.
25. Voß, S.; Martello, S.; Osman, I.H.; Roucairol, C. (Eds.) *Meta-Heuristics: Advances and Trends in Local Search Paradigms for Optimization*; Springer: Boston, MA, USA, 1998; ISBN 978-0-7923-8369-7.
26. Pop, C.B.; Cioara, T.; Anghel, I.; Antal, M.; Chifu, V.R.; Antal, C.; Salomie, I. Review of bio-inspired optimization applications in renewable-powered smart grids: Emerging population-based metaheuristics. *Energy Rep.* **2022**, *8*, 11769–11798. [CrossRef]
27. Sörensen, K.; Sevaux, M.; Glover, F. A History of Metaheuristics. In *Handbook of Heuristics*; Springer International Publishing: Cham, Switzerland, 2018; pp. 1–18.
28. Salcedo-Sanz, S. Modern meta-heuristics based on nonlinear physics processes: A review of models and design procedures. *Phys. Rep.* **2016**, *655*, 1–70. [CrossRef]
29. Batrinu, F.; Carpaneto, E.; Chicco, G. A unified scheme for testing alternative techniques for distribution system minimum loss reconfiguration. In Proceedings of the 2005 International Conference on Future Power Systems, Amsterdam, The Netherlands, 18 November 2005; Volume 2005, p. 6.
30. Dokeroglu, T.; Sevinc, E.; Kucukyilmaz, T.; Cosar, A. A survey on new generation metaheuristic algorithms. *Comput. Ind. Eng.* **2019**, *137*, 106040. [CrossRef]
31. Mirjalili, S.; Lewis, A. The Whale Optimization Algorithm. *Adv. Eng. Softw.* **2016**, *95*, 51–67. [CrossRef]
32. Faris, H.; Mafarja, M.M.; Heidari, A.A.; Aljarah, I.; Al-Zoubi, A.M.; Mirjalili, S.; Fujita, H. An efficient binary Salp Swarm Algorithm with crossover scheme for feature selection problems. *Knowl.-Based Syst.* **2018**, *154*, 43–67. [CrossRef]
33. Holland, J.H. Genetic algorithms. *Sci. Am.* **1992**, *267*, 66–72. [CrossRef]
34. Storn, R.; Price, K. Differential Evolution—A Simple and Efficient Heuristic for Global Optimization over Continuous Spaces. *J. Glob. Optim.* **1997**, *11*, 341–359. [CrossRef]
35. Simon, D. Biogeography-Based Optimization. *IEEE Trans. Evol. Comput.* **2008**, *12*, 702–713. [CrossRef]
36. Bozorg-Haddad, O.; Solgi, M.; Loáiciga, H.A. Central Force Optimization. In *Meta-Heuristic and Evolutionary Algorithms for Engineering Optimization*; John Wiley & Sons, Inc.: Hoboken, NJ, USA, 2017; pp. 175–184.
37. Erol, O.K.; Eksin, I. A new optimization method: Big Bang–Big Crunch. *Adv. Eng. Softw.* **2006**, *37*, 106–111. [CrossRef]
38. Rashedi, E.; Nezamabadi-pour, H.; Saryazdi, S. GSA: A Gravitational Search Algorithm. *Inf. Sci.* **2009**, *179*, 2232–2248. [CrossRef]
39. Ismaeel, A.A.K.; Houssein, E.H.; Oliva, D.; Said, M. Gradient-Based Optimizer for Parameter Extraction in Photovoltaic Models. *IEEE Access* **2021**, *9*, 13403–13416. [CrossRef]
40. Kumar, M.; Kulkarni, A.J.; Satapathy, S.C. Socio evolution & learning optimization algorithm: A socio-inspired optimization methodology. *Futur. Gener. Comput. Syst.* **2018**, *81*, 252–272. [CrossRef]
41. Bayzidi, H.; Talatahari, S.; Saraee, M.; Lamarche, C.-P. Social Network Search for Solving Engineering Optimization Problems. *Comput. Intell. Neurosci.* **2021**, *2021*, 8548639. [CrossRef]

42. Verij Kazemi, M.; Fazeli Veysari, E. A new optimization algorithm inspired by the quest for the evolution of human society: Human felicity algorithm. *Expert Syst. Appl.* **2022**, *193*, 116468. [CrossRef]
43. Kennedy, J.; Eberhart, R. Particle swarm optimization. In Proceedings of the ICNN'95—International Conference on Neural Networks, Perth, WA, Australia, 27 November–1 December 1995; Volume 4, pp. 1942–1948.
44. Mirjalili, S.; Gandomi, A.H.; Mirjalili, S.Z.; Saremi, S.; Faris, H.; Mirjalili, S.M. Salp Swarm Algorithm: A bio-inspired optimizer for engineering design problems. *Adv. Eng. Softw.* **2017**, *114*, 163–191. [CrossRef]
45. Naruei, I.; Keynia, F. A new optimization method based on COOT bird natural life model. *Expert Syst. Appl.* **2021**, *183*, 115352. [CrossRef]
46. Baykasoğlu, A.; Ozsoydan, F.B. Evolutionary and population-based methods versus constructive search strategies in dynamic combinatorial optimization. *Inf. Sci.* **2017**, *420*, 159–183. [CrossRef]
47. Faramarzi, A.; Heidarinejad, M.; Mirjalili, S.; Gandomi, A.H. Marine Predators Algorithm: A nature-inspired metaheuristic. *Expert Syst. Appl.* **2020**, *152*, 113377. [CrossRef]
48. Alsattar, H.A.; Zaidan, A.A.; Zaidan, B.B. Novel meta-heuristic bald eagle search optimisation algorithm. *Artif. Intell. Rev.* **2020**, *53*, 2237–2264. [CrossRef]
49. Mirjalili, S.; Mirjalili, S.M.; Lewis, A. Grey Wolf Optimizer. *Adv. Eng. Softw.* **2014**, *69*, 46–61. [CrossRef]
50. Zhao, W.; Wang, L.; Zhang, Z. Artificial ecosystem-based optimization: A novel nature-inspired meta-heuristic algorithm. *Neural Comput. Appl.* **2020**, *32*, 9383–9425. [CrossRef]
51. Chou, J.-S.; Molla, A. Recent advances in use of bio-inspired jellyfish search algorithm for solving optimization problems. *Sci. Rep.* **2022**, *12*, 19157. [CrossRef] [PubMed]
52. Geem, Z.W.; Kim, J.H.; Loganathan, G.V. A New Heuristic Optimization Algorithm: Harmony Search. *Simulation* **2001**, *76*, 60–68. [CrossRef]
53. Meng, Z.; Pan, J.-S. Monkey King Evolution: A new memetic evolutionary algorithm and its application in vehicle fuel consumption optimization. *Knowl.-Based Syst.* **2016**, *97*, 144–157. [CrossRef]
54. Martínez-Álvarez, F.; Asencio-Cortés, G.; Torres, J.F.; Gutiérrez-Avilés, D.; Melgar-García, L.; Pérez-Chacón, R.; Rubio-Escudero, C.; Riquelme, J.C.; Troncoso, A. Coronavirus Optimization Algorithm: A Bioinspired Metaheuristic Based on the COVID-19 Propagation Model. *Big Data* **2020**, *8*, 308–322. [CrossRef]
55. Al-Betar, M.A.; Alyasseri, Z.A.A.; Awadallah, M.A.; Abu Doush, I. Coronavirus herd immunity optimizer (CHIO). *Neural Comput. Appl.* **2021**, *33*, 5011–5042. [CrossRef] [PubMed]
56. Dorigo, M.; Di Caro, G. Ant colony optimization: A new meta-heuristic. In Proceedings of the Proceedings of the 1999 Congress on Evolutionary Computation-CEC99 (Cat. No. 99TH8406), Washington, DC, USA, 6–9 July 1999; pp. 1470–1477.
57. Karaboga, D.; Basturk, B. An Artificial Bee Colony (ABC) Algorithm for Numeric function Optimization. In Proceedings of the IEEE Swarm Intelligence Symposium, Indianapolis, IN, USA, 24–26 April 2006; pp. 789–798.
58. Dhiman, G.; Kumar, V. Spotted hyena optimizer: A novel bio-inspired based metaheuristic technique for engineering applications. *Adv. Eng. Softw.* **2017**, *114*, 48–70. [CrossRef]
59. Pierezan, J.; Dos Santos Coelho, L. Coyote Optimization Algorithm: A New Metaheuristic for Global Optimization Problems. In Proceedings of the 2018 IEEE Congress on Evolutionary Computation (CEC), Rio de Janeiro, Brazil, 8–13 July 2018; pp. 1–8.
60. Arora, S.; Singh, S. Butterfly optimization algorithm: A novel approach for global optimization. *Soft Comput.* **2019**, *23*, 715–734. [CrossRef]
61. Heidari, A.A.; Mirjalili, S.; Faris, H.; Aljarah, I.; Mafarja, M.; Chen, H. Harris hawks optimization: Algorithm and applications. *Futur. Gener. Comput. Syst.* **2019**, *97*, 849–872. [CrossRef]
62. Chou, J.-S.; Truong, D.-N. A novel metaheuristic optimizer inspired by behavior of jellyfish in ocean. *Appl. Math. Comput.* **2021**, *389*, 125535. [CrossRef]
63. Kaveh, A.; Talatahari, S. A novel heuristic optimization method: Charged system search. *Acta Mech.* **2010**, *213*, 267–289. [CrossRef]
64. Eskandar, H.; Sadollah, A.; Bahreininejad, A.; Hamdi, M. Water cycle algorithm—A novel metaheuristic optimization method for solving constrained engineering optimization problems. *Comput. Struct.* **2012**, *110–111*, 151–166. [CrossRef]
65. Kaveh, A.; Khayatazad, M. A new meta-heuristic method: Ray Optimization. *Comput. Struct.* **2012**, *112–113*, 283–294. [CrossRef]
66. Hatamlou, A. Black hole: A new heuristic optimization approach for data clustering. *Inf. Sci.* **2013**, *222*, 175–184. [CrossRef]
67. Abedinpourshotorban, H.; Mariyam Shamsuddin, S.; Beheshti, Z.; Jawawi, D.N.A. Electromagnetic field optimization: A physics-inspired metaheuristic optimization algorithm. *Swarm Evol. Comput.* **2016**, *26*, 8–22. [CrossRef]
68. Mirjalili, S. SCA: A Sine Cosine Algorithm for solving optimization problems. *Knowl.-Based Syst.* **2016**, *96*, 120–133. [CrossRef]
69. Siddique, N.; Adeli, H. Nature-Inspired Chemical Reaction Optimisation Algorithms. *Cognit. Comput.* **2017**, *9*, 411–422. [CrossRef]
70. Yadav, A.; Kumar, N. Artificial electric field algorithm for engineering optimization problems. *Expert Syst. Appl.* **2020**, *149*, 113308. [CrossRef]
71. Xie, X.-F.; Zhang, W.-J.; Yang, Z.-L. Social cognitive optimization for nonlinear programming problems. In Proceedings of the International Conference on Machine Learning and Cybernetics, Beijing, China, 4–5 November 2002; Volume 2, pp. 779–783.
72. Rao, R.V.; Savsani, V.J.; Vakharia, D.P. Teaching-Learning-Based Optimization: An optimization method for continuous non-linear large scale problems. *Inf. Sci.* **2012**, *183*, 1–15. [CrossRef]
73. Moosavian, N.; Roodsari, B.K. Soccer League Competition Algorithm, a New Method for Solving Systems of Nonlinear Equations. *Int. J. Intell. Sci.* **2014**, *4*, 7–16. [CrossRef]

74. Satapathy, S.; Naik, A. Social group optimization (SGO): A new population evolutionary optimization technique. *Complex Intell. Syst.* **2016**, *2*, 173–203. [CrossRef]
75. Zhang, Y.; Jin, Z. Group teaching optimization algorithm: A novel metaheuristic method for solving global optimization problems. *Expert Syst. Appl.* **2020**, *148*, 113246. [CrossRef]
76. Dagar, A.; Gupta, P.; Niranjan, V. Microgrid protection: A comprehensive review. *Renew. Sustain. Energy Rev.* **2021**, *149*, 111401. [CrossRef]
77. Lidula, N.W.A.; Rajapakse, A.D. Microgrids research: A review of experimental microgrids and test systems. *Renew. Sustain. Energy Rev.* **2011**, *15*, 186–202. [CrossRef]
78. Haller, M.Y.; Amstad, D.; Dudita, M.; Englert, A.; Häberle, A. Combined heat and power production based on renewable aluminium-water reaction. *Renew. Energy* **2021**, *174*, 879–893. [CrossRef]
79. Ferahtia, S.; Djeroui, A.; Rezk, H.; Houari, A.; Zeghlache, S.; Machmoum, M. Optimal control and implementation of energy management strategy for a DC microgrid. *Energy* **2022**, *238*, 121777. [CrossRef]
80. Figaj, R. Performance assessment of a renewable micro-scale trigeneration system based on biomass steam cycle, wind turbine, photovoltaic field. *Renew. Energy* **2021**, *177*, 193–208. [CrossRef]
81. Yang, L.; Tai, N.; Fan, C.; Meng, Y. Energy regulating and fluctuation stabilizing by air source heat pump and battery energy storage system in microgrid. *Renew. Energy* **2016**, *95*, 202–212. [CrossRef]
82. Fossati, J.P.; Galarza, A.; Martín-Villate, A.; Fontán, L. A method for optimal sizing energy storage systems for microgrids. *Renew. Energy* **2015**, *77*, 539–549. [CrossRef]
83. Driesen, J.; Katiraei, F. Design for distributed energy resources. *IEEE Power Energy Mag.* **2008**, *6*, 30–39. [CrossRef]
84. Del Valle, Y.; Venayagamoorthy, G.K.G.K.; Mohagheghi, S.; Hernandez, J.C.J.-C.; Harley, R.G.R.G. Particle swarm optimization: Basic concepts, variants and applications in power systems. *IEEE Trans. Evol. Comput.* **2008**, *12*, 171–195. [CrossRef]
85. Zheng, Q.P.; Wang, J.; Liu, A.L. Stochastic Optimization for Unit Commitment—A Review. *IEEE Trans. Power Syst.* **2015**, *30*, 1913–1924. [CrossRef]
86. Tejada-Arango, D.A.; Lumbreras, S.; Sanchez-Martin, P.; Ramos, A. Which Unit-Commitment Formulation is Best? A Comparison Framework. *IEEE Trans. Power Syst.* **2020**, *35*, 2926–2936. [CrossRef]
87. Kazarlis, S.A.; Bakirtzis, A.G.; Petridis, V. A genetic algorithm solution to the unit commitment problem. *IEEE Trans. Power Syst.* **1996**, *11*, 83–92. [CrossRef]
88. Muralikrishnan, N.; Jebaraj, L.; Rajan, C.C.A. A Comprehensive Review on Evolutionary Optimization Techniques Applied for Unit Commitment Problem. *IEEE Access* **2020**, *8*, 132980–133014. [CrossRef]
89. Logenthiran, T.; Srinivasan, D. Particle Swarm Optimization for unit commitment problem. In Proceedings of the 2010 IEEE 11th International Conference on Probabilistic Methods Applied to Power Systems, Singapore, 14–17 June 2010; pp. 642–647.
90. Kamboj, V.K. A novel hybrid PSO–GWO approach for unit commitment problem. *Neural Comput. Appl.* **2016**, *27*, 1643–1655. [CrossRef]
91. Jang, S.H.; Roh, J.H.; Kim, W.; Sherpa, T.; Kim, J.H.; Park, J.B. A novel binary ant colony optimization: Application to the unit commitment problem of power systems. *J. Electr. Eng. Technol.* **2011**, *6*, 174–181. [CrossRef]
92. Yuan-Kang, W.; Chih-Cheng, H.; Chun-Liang, L. Resolution of the unit commitment problems by using the hybrid Taguchi-ant colony system algorithm. *Int. J. Electr. Power Energy Syst.* **2013**, *49*, 188–198. [CrossRef]
93. Walters, D.C.; Sheble, G.B. Genetic algorithm solution of economic dispatch with valve point loading. *IEEE Trans. Power Syst.* **1993**, *8*, 1325–1332. [CrossRef]
94. Bakirtzis, A.; Petridis, V.; Kazarlis, S. Genetic algorithm solution to the economic dispatch problem. *IEE Proc. Gener. Transm. Distrib.* **1994**, *141*, 377–382. [CrossRef]
95. Abbas, G.; Gu, J.; Farooq, U.; Raza, A.; Asad, M.U.; El-Hawary, M.E. Solution of an Economic Dispatch Problem Through Particle Swarm Optimization: A Detailed Survey—Part II. *IEEE Access* **2017**, *5*, 24426–24445. [CrossRef]
96. Duvvuru, N.; Swarup, K.S. A hybrid interior point assisted differential evolution algorithm for economic dispatch. *IEEE Trans. Power Syst.* **2011**, *26*, 541–549. [CrossRef]
97. Ferahtia, S.; Rezk, H.; Djeroui, A.; Houari, A.; Fathy, A.; Abdelkareem, M.A.; Olabi, A.G. Optimal heuristic economic management strategy for microgrids based PEM fuel cells. *Int. J. Hydrogen Energy* **2022**, *in press*. [CrossRef]
98. Ferahtia, S.; Rezk, H.; Abdelkareem, M.A.; Olabi, A.G. Optimal techno-economic energy management strategy for building's microgrids based bald eagle search optimization algorithm. *Appl. Energy* **2022**, *306*, 118069. [CrossRef]
99. Tang, Y.; Dvijotham, K.; Low, S. Real-Time Optimal Power Flow. *IEEE Trans. Smart Grid* **2017**, *8*, 2963–2973. [CrossRef]
100. Momoh, J.A.; Zhu, J.Z. Improved interior point method for off problems. *IEEE Trans. Power Syst.* **1999**, *14*, 1114–1120. [CrossRef]
101. NIU, M.; WAN, C.; XU, Z. A review on applications of heuristic optimization algorithms for optimal power flow in modern power systems. *J. Mod. Power Syst. Clean Energy* **2014**, *2*, 289–297. [CrossRef]
102. Carvalho, L.M.; Loureiro, F.; Sumaili, J.; Keko, H.; Miranda, V.; Marcelino, C.G.; Wanner, E.F. Statistical tuning of DEEPSO soft constraints in the Security Constrained Optimal Power Flow problem. In Proceedings of the 2015 18th International Conference on Intelligent System Application to Power Systems (ISAP), Porto, Portugal, 11–16 September 2015; pp. 1–7.
103. Ghazi, G.A.; Hasanien, H.M.; Al-Ammar, E.A.; Turky, R.A.; Ko, W.; Park, S.; Choi, H.J. African Vulture Optimization Algorithm-Based PI Controllers for Performance Enhancement of Hybrid Renewable-Energy Systems. *Sustainibility* **2022**, *14*, 8172. [CrossRef]

104. Carpaneto, E.; Chicco, G. Distribution system minimum loss reconfiguration in the Hyper-Cube Ant Colony Optimization framework. *Electr. Power Syst. Res.* **2008**, *78*, 2037–2045. [CrossRef]
105. Carreno, E.M.; Romero, R.; Padilha-Feltrin, A. An efficient codification to solve distribution network reconfiguration for loss reduction problem. *IEEE Trans. Power Syst.* **2008**, *23*, 1542–1551. [CrossRef]
106. Wang, C.; Cheng, H.Z. Optimization of Network Configuration in Large Distribution Systems Using Plant Growth Simulation Algorithm. *IEEE Trans. Power Syst.* **2008**, *23*, 119–126. [CrossRef]
107. Sathish Kumar, K.; Jayabarathi, T. Power system reconfiguration and loss minimization for an distribution systems using bacterial foraging optimization algorithm. *Int. J. Electr. Power Energy Syst.* **2012**, *36*, 13–17. [CrossRef]
108. Lotfipour, A.; Afrakhte, H. A discrete Teaching–Learning-Based Optimization algorithm to solve distribution system reconfiguration in presence of distributed generation. *Int. J. Electr. Power Energy Syst.* **2016**, *82*, 264–273. [CrossRef]
109. Gideon Ude, N.; Yskandar, H.; Coneth Graham, R. A comprehensive state-of-the-art survey on the transmission network expansion planning optimization algorithms. *IEEE Access* **2019**, *7*, 123158–123181. [CrossRef]
110. Da Silva, E.L.; Gil, H.A.; Areiza, J.M. Transmission network expansion planning under an improved genetic algorithm. *IEEE Trans. Power Syst.* **2000**, *15*, 1168–1174. [CrossRef]
111. Limsakul, P.; Pothiya, S.; Leeprechanon, N. Application of ant colony optimization to transmission network expansion planning with security constraint. In Proceedings of the 8th International Conference on Advances in Power System Control, Operation and Management (APSCOM 2009), Hong Kong, China, 8–11 November 2009; p. 50.
112. Jin, Y.-X.; Cheng, H.-Z.; Yan, J.; Zhang, L. New discrete method for particle swarm optimization and its application in transmission network expansion planning. *Electr. Power Syst. Res.* **2007**, *77*, 227–233. [CrossRef]
113. Rastgou, A.; Moshtagh, J. Improved harmony search algorithm for transmission expansion planning with adequacy–security considerations in the deregulated power system. *Int. J. Electr. Power Energy Syst.* **2014**, *60*, 153–164. [CrossRef]
114. Wang, Q.; Zhang, L.Z.; Shu, J.; Wang, N. Application of improved shuffled frog leaping algorithm based on threshold selection strategy in transmission network planning. *Power Syst. Prot. Control.* **2011**, *39*, 34–39.
115. Shaheen, A.M.; El-Sehiemy, R.A. Application of multi-verse optimizer for transmission network expansion planning in power systems. In Proceedings of the 2019 International Conference on Innovative Trends in Computer Engineering (ITCE), Aswan, Egypt, 2–4 February 2019; pp. 371–376.
116. Fletcher, R.H.; Strunz, K. Optimal distribution system horizon planning—part I: Formulation. *IEEE Trans. Power Syst.* **2007**, *22*, 791–799. [CrossRef]
117. Vahidinasab, V.; Tabarzadi, M.; Arasteh, H.; Alizadeh, M.I.; Mohammad Beigi, M.; Sheikhzadeh, H.R.; Mehran, K.; Sepasian, M.S. Overview of Electric Energy Distribution Networks Expansion Planning. *IEEE Access* **2020**, *8*, 34750–34769. [CrossRef]
118. Suresh, K.; Lawrence, L. Power Distribution Planning: A Review of Models and Issues. *IEEE Trans. Power Syst.* **1997**, *12*, 9.
119. Yousefpour, K.; Javad, S.; Molla, H.; Hosseini, S.M. A Dynamic Approach for Distribution System Planning Using Particle Swarm Optimization. *Int. J. Control Sci. Eng.* **2015**, *5*, 10–17. [CrossRef]
120. Hippert, H.S.; Pedreira, C.E.; Souza, R.C. Neural networks for short-term load forecasting: A review and evaluation. *IEEE Trans. Power Syst.* **2001**, *16*, 44–55. [CrossRef]
121. Mamun, A.A.; Sohel, M.; Mohammad, N.; Haque Sunny, M.S.; Dipta, D.R.; Hossain, E. A Comprehensive Review of the Load Forecasting Techniques Using Single and Hybrid Predictive Models. *IEEE Access* **2020**, *8*, 134911–134939. [CrossRef]
122. Akhter, M.N.; Mekhilef, S.; Mokhlis, H.; Shah, N.M. Review on forecasting of photovoltaic power generation based on machine learning and metaheuristic techniques. *IET Renew. Power Gener.* **2019**, *13*, 1009–1023. [CrossRef]
123. Li, S.; Goel, L.; Wang, P. An ensemble approach for short-term load forecasting by extreme learning machine. *Appl. Energy* **2016**, *170*, 22–29. [CrossRef]
124. Froger, A.; Gendreau, M.; Mendoza, J.E.; Pinson, É.; Rousseau, L.M. Maintenance scheduling in the electricity industry: A literature review. *Eur. J. Oper. Res.* **2016**, *251*, 695–706. [CrossRef]
125. Kim, H.; Hayashi, Y.; Nara, K. An algorithm for thermal unit maintenance scheduling through combined use of ga sa and ts. *IEEE Trans. Power Syst.* **1997**, *12*, 329–335. [CrossRef]
126. Kumari, B.; Aggarwal, M. A Comprehensive Review of Traditional and Smart MPPT Techniques in PMSG based Wind Energy Conversion System. In Proceedings of the 2019 International Conference on Power Electronics, Control and Automation (ICPECA), New Delhi, India, 16–17 November 2019. [CrossRef]
127. Rezk, H.; Fathy, A.; Abdelaziz, A.Y. A comparison of different global MPPT techniques based on meta-heuristic algorithms for photovoltaic system subjected to partial shading conditions. *Renew. Sustain. Energy Rev.* **2017**, *74*, 377–386. [CrossRef]
128. Sundareswaran, K.; Sankar, P.; Nayak, P.S.R.; Simon, S.P.; Palani, S. Enhanced Energy Output From a PV System Under Partial Shaded Conditions Through Artificial Bee Colony. *IEEE Trans. Sustain. Energy* **2015**, *6*, 198–209. [CrossRef]
129. Kumar, C.S.; Rao, R.S. A Novel Global MPP Tracking of Photovoltaic System based on Whale Optimization Algorithm. *Int. J. Renew. Energy Dev.* **2016**, *5*, 225–232. [CrossRef]
130. Mohanty, S.; Subudhi, B.; Ray, P.K. A New MPPT Design Using Grey Wolf Optimization Technique for Photovoltaic System Under Partial Shading Conditions. *IEEE Trans. Sustain. Energy* **2016**, *7*, 181–188. [CrossRef]
131. Titri, S.; Larbes, C.; Toumi, K.Y.; Benatchba, K. A new MPPT controller based on the Ant colony optimization algorithm for Photovoltaic systems under partial shading conditions. *Appl. Soft Comput.* **2017**, *58*, 465–479. [CrossRef]

132. Teshome, D.F.; Lee, C.H.; Lin, Y.W.; Lian, K.L. A modified firefly algorithm for photovoltaic maximum power point tracking control under partial shading. *IEEE J. Emerg. Sel. Top. Power Electron.* **2017**, *5*, 661–671. [CrossRef]
133. Li, H.; Yang, D.; Su, W.; Lu, J.; Yu, X. An Overall Distribution Particle Swarm Optimization MPPT Algorithm for Photovoltaic System Under Partial Shading. *IEEE Trans. Ind. Electron.* **2019**, *66*, 265–275. [CrossRef]
134. Mirza, A.F.; Ling, Q.; Javed, M.Y.; Mansoor, M. Novel MPPT techniques for photovoltaic systems under uniform irradiance and Partial shading. *Sol. Energy* **2019**, *184*, 628–648. [CrossRef]
135. Shi, J.Y.; Zhang, D.Y.; Xue, F.; Li, Y.J.; Qiao, W.; Yang, W.J.; Xu, Y.M.; Yan, T. Moth-flame optimization-based maximum power point tracking for photovoltaic systems under partial shading conditions. *J. Power Electron.* **2019**, *19*, 1248–1258. [CrossRef]
136. Eltamaly, A.M. An Improved Cuckoo Search Algorithm for Maximum Power Point Tracking of Photovoltaic Systems under Partial Shading Conditions. *Energies* **2021**, *14*, 953. [CrossRef]
137. Mirza, A.F.; Mansoor, M.; Ling, Q.; Yin, B.; Javed, M.Y. A Salp-Swarm Optimization based MPPT technique for harvesting maximum energy from PV systems under partial shading conditions. *Energy Convers. Manag.* **2020**, *209*, 112625. [CrossRef]
138. Yang, B.; Yu, T.; Shu, H.; Zhang, X.; Qu, K.; Jiang, L. Democratic joint operations algorithm for optimal power extraction of PMSG based wind energy conversion system. *Energy Convers. Manag.* **2018**, *159*, 312–326. [CrossRef]
139. Mokhtari, Y.; Rekioua, D. High performance of Maximum Power Point Tracking Using Ant Colony algorithm in wind turbine. *Renew. Energy* **2018**, *126*, 1055–1063. [CrossRef]
140. Qais, M.H.; Hasanien, H.M.; Alghuwainem, S. A Grey Wolf Optimizer for Optimum Parameters of Multiple PI Controllers of a Grid-Connected PMSG Driven by Variable Speed Wind Turbine. *IEEE Access* **2018**, *6*, 44120–44128. [CrossRef]
141. Fathy, A.; El-baksawi, O. Grasshopper optimization algorithm for extracting maximum power from wind turbine installed in Al-Jouf region. *J. Renew. Sustain. Energy* **2019**, *11*, 033303. [CrossRef]
142. Maroufi, O.; Choucha, A.; Chaib, L. Hybrid fractional fuzzy PID design for MPPT-pitch control of wind turbine-based bat algorithm. *Electr. Eng.* **2020**, *102*, 2149–2160. [CrossRef]
143. Qais, M.H.; Hasanien, H.M.; Alghuwainem, S. Enhanced whale optimization algorithm for maximum power point tracking of variable-speed wind generators. *Appl. Soft Comput.* **2020**, *86*, 105937. [CrossRef]
144. Qais, M.; Hasanien, H.M.; Alghuwainem, S. Salp swarm algorithm-based TS-FLCs for MPPT and fault ride-through capability enhancement of wind generators. *ISA Trans.* **2020**, *101*, 211–224. [CrossRef]
145. Anh Nguyen, T.N.; Pham, D.C.; Chan Thanh, N.H.; Nguyen, A.N. Implementation of Equilibrium Optimizer Algorithm for MPPT in a wind turbine with PMSG. *WSEAS Trans. Syst. Control* **2021**, *16*, 216–223. [CrossRef]
146. Hannachi, M.; Elbeji, O.; Benhamed, M.; Sbita, L. Optimal torque maximum power point technique for wind turbine: Proportional–integral controller tuning based on particle swarm optimization. *Wind Eng.* **2021**, *45*, 337–350. [CrossRef]
147. Rajesh, P.; Shajin, F.H.; Cherukupalli, K. An efficient hybrid tunicate swarm algorithm and radial basis function searching technique for maximum power point tracking in wind energy conversion system. *J. Eng. Des. Technol.* **2021**. *ahead-of-print*. [CrossRef]
148. Zhu, J.; Dewi Darma, M.S.; Knapp, M.; Sørensen, D.R.; Heere, M.; Fang, Q.; Wang, X.; Dai, H.; Mereacre, L.; Senyshyn, A.; et al. Investigation of lithium-ion battery degradation mechanisms by combining differential voltage analysis and alternating current impedance. *J. Power Sources* **2020**, *448*, 227575. [CrossRef]
149. Tang, A.; Yang, Y.; Yu, Q.; Zhang, Z.; Yang, L. A Review of Life Prediction Methods for PEMFCs in Electric Vehicles. *Sustainability* **2022**, *14*, 9842. [CrossRef]
150. Schnatmann, A.K.; Schoden, F.; Schwenzfeier-Hellkamp, E. Sustainable PV Module Design—Review of State-of-the-Art Encapsulation Methods. *Sustainability* **2022**, *14*, 9971. [CrossRef]
151. Forman, J.C.; Moura, S.J.; Stein, J.L.; Fathy, H.K. Genetic identification and fisher identifiability analysis of the Doyle-Fuller-Newman model from experimental cycling of a LiFePO 4 cell. *J. Power Sources* **2012**, *210*, 263–275. [CrossRef]
152. Sangwan, V.; Sharma, A.; Kumar, R.; Rathore, A.K. Estimation of battery parameters of the equivalent circuit models using meta-heuristic techniques. In Proceedings of the 2016 IEEE 1st International Conference on Power Electronics, Intelligent Control and Energy Systems (ICPEICES), Delhi, India, 4–6 July 2017. [CrossRef]
153. Rahman, M.A.; Anwar, S.; Izadian, A. Electrochemical model parameter identification of a lithium-ion battery using particle swarm optimization method. *J. Power Sources* **2016**, *307*, 86–97. [CrossRef]
154. Lai, X.; Gao, W.; Zheng, Y.; Ouyang, M.; Li, J.; Han, X.; Zhou, L. A comparative study of global optimization methods for parameter identification of different equivalent circuit models for Li-ion batteries. *Electrochim. Acta* **2019**, *295*, 1057–1066. [CrossRef]
155. Chun, H.; Kim, M.; Kim, J.; Kim, K.; Yu, J.; Kim, T.; Han, S. Adaptive Exploration Harmony Search for Effective Parameter Estimation in an Electrochemical Lithium-Ion Battery Model. *IEEE Access* **2019**, *7*, 131501–131511. [CrossRef]
156. Zhou, S.; Liu, X.; Hua, Y.; Zhou, X.; Yang, S. Adaptive model parameter identification for lithium-ion batteries based on improved coupling hybrid adaptive particle swarm optimization- simulated annealing method. *J. Power Sources* **2021**, *482*, 228951. [CrossRef]
157. Jusoh, M.A.; Daud, M.Z. Accurate battery model parameter identification using heuristic optimization. *Int. J. Power Electron. Drive Syst.* **2020**, *11*, 333–341. [CrossRef]
158. Lorestani, A.; Chebeir, J.; Ahmed, R.; Cotton, J.S. A new optimization algorithm for parameters identification of electric vehicles' battery. In Proceedings of the 2020 IEEE Power & Energy Society General Meeting (PESGM), Montreal, QC, Canada, 2–6 August 2020. [CrossRef]

159. Ferahtia, S.; Djeroui, A.; Rezk, H.; Chouder, A.; Houari, A.; Machmoum, M. Optimal parameter identification strategy applied to lithium-ion battery model. *Int. J. Energy Res.* **2021**, *45*, 16741–16753. [CrossRef]
160. Ferahtia, S.; Djeroui, A.; Rezk, H.; Chouder, A.; Houari, A.; Machmoum, M. Adaptive Droop based Control Strategy for DC Microgrid Including Multiple Batteries Energy Storage Systems. *J. Energy Storage* **2022**, *48*, 103983. [CrossRef]
161. Kim, J.; Chun, H.; Baek, J.; Han, S. Parameter identification of lithium-ion battery pseudo-2-dimensional models using genetic algorithm and neural network cooperative optimization. *J. Energy Storage* **2022**, *45*, 103571. [CrossRef]
162. Houssein, E.H.; Hashim, F.A.; Ferahtia, S.; Rezk, H. Battery parameter identification strategy based on modified coot optimization algorithm. *J. Energy Storage* **2022**, *46*, 103848. [CrossRef]
163. Fathy, A.; Ferahtia, S.; Rezk, H.; Yousri, D.; Abdelkareem, M.A.; Olabi, A.G. Robust parameter estimation approach of Lithium-ion batteries employing bald eagle search algorithm. *Int. J. Energy Res.* **2022**, *46*, 10564–10575. [CrossRef]
164. Ferahtia, S.; Rezk, H.; Djerioui, A.; Houari, A.; Motahhir, S.; Zeghlache, S. Modified bald eagle search algorithm for lithium-ion battery model parameters extraction. *ISA Trans.* **2022**, *in press*. [CrossRef]
165. Pan, T.-C.; Liu, E.-J.; Ku, H.-C.; Hong, C.-W. Parameter identification and sensitivity analysis of lithium-ion battery via whale optimization algorithm. *Electrochim. Acta* **2022**, *404*, 139574. [CrossRef]
166. Cheng, Y.S. Identification of Parameters for Equivalent Circuit Model of Li-Ion Battery Cell with Population Based Optimization Algorithms. *SSRN Electron. J.* **2022**. [CrossRef]
167. Rizk-Allah, R.M.; Zineldin, M.I.; Mousa, A.A.A.; Abdel-Khalek, S.; Mohamed, M.S.; Snášel, V. On a Novel Hybrid Manta Ray Foraging Optimizer and Its Application on Parameters Estimation of Lithium-Ion Battery. *Int. J. Comput. Intell. Syst.* **2022**, *15*, 62. [CrossRef]
168. Askarzadeh, A.; Rezazadeh, A. Optimization of PEMFC model parameters with a modified particle swarm optimization. *Int. J. Energy Res.* **2011**, *35*, 1258–1265. [CrossRef]
169. Sun, Z.; Wang, N.; Bi, Y.; Srinivasan, D. Parameter identification of PEMFC model based on hybrid adaptive differential evolution algorithm. *Energy* **2015**, *90*, 1334–1341. [CrossRef]
170. Ali, M.; El-Hameed, M.A.; Farahat, M.A. Effective parameters' identification for polymer electrolyte membrane fuel cell models using grey wolf optimizer. *Renew. Energy* **2017**, *111*, 455–462. [CrossRef]
171. El-Fergany, A.A. Extracting optimal parameters of PEM fuel cells using Salp Swarm Optimizer. *Renew. Energy* **2018**, *119*, 641–648. [CrossRef]
172. Fathy, A.; Rezk, H. Multi-verse optimizer for identifying the optimal parameters of PEMFC model. *Energy* **2018**, *143*, 634–644. [CrossRef]
173. Zhang, G.; Xiao, C.; Razmjooy, N. Optimal parameter extraction of PEM fuel cells by meta-heuristics. *Int. J. Ambient Energy* **2022**, *43*, 2510–2519. [CrossRef]
174. Diab, A.A.Z.; Tolba, M.A.; El-Magd, A.G.A.; Zaky, M.M.; El-Rifaie, A.M. Fuel Cell Parameters Estimation via Marine Predators and Political Optimizers. *IEEE Access* **2020**, *8*, 166998–167018. [CrossRef]
175. Qin, F.; Liu, P.; Niu, H.; Song, H.; Yousefi, N. Parameter estimation of PEMFC based on Improved Fluid Search Optimization Algorithm. *Energy Rep.* **2020**, *6*, 1224–1232. [CrossRef]
176. Menesy, A.S.; Sultan, H.M.; Korashy, A.; Banakhr, F.A.; Ashmawy, M.G.; Kamel, S. Effective Parameter Extraction of Different Polymer Electrolyte Membrane Fuel Cell Stack Models Using a Modified Artificial Ecosystem Optimization Algorithm. *IEEE Access* **2020**, *8*, 31892–31909. [CrossRef]
177. Cao, Y.; Li, Y.; Zhang, G.; Jermsittiparsert, K.; Nasseri, M. An efficient terminal voltage control for PEMFC based on an improved version of whale optimization algorithm. *Energy Rep.* **2020**, *6*, 530–542. [CrossRef]
178. Houssein, E.H.; Helmy, B.E.; Rezk, H.; Nassef, A.M. An enhanced Archimedes optimization algorithm based on Local escaping operator and Orthogonal learning for PEM fuel cell parameter identification. *Eng. Appl. Artif. Intell.* **2021**, *103*, 104309. [CrossRef]
179. Fathy, A.; Abdel Aleem, S.H.E.; Rezk, H. A novel approach for PEM fuel cell parameter estimation using LSHADE-EpSin optimization algorithm. *Int. J. Energy Res.* **2021**, *45*, 6922–6942. [CrossRef]
180. Zhu, Y.; Yousefi, N. Optimal parameter identification of PEMFC stacks using Adaptive Sparrow Search Algorithm. *Int. J. Hydrogen Energy* **2021**, *46*, 9541–9552. [CrossRef]
181. Houssein, E.H.; Hashim, F.A.; Ferahtia, S.; Rezk, H. An efficient modified artificial electric field algorithm for solving optimization problems and parameter estimation of fuel cell. *Int. J. Energy Res.* **2021**, *45*, 20199–20218. [CrossRef]
182. Rezk, H.; Ferahtia, S.; Djeroui, A.; Chouder, A.; Houari, A.; Machmoum, M.; Abdelkareem, M.A. Optimal parameter estimation strategy of PEM fuel cell using gradient-based optimizer. *Energy* **2022**, *239*, 122096. [CrossRef]
183. Wilberforce, T.; Rezk, H.; Olabi, A.G.; Epelle, E.I.; Abdelkareem, M.A. Comparative analysis on parametric estimation of a PEM fuel cell using metaheuristics algorithms. *Energy* **2023**, *262*, 125530. [CrossRef]
184. Rezk, H.; Olabi, A.G.; Ferahtia, S.; Sayed, E.T. Accurate parameter estimation methodology applied to model proton exchange membrane fuel cell. *Energy* **2022**, *255*, 124454. [CrossRef]
185. Qing, Z.; Hongda, L.; Cheng, D. Fireworks Explosion Optimization algorithm for parameter identification of PV model. In Proceedings of the 2016 IEEE 8th International Power Electronics and Motion Control Conference (IPEMC-ECCE Asia), Hefei, China, 22–26 May 2016; pp. 1587–1591.
186. Wu, Z.; Xie, Z.; Liu, C. An improved lion swarm optimization for parameters identification of photovoltaic cell models. *Trans. Inst. Meas. Control* **2020**, *42*, 1191–1203. [CrossRef]

187. Ebrahimi, S.M.; Salahshour, E.; Malekzadeh, M. Francisco Gordillo Parameters identification of PV solar cells and modules using flexible particle swarm optimization algorithm. *Energy* **2019**, *179*, 358–372. [CrossRef]
188. Chen, H.; Jiao, S.; Wang, M.; Heidari, A.A.; Zhao, X. Parameters identification of photovoltaic cells and modules using diversification-enriched Harris hawks optimization with chaotic drifts. *J. Clean. Prod.* **2020**, *244*, 118778. [CrossRef]
189. Zhang, H.; Heidari, A.A.; Wang, M.; Zhang, L.; Chen, H.; Li, C. Orthogonal Nelder-Mead moth flame method for parameters identification of photovoltaic modules. *Energy Convers. Manag.* **2020**, *211*, 112764. [CrossRef]
190. Ahmadianfar, I.; Gong, W.; Heidari, A.A.; Golilarz, N.A.; Samadi-Koucheksaraee, A.; Chen, H. Gradient-based optimization with ranking mechanisms for parameter identification of photovoltaic systems. *Energy Rep.* **2021**, *7*, 3979–3997. [CrossRef]
191. Yousri, D.; Rezk, H.; Fathy, A. Identifying the parameters of different configurations of photovoltaic models based on recent artificial ecosystem-based optimization approach. *Int. J. Energy Res.* **2020**, *44*, 11302–11322. [CrossRef]
192. Ye, X.; Liu, W.; Li, H.; Wang, M.; Chi, C.; Liang, G.; Chen, H.; Huang, H. Modified Whale Optimization Algorithm for Solar Cell and PV Module Parameter Identification. *Complexity* **2021**, *2021*, 8878686. [CrossRef]
193. Sun, L.; Wang, J.; Tang, L. A Powerful Bio-Inspired Optimization Algorithm Based PV Cells Diode Models Parameter Estimation. *Front. Energy Res.* **2021**, *9*, 675925. [CrossRef]
194. Abdel-Basset, M.; Mohamed, R.; Chakrabortty, R.K.; Sallam, K.; Ryan, M.J. An efficient teaching-learning-based optimization algorithm for parameters identification of photovoltaic models: Analysis and validations. *Energy Convers. Manag.* **2021**, *227*, 113614. [CrossRef]
195. Naeijian, M.; Rahimnejad, A.; Ebrahimi, S.M.; Pourmousa, N.; Gadsden, S.A. Parameter estimation of PV solar cells and modules using Whippy Harris Hawks Optimization Algorithm. *Energy Rep.* **2021**, *7*, 4047–4063. [CrossRef]
196. Lei, W.; He, Q.; Yang, L.; Jiao, H. Solar Photovoltaic Cell Parameter Identification Based on Improved Honey Badger Algorithm. *Sustainability* **2022**, *14*, 8897. [CrossRef]
197. El-Dabah, M.A.; El-Sehiemy, R.A.; Hasanien, H.M.; Saad, B. Photovoltaic model parameters identification using Northern Goshawk Optimization algorithm. *Energy* **2023**, *262*, 125522. [CrossRef]
198. Beşkirli, A.; Dağ, İ. Parameter extraction for photovoltaic models with tree seed algorithm. *Energy Rep.* **2023**, *9*, 174–185. [CrossRef]
199. Selcuk, A.A. A Guide for Systematic Reviews: PRISMA. *Turkish Arch. Otorhinolaryngol.* **2019**, *57*, 57–58. [CrossRef]
200. Pasha, J.; Nwodu, A.L.; Fathollahi-Fard, A.M.; Tian, G.; Li, Z.; Wang, H.; Dulebenets, M.A. Exact and metaheuristic algorithms for the vehicle routing problem with a factory-in-a-box in multi-objective settings. *Adv. Eng. Inform.* **2022**, *52*, 101623. [CrossRef]
201. Rabbani, M.; Oladzad-Abbasabady, N.; Akbarian-Saravi, N. Ambulance Routing in Disaster Response Considering Variable Patient Condition: Nsga-Ii and Mopso Algorithms. *J. Ind. Manag. Optim.* **2022**, *18*, 1035–1062. [CrossRef]
202. Dulebenets, M.A. An Adaptive Polyploid Memetic Algorithm for scheduling trucks at a cross-docking terminal. *Inf. Sci.* **2021**, *565*, 390–421. [CrossRef]
203. Zhao, H.; Zhang, C. An online-learning-based evolutionary many-objective algorithm. *Inf. Sci.* **2020**, *509*, 1–21. [CrossRef]