sustainability

MDPI

Review

Review of Metaheuristic Optimization Algorithms for Power Systems Problems

Ahmed M. Nassef [1,2,*], Mohammad Ali Abdelkareem [3], Hussein M. Maghrabie [4] and Ahmad Baroutaji [5]

[1] Department of Electrical Engineering, College of Engineering in Wadi Alddawasir, Prince Sattam Bin Abdulaziz University, Wadi Alddawasir 11991, Saudi Arabia
[2] Computers and Automatic Control Engineering Department, Faculty of Engineering, Tanta University, Tanta 31733, Egypt
[3] Department of Sustainable and Renewable Energy Engineering, University of Sharjah, Sharjah P.O. Box 27272, United Arab Emirates; mabdulkareem@sharjah.ac.ae
[4] Faculty of Engineering, South Valley University, Qena 83523, Egypt; hussein_mag@eng.svu.edu.eg
[5] School of Engineering and Applied Science, Aston University, Aston Triangle, Birmingham B4 7ET, UK; a.baroutaji@aston.ac.uk
* Correspondence: a.nasef@psau.edu.sa

Abstract: Metaheuristic optimization algorithms are tools based on mathematical concepts that are used to solve complicated optimization issues. These algorithms are intended to locate or develop a sufficiently good solution to an optimization issue, particularly when information is sparse or inaccurate or computer capability is restricted. Power systems play a crucial role in promoting environmental sustainability by reducing greenhouse gas emissions and supporting renewable energy sources. Using metaheuristics to optimize the performance of modern power systems is an attractive topic. This research paper investigates the applicability of several metaheuristic optimization algorithms to power system challenges. Firstly, this paper reviews the fundamental concepts of metaheuristic optimization algorithms. Then, six problems regarding the power systems are presented and discussed. These problems are optimizing the power flow in transmission and distribution networks, optimizing the reactive power dispatching, optimizing the combined economic and emission dispatching, optimal Volt/Var controlling in the distribution power systems, and optimizing the size and placement of DGs. A list of several used metaheuristic optimization algorithms is presented and discussed. The relevant results approved the ability of the metaheuristic optimization algorithm to solve the power system problems effectively. This, in particular, explains their wide deployment in this field.

Keywords: metaheuristic; optimization; power systems; transmission networks; power dispatching; emission dispatching; distribution power network; distributed generations (DGs)

Citation: Nassef, A.M.; Abdelkareem, M.A.; Maghrabie, H.M.; Baroutaji, A. Review of Metaheuristic Optimization Algorithms for Power Systems Problems. *Sustainability* **2023**, *15*, 9434. https://doi.org/10.3390/su15129434

Academic Editors: Shuhua Fang and Yagang Zhang

Received: 11 May 2023
Revised: 30 May 2023
Accepted: 9 June 2023
Published: 12 June 2023

1. Introduction

Optimization is a mathematical and computer science discipline that explores strategies and approaches for finding the perfect solution to the considered optimization issue. Solving such problems involves minimizing or maximizing one or multiple objective functions using the dependent optimization variables, which can be integers or real values [1]. Engineering, economics, logistics, medicine, and other disciplines can use optimization algorithms for decision-making. Traditional (or exact) optimization methods, including linear programming (LP) [2], nonlinear programming (NLP) [3], and dynamic programming (DP) [4], have been established to address multiple optimization issues. These algorithms have several advantages, such as being time efficient and ensuring convergence to local optima. Nevertheless, these optimization methods suffer from significant problems, such as escaping from local solutions, divergence probability, complex handling constraints, or computational challenges in computing first or second-order derivatives [5]. Metaheuristic algorithms can solve optimization problems with a lower possibility of falling into the previously mentioned problems [6]. In contrast to traditional algorithms, metaheuristic algorithms are often based on empirically inspired theoretical foundations. They can be inspired by natural phenomena or the behavior of living beings. They are flexible algorithms that can be adjusted, combined, or modified to fit the intended problem, such as combining three algorithms to resolve the power system stability [7]. These algorithms stochastically explore high-dimensional search spaces, offering robustness and global search capacity benefits. However, their stochastic behavior cannot guarantee a successful optimal solution selection [8]. These algorithms have been used for multiple fields, such as medicine [9], industry [10], and chemical applications [11,12].

Enhancing the power system performance is one of the sustainable development objectives. For this reason, power systems are quickly evolving with the large-scale adoption of renewable energy sources (RESs) and the extensive incorporation of modern ICT technologies [13]. The integration of smart grid technologies into power systems also promotes environmental sustainability by enabling more efficient use of electricity through demand response programs that encourage consumers to shift their usage during peak hours when electricity is expensive or generated from non-renewable resources. This advancement, however, may entail increased difficulties in system operation and control [14]. To tackle diverse power optimization issues, effective optimization techniques are required. On the other hand, optimizing a power system, including various constraints to achieve a specified degree of performance, has to be considered in the problem formulation. In this procedure, each constraint helps the optimizer be more efficient when handling the system behavior. Physical characteristics and the available information for each system component determine the system elements. The constraints might be based on the capacity, accessibility, and cost of the components. These constraints ensure system reliability. Optimization algorithms are required to enhance the performance of the power system against the uncertainties in the generation and demand while meeting all system constraints [15]. Power network issues cannot be efficiently solved by deterministic control and management systems due to a number of issues, including the uncertainties brought forth by irregular renewable generators and fluctuating electricity demand [16]. Using machine learning theories to enhance deterministic algorithms can provide better performance [17,18]. However, this will increase the complexity. Metaheuristic algorithms can be employed to solve multiple problems in the field of power systems. Furthermore, adopting these algorithms to solve power systems issues is becoming increasingly appealing due to power engineers' vast diversity and complexity of difficulties [19]. A comprehensive review of the application of metaheuristic optimization algorithms to enhance the parameter identification of several power systems has been reported in [20]. This paper focused on the deployment of the metaheuristics on the extraction of the parameters of the PV systems, the Li-ion batteries, and the PEM fuel cells. A comprehensive review of the role of metaheuristics in optimizing microgrid operation and management problems is presented [21].

The proposed paper has many common points with the other articles that talk about metaheuristic optimization algorithms and their applications in electrical engineering. As mentioned previously, enhancing the power system performance is crucial. For this reason, we have focused in this paper on deploying metaheuristic optimization algorithms to optimize power system performance. So, this study provides a comprehensive review of several electrical engineering problems. Then, this study provides an overview of the most common metaheuristic algorithms for resolving these optimization issues in the power systems field. We have cited and discussed some papers that present the employment of metaheuristic optimization algorithms to solve these problems. This paper is organized as illustrated in Figure 1. The paper starts with an introduction that presents the paper's context, its objectives, and the research gap. Then, the metaheuristic optimization algorithms are explained in Section 2, including a global presentation of these algorithms, their fundamental properties, and classification. The main problems of the power systems are presented and discussed in Section 3. A set of papers that use metaheuristic optimization algorithms for solving these problems are also presented. Then, this paper ends with a conclusion that summarizes the whole paper.

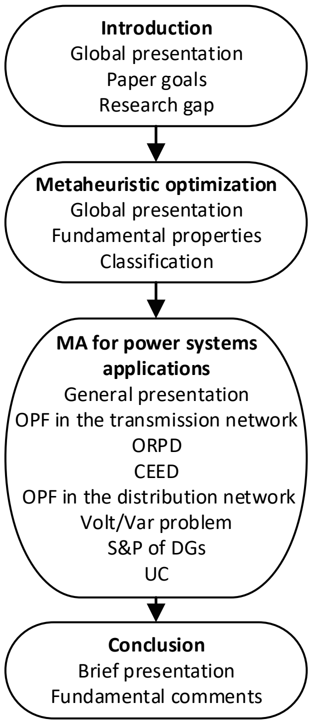

Figure 1. Paper organization.

2. Metaheuristic Optimization

2.1. Overview

The optimization process may be presented as the process of determining the best method to use existing resources while not breaking any restrictions that may exist. This strategy consists of multiple steps: mathematically defining a system model that reproduces its behavior, determining its variables and constraints, establishing the objective function, and, finally, seeking the states that produce the most desirable results by maximizing or minimizing the objective function. The optimization search strategy can be performed using any of its appropriate categories, such as quantum-based techniques, meta-heuristic-based approaches, and multi-objective-based techniques [22]. However, the main purpose of solving complicated optimization issues is to find a solution, regardless of how good it is. When at least a solution is found, numerous methods can be used to enhance it. This is the fundamental principle behind developing metaheuristic optimization algorithms.

Meta means upper level or beyond, while heuristic means to know, find, or direct an investigation, which is where the word heuristics originates. On the other hand, heuristics represents a collection of rules applied while addressing a problem based on experience [23]. Metaheuristics are approximate methods that combine basic heuristic principles to produce a more efficient exploration and exploitation of research space [24], where the search space is the space that includes all the possible solutions that are bounded by the physical system limitations. The dimensions of the search space depend on the number of optimization variables that represent the set of the required parameter. Voß et al. [25] define a metaheuristic as a repeated process that leads and modifies tasks while employing subordinate heuristics to facilitate obtaining optimal or near-optimal outcomes. The MA can function with single or many solutions using a minimization or maximizing approach at each iteration. Metaheuristic algorithms have been created to deal with the increasing complexities of the problem, particularly with the inclusion of uncertainties into the system, which may surpass the constraints of traditional algorithms.

Designing and implementing a new metaheuristic optimization algorithm takes time, but there are several pressing basic needs for them that motivate academics to develop a new algorithm [26]. Some new research papers have focused on integrating these algorithms with features of artificial intelligence (AI) to improve their performance [27–29]. Many academic papers, including [30,31], have described their fundamental properties and advantages as follows:

- The fundamental principles of these algorithms may be explained abstractly without reference to any specific situation, from simple local search techniques to complicated learning processes.
- Metaheuristic algorithms are ways of directing the search process to explore the search space efficiently. They often use updating coefficients that balance global and local search methods. These coefficients are initialized with large values, raising the global searching ability. At the end of the optimization process, this coefficient should be small to converge to the best solutions.
- Metaheuristic algorithms use domain-specific information in the form of heuristics regulated by a higher-level approach.
- The objective function in the metaheuristic algorithm formulation does not include the gradient or Hessian matrix. Therefore, they are no-deterministic algorithms, providing near-optimal solutions.
- These algorithms memorize the results of the previous searches and are used to guide the actual search process.
- These algorithms contain a number of parameters that must be adapted to the considered task, as well as techniques to prevent becoming stuck in local solutions in the search space. Considering the solved problem, these parameters are selected to provide better performance [32].

2.2. Basic Concepts

Each MOA has its own set of mechanics. Because numerous methods are available, a significant question arises: how much difference is there between one MOA and another? To answer the question, a collection of core concepts was proposed [33]. These concepts are presented in Table 1.

Table 1. List of the concepts of the metaheuristic optimization algorithms.

<table>
<tr><th>Concept</th><th colspan="2">Description</th></tr>
<tr><td>Parallelism (used for population-based algorithms)</td><td colspan="2">A number of individuals are assigned simultaneously to perform a single function, and the results are compared. This idea affects the evolution of individuals inside the population or produces new ones.</td></tr>
<tr><td rowspan="4">Acceptance</td><td colspan="2">Case 1: Accept interim solutions that weaken objective function as a result of the expansion of the search space.</td></tr>
<tr><td rowspan="2">Case 2: Management of the constraints of the objective function</td><td>Method 1: Any solution that includes any violation is rejected. When the initial conditions meet any conceivable solution, this procedure is used.</td></tr>
<tr><td>Method 2: In this case, all solutions are automatically accepted, and the initial conditions could correspond to inconceivable solutions. If any solution can be assigned a numerical value, this approach is used.</td></tr>
<tr><td colspan="2">Case 3: Adding constraints on approved solutions that improve the best solution by at least the restricting level. When comparing values produced from previous calculations, this strategy aids in avoiding numerical issues.</td></tr>
<tr><td>Elitism (for population-based algorithms)</td><td colspan="2">The elitism concept is used to uphold the best-found solutions and utilize them as a reference for the following iteration or update them if other best solutions are identified.</td></tr>
</table>

Table 1. *Cont.*

<table>
<tr><th>Concept</th><th colspan="2">Description</th></tr>
<tr><td>Selection</td><td colspan="2">A probability-based approach for producing new random solutions from existing ones.</td></tr>
<tr><td>Decay</td><td rowspan="2">Allows for more initial flexibility, followed by incremental flexibility constraints.</td><td>Each repetition includes a multiplicative factor of less than one.</td></tr>
<tr><td>Reinforcement</td><td>Each repetition includes a multiplicative factor greater than one.</td></tr>
<tr><td>Immunity</td><td colspan="2">Identifying characteristics of certain solutions that lead to appropriate setups. It promotes solutions with characteristics similar to those criteria.</td></tr>
<tr><td>Self-Adaptation</td><td colspan="2">A method that permits adjusting the algorithms' parameters based on the optimization progression.</td></tr>
<tr><td>Topology</td><td colspan="2">This concept is involved if the examined problem must be subjected to special limitations.</td></tr>
</table>

2.3. Classification

A metaheuristic algorithm should have exploration and exploitation capabilities allowing it to obtain the global optimum solution. Its principal characteristics are its ability to explore wide search spaces quickly, locate global solutions, and prevent falling into local optimums. Exploration is the capacity to extend the search space, whereas exploitation is the capacity to locate the optimal solution from the surrounding solutions. The principal distinctions between existing algorithms are their attempt to balance exploration and exploitation. Trajectory-based and population-based algorithms are the two main categories of metaheuristic optimization algorithms. The number of tentative solutions employed in each algorithmic step is the primary distinction between these two categories [30].

- Trajectory-based (single solution) algorithms, including tabu search (TS), hill climbing (HC), and simulated annealing (SA), start with a single solution and replace it with a better solution located nearby at each iteration.
- Population-based algorithms employ a group of possible solutions at the same task to address the same task. The population is randomly initialized, and an iterative method is used to improve it. After each iteration, a new generation is created based on the elitism strategy. The best-adapted individuals (representing the elite group) from the last generation are moved to the new generation. Meanwhile, the newly generated individuals have a relationship with this elite.

On the other hand, these algorithms can be classified according to the inspiration source of the following four categories

- Evolutionary algorithms are biological evolution-inspired algorithms, which include genetic recombination, mutation, and natural selection.
- Swarm-based algorithms use the collective behavior of multiple individuals. Each individual wants to engage with others to develop themselves based on the collective experience of the swarm.
- Physics-based algorithms are based on physical concepts, such as electromagnetism, momentum, and gravity.
- Human-based algorithms are algorithms based on human social acts.

The classification of these algorithms is presented in Figure 2. This figure illustrates the classification according to the number of solutions above the dashed red line and according to the inspiration source below it.

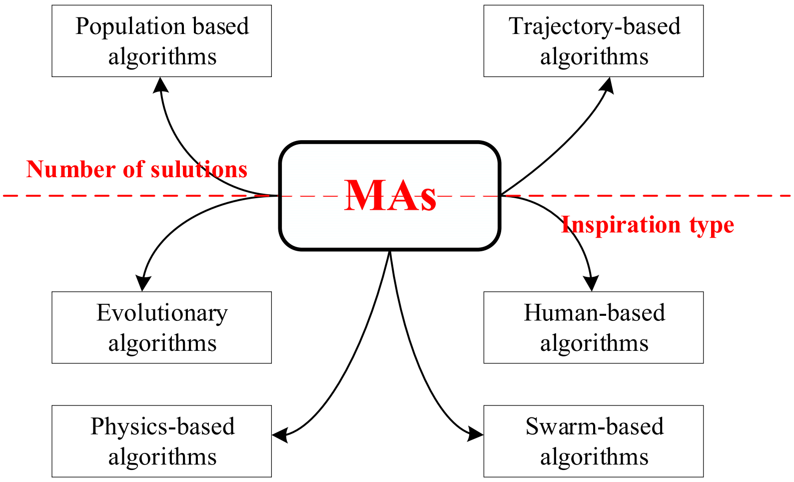

Figure 2. Metaheuristic optimization classifications.

2.4. Formulation

The optimization problem formulation can be expressed as a function of the primary objective function $F(x)$, the constraints function $g(x)$, and the modified objective function $h(x)$ as:

$$\begin{cases} F(x,y) \\ g(x,y) = 0 \\ h(x,y) \leq 0 \end{cases} \tag{1}$$

where x expresses the optimization variables, and y expresses the dependent variables.

3. Metaheuristic Algorithms for Power System Applications

A power system combines electronic parts that provide, transmit, and consume electricity, such as the electrical grid, which supplies electricity to individuals and businesses over a broad region. The electrical grid is divided into three parts: generator systems that generate electricity, transmission systems that carry power from producing centers to load centers, and distribution systems that distribute power to adjacent households and companies [34]. A typical power system is presented in Figure 3. The transmission system uses aerial electric transmission wires to connect generating stations to substations and load centers. The distribution system employs aerial or underground transmission wires and distributes electricity to a whole district [35].

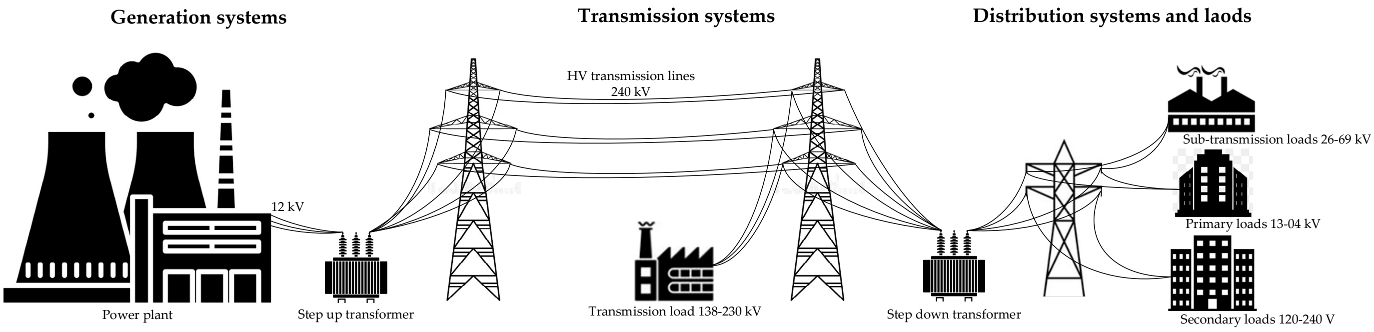

Figure 3. The studied power systems' problems.

Metaheuristic optimization algorithms can be used to solve a large number of optimization issues in the context of power systems. The most prevalent metaheuristic technique applications in power system optimization are briefly described here.

After specifying the studied problem, a model of the considered power system is required to evaluate the candidate solutions provided by the optimizer. Then, the objective function will be determined based on the desired goals. Its equality constraints are determined based on the system specifications. On the other hand, these constraints will be used to determine the optimization search space limits. Then, the optimizer sends the candidate solutions to the model. Based on its outputs, the objective function block will calculate the fitness and send it to the optimizer to update the candidate solutions based on the fitness of each solution. This iterative process will repeat until the last iteration of the fitness value achieves the stop criterion. Figure 4 summarizes these steps.

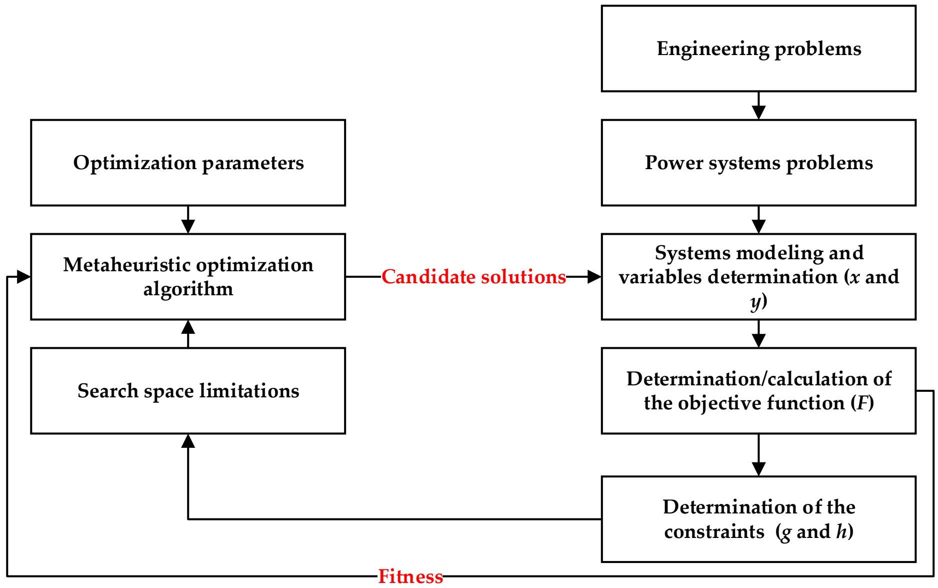

Figure 4. The main steps for solving power systems problems.

3.1. Optimal Power Flow for Transmission Power Systems

The power networks are large-scale, dynamic systems with various users, cables, transformers, and generation units. A power system's primary goal is to safely, consistently, and cost-effectively supply users with enough high-quality energy. Several system factors are control variables, such as the generator's active power, the compensator's reactive power, and the common bus voltage. They may be regulated independently and directly influence power flows and the system's stability. Other variables, such as the voltages of the load bus, the reactive power, and the power flows in the branches, are included as dependent variables [36,37]. Changing the control variables combinations can lead to the power-balance equation, but only certain combinations permit achieving the predefined objectives. Determining the best combinations which provide the desired state can be achieved by solving the optimal power flow problem (OPF) issue [38]. By making optimal adjustments to the control variables, the considered objective function may include reducing fuel consumption, power loss, and attenuating voltage deviation (VD), respecting the system restrictions. Both deterministic (traditional) and metaheuristic optimization algorithms can be used to overcome this issue [39]. Gradient, Newton's approach, linear programming (LP), and quadratic programming (QP) are examples of classical optimization methods applied to OPF issues. Unfortunately, due to the high nonlinearity and nonconvexity issues, these approaches cannot give a global solution and only obtain local solutions [40].

The optimization variables in this problem are the ith generator's active power (PG_i), its voltage (VG_i), shunt Var compensations (QC_i), and transformer tap settings (T_i). On the other hand, the dependent variables include the power of the slack bus (PG_{sl}), the voltage of the load bus (VL_i), the reactive power (QG_i), and the loadings in the ith transmission line (Sl_i) [41]. Accordingly, vectors **x** and **y** can be expressed as

$$\begin{array}{l} x = \left[PG_2 \ldots PG_{ng}, VG_1 \ldots VG_{ng}, T_1 \ldots T_{nt}, QC_1 \ldots QC_{nc}\right] \\ y = \left[PG_1 (= PG_{sl}), VL_1 \ldots VL_{nl}, QG_1 \ldots QG_{ng}, Sl_1 \ldots Sl_{ntl}\right] \end{array} \tag{2}$$

where ng is the number of generators, nt is the number of transformers, nc is the number of Var compensators, nl is the number of loads, and ntl is the number of transmission lines

The equality constraints can be expressed as

$$\begin{cases} PG_i - P_{load\_i} - V_i \sum_{j=1}^{nb} V_j \left(\alpha_{ij} \cos(\theta_{ij}) + \beta_{ij} \sin(\theta_{ij})\right) = 0 \\ QG_i - Q_{load\_i} - V_i \sum_{j=1}^{nb} V_j \left(\alpha_{ij} \sin(\theta_{ij}) + \beta_{ij} \cos(\theta_{ij})\right) = 0 \end{cases} \tag{3}$$

where nb is the number of buses, P_{load_i} and Q_{load_i} are the load's active and reactive power, θ_{ij} is the i-j buses angle, and $\alpha_{ij,}$ and β_{ij} represent real and imaginary parts extracted from the admittance matrix.

The inequality constraints can be expressed as

$$\begin{array}{l} PG_i^{\min} \le PG_i \le PG_i^{\max},\ i = 1 \cdots ng \\ VG_i^{\min} \le VG_i \le VG_i^{\max},\ i = 1 \cdots ng \\ T_i^{\min} \le T_i \le T_i^{\max},\ i = 1 \cdots nt \\ QC_i^{\min} \le QC_i \le QC_i^{\max},\ i = 1 \cdots nc \\ VL_i^{\min} \le VL_i \le VL_i^{\max},\ i = 1 \cdots nl \\ QG_i^{\min} \le QG_i \le QG_i^{\max},\ i = 1 \cdots ng \\ Sl_i \le Sl_i^{\max},\ i = 1 \cdots ntl \end{array} \tag{4}$$

According to [42], the objective function for the operating cost can be constructed as follows

$$\min F(x, y) = \min \sum_{i=1}^{ng} \left(PD_i{}^2 \cdot c_{1\_i} + PD_i \cdot c_{2\_i} + c_{3\_i}\right) \tag{5}$$

where c_{123_i} denotes the cost coefficients.

The objective function for the loose reduction can be formulated as follows

$$\min F(x, y) = \min \sum_{i=1}^{ntl} P_{loss\_i} \tag{6}$$

where P_{loss_i} represents the power loses at the ith transmission line. Its value can be calculated as follows

$$P_{loss\_ab} = \alpha_{ab} \left(V_a^2 + V_b^2 - 2 V_a V_b \cos(\theta_a - \theta_b)\right) \tag{7}$$

where a and b are the ath and the bth buses, α_{ab} denotes the transmission lines conductance between buses a and b, V_a and V_b are the voltage, and θ_a and θ_b are the angles between the buses.

The objective function for the voltage profile enhancement can be formulated as follows

$$\min F(x, y) = \min \sum_{i=1}^{nl} \left|V_i^{ref} - V_i\right| \tag{8}$$

where V_i is the ith bus voltage and V_i^{ref} is its reference value.

Various metaheuristic optimization algorithms for tackling the OPF issue have been proposed during the last two decades. Their principal benefit over traditional (exact) optimization algorithms is that they can handle objective function differentiability, nonlinearity, nonconvexity, and constraints. One of the most extensively utilized metaheuristic algorithms for OPF issues is the genetic algorithm (GA). As explained in [43], restrictive terms, including quadratic penalty terms in the objective function, are added to dependent variables, such as the bus power, reactive generator power, the voltages in the load buses, and transmission line loadings. Authors in [42] used the GA for the OPF problem for the first time. They developed an enhanced GA based on the coding system's dynamical hierarchy. Authors of [43] developed an improved GA specific for more significant OPF issues. Unlike the method reported in [42], their proposed method used discrete control variables to simulate switchable shunt devices and transformer taps. Authors in [44] suggest a GA-based strategy considering FACTS (flexible AC transmission system) devices. Following single-line outages, the FACTS devices reduce line overloads in the electrical system. The authors [45] suggested an effective parallel GA considering shunt FACTS devices under extreme loading circumstances to reduce execution times and enhance the quality of the solutions in real-world, large-scale OPF issues. The OPF issue is divided into two sub-issues: controlling the active power to reduce the operating cost and managing the reactive power to regulate the generator's voltage, attenuate the VD, and decrease the losses of the transmission lines. In [46], a customized GA with population size adjustment is utilized to solve OPF with multi-objective functions, such as cost minimization and voltage-profile enhancement.

Particle swarm optimization also has been utilized widely to resolve OPF issues. Authors in [47] used the PSO in the OPF issue for the first time. The authors [48] used an improved PSO (IPSO) version. The conventional PSO has been improved by introducing a biological notion of the passive congregation. A modified PSO has been proposed in [49] to resolve the OPF issues. Particles in this modified PSO increase the possibility of finding the global solution while decreasing the particles' initial positions effect. The authors of [50] employed the PSO incorporated with reconstruction operators while keeping operational security restrictions and capacity needs. In [51], a hybrid fuzzy logic PSO strategy (FLPSO) is used to improve power system security. For the multi-objective OPF, the reported works in [52] suggested an improved PSO (IPSO) by the chaotic approach to calculate the PSO parameters, such as inertia weight and self-adaptive acceleration coefficients. A fuzzy decision-based process is employed in this strategy to choose the optimal acceptable option from the Pareto set provided by the IPSO. The reported study in [53] presented a developed evolutionary PSO comprising thermal and wind turbine generators, taking into account up-spinning reserves, down-spinning reserves, and the operating restrictions of the generation unit.

Numerous researchers have used differential evolution (DE) to tackle OPF issues. In [54,55], the authors employed the DE to reduce the cost of consumed fuel by the generator with FACTS. A DE technique was utilized in [56] for two OPF subproblems: active power dispatching and cost/emission reduction as a multi-objective function. The reactive power dispatch, the power loss, and VD can be included in another multi-objective function. Authors of [57] developed a robust DE algorithm based on adaptive recombination operators. The used generator model has valve loading implications, numerous fuel alternatives, and banned working zones. A modified DE with nonconvex generator fuel cost curves is suggested in [58]. The authors of [59] presented a forced-initialization-based DE to reduce fuel costs, minimize power losses, and enhance voltage profiles and stability. The paper [60] presents the earliest utilization of the gravity search algorithm (GSA) to the OPF issue. The authors evaluated a variety of objective functions, including the improvement of voltage stability in standard and emergency cases, the piecewise quadratic cost function for fuel cost reduction, and the objective function that includes the valve-point impact. A multi-objective OPF problem, including fuel cost, power loss, and VD, has been resolved using GSA [61]. The authors in [62] proposed a more robust GSA to improve exploration capabilities and prevent getting caught in local minima. The GSA is incorporated with a mutation operator to create new masses throughout the solution space. The resolving technique is divided into two stages: economic dispatch is used to develop initial candidate solutions, and security-constrained is used to discover the global optimum. Other metaheuristic optimization algorithms for resolving the OPF problem are listed in Table 2. As provided in this table, the ACO has been widely used to solve this problem, and the GWO is one of the MOAs most frequently used to solve this problem.

Table 2. List of metaheuristic optimization algorithms for the OPF problem in transmission networks.

Refs.	Algorithm	Description and Objectives					
		Fuel Cost	P/Q	VD	Transformer Tap Set	Transmission Losses	Emissions
[63,64]	Ant colony optimization (ACO)	x	x	x	x	x	
[65]	Ant colony optimization (ACO)	x		x			
[66]	Ant colony optimization (ACO)	x		x		x	
[67]	Backtracking search algorithm (BSA)		x	x	x		
[68]	Colliding bodies optimization (CBO)		x	x	x		
[69]	Black-hole optimization (BHO)		x	x	x	x	
[70]	Gray wolf optimizer (GWO)		x	x	x		
[71]	Firefly algorithm (FFA)	x					x
[72]	Cuckoo search (CS)	x	x			x	x
[73]	Moth swarm algorithm (MSA)		x	x	x		
[74]	Krill herd algorithm (KHA)	x		x			
[75,76]	opposition-based Krill herd algorithm			x			
[77]	Shuffled frog leaping algorithm (SFLA)			x			
[78]	Bacterial foraging algorithm (BFA)	x		x	x	x	
[79]	modified Bacterial foraging algorithm	x	x	x			
[80]	Sine cosine algorithm (SCA)	x	x	x		x	
[81]	Jaya algorithm (JA)	x	x	x			
[82]	Salp swarm algorithm (SSA)	x					
[83]	Honey Badger Optimizer (HBO)		x	x		x	
[84]	Quasi-Oppositional-Chaotic Symbiotic Organisms Search algorithm		x	x		x	

The OPF issue solution's goal is to meet various operational limitations while optimizing a specified objective function by adjusting the power system control variables as best as possible. These control variables include the active power, voltages, tap settings for transformers, shunt Var compensations, etc. The findings in the literature study demonstrate that the metaheuristic algorithms deliver reliable, high-quality, efficient, resilient solutions.

3.2. Optimal Reactive Power Dispatching

Optimal reactive power dispatch (ORPD) is one of the essential prerequisites for an electric power system's economic and secure functioning. By adequately coordinating the equipment that controls the reactive power fluxes, the ORPD is achieved [85]. The purpose of resolving ORPD is to solve the selected objective function that may include power loss or VD by making the best possible adjustments to the control variables while simultaneously meeting a number of operating restrictions [86]. Precisely, the goals of ORPD are to minimize active power loss [38], enhance voltage profile [87], reduce transmission costs [88], and increase voltage stability [89].

The ORPD problem may be expressed as a constrained nonlinear optimization problem. The optimization variables include the voltage of each generator *i*th (VG_i), shunt Var compensations (QC_i), and transformer tap settings (T_i). On the other hand, the dependent variables include the power of the slack bus (PG_{sl}), the voltage of the load bus (VL_i), reactive power (QG_i), and loadings in the transmission line (Sl_i). The vectors x and y are presented as

$$\begin{aligned} x &= \left[VG_1 \ldots VG_{ng}, T_1 \ldots T_{nt}, QC_1 \ldots QC_{nc}\right] \\ y &= \left[PG_1 (= PG_{sl}), VL_1 \ldots VL_{nl}, QG_1 \ldots QG_{ng}, Sl_1 \ldots Sl_{ntl}\right] \end{aligned} \tag{9}$$

The equality and inequality constraints are similar to the ORPD. The objective function can include the ones mentioned in the ORPD associated with other terms related to the inequality constraints. The objective function can include overall cost, minimizing power losses in the transmission line, maximizing the power handling capacity, and minimizing the stability index. It can be formulated as follows [90]:

$$F_{RRPD} = F + \alpha_V \sum\nolimits_{i=1}^{nl} \left(V_i - V_i^{\text{lim}}\right)^2 + \alpha_Q \sum\nolimits_{i=1}^{ng} \left(QG_i - QG_i^{\text{lim}}\right)^2 \tag{10}$$

where α_V and α_Q are penalty coefficients. V_i^{lim} and QG_i^{lim} are limiting values of the two dependent variables, VL and QG. The term F can be defended as (A multi agent-based particle swarm optimization approach for reactive power dispatch; Optimal reactive power dispatch using an adaptive genetic algorithm):

$$F = \sum\nolimits_{k=1}^{nb} g_k \left(V_i^2 + V_j^2 - 2V_i V_j \cos(\theta_{ij})\right) \tag{11}$$

where g_k is the branch conductance.

This function is submitted to the following constraints:

$$\begin{aligned} V_i^{\min} \le V_i \le V_i^{\max}, \\ QG_i^{\min} \le QG_i \le QG_i^{\max}, \end{aligned} \tag{12}$$

Numerous metaheuristic algorithms have been used recently to resolve this. Their key benefit over traditional (exact) optimization algorithms is that specifications on the objective function's nonconvexity, differentiability, and continuity or kinds of control variables do not constrain them. Considering various objective functions and restrictions, these techniques may also be used in real-world power systems. According to [91], the OPRD problem has received a great deal of interest in the scientific community, where numerous metaheuristic algorithms have been reported in the literature review. A list of several metaheuristic algorithms for solving the ORPD problem is reported in Table 3. The PSO and the GA are well-known MOAs that have been extensively deployed for this problem.

The ORPD findings from different optimization algorithms proposed in the literature review were accurately presented. From their results, the metaheuristic optimization algorithms allow for the development of superior solutions to the ORPD problem.

Table 3. List of metaheuristic optimization algorithms for the ORPD problem.

Ref.	Algorithm	Objectives					
		Voltage Profile	Voltage Stability	Power Losses	Transformer Tap set	Power Losses	VAR Compensation
[92]	Particle swarm optimization (PSO)	x					
[93]	Multi-agent and PSO	x	x				
[94]	Learning PSO	x	x				

Table 3. *Cont.*

Ref.	Algorithm	Objectives					
		Voltage Profile	Voltage Stability	Power Losses	Transformer Tap set	Power Losses	VAR Compensation
[95]	Differential evolution (DE)	x	x			x	
[96]	Quasi-oppositional DE	x	x		x		x
[97]	Adaptive DE	x				x	
[98]	Genetic algorithm (GA)	x			x		x
[99]	Biogeography-based optimization (BBO)	x	x	x			
[100]	Gravitational search algorithm (GSA)			x			
[101]	Opposition-based GSA	x	x				
[102]	Chaotic krill herd algorithm (CKHA)	x	x				
[103]	Harmony search (HS)	x	x	x			
[104]	Teaching learning-based optimization (TLBO)	x	x	x			
[105]	Ant colony optimization (ACO)	x	x				
[106]	Gray wolf optimizer (GWO)	x		x			
[107]	Exchange market algorithm (EMA)	x	x				
[108]	Firefly Algorithm (FA)	x	x				

3.3. Optimal Combined Economic and Emission Dispatching

Resolving the economic dispatching (*ED*) issue tries to reduce the generated electricity cost by optimizing the generating units' commitment while fulfilling all unit and system restrictions. The *ED* cost function (in $/h) can be described as follows:

$$F_{ED} = \sum_{i=1}^{n} \left(a_i P_{Gi}^2 + b_i P_{Gi} + c_i \right) \tag{13}$$

where a_i, b_i, and c_i are the cost coefficients of the ith DG. This function has the following constraints:

$$\sum_{i=1}^{n} P_{Gi} = P_{load} + P_{looses} \tag{14}$$

$$P_{Gi}^{\min} \leq P_{Gi} \leq P_{Gi}^{\max} \tag{15}$$

Under power balance and unit capacity limitations, the emission dispatch objective function (in kg/h) is stated as follows

$$F_E = \sum_{i=1}^{n} \left(PD_i^{\,2} \cdot A_i + PD_i \cdot B_i + C_i + \xi_i e^{\lambda_i PD_i} \right) \tag{16}$$

where A_i, B_i, C_i, ξ_i, and λ_i are the emission coefficients of the ith DG.

However, the ED ignores the pollutant emissions of thermal plants' fossil fuels and other environmental requirements. To this end, the ED has been combined with the requirement of formulating the combined economic and emission dispatch (CEED) problem. The CEED is a complex, multi-objective problem with two goals: reducing fuel costs and emissions from thermal power facilities [109]. This can increase the nonlinearity and complexity of the ED problem. Usually, there are three methods used to resolve this problem [110]. The emission is constrained with an allowed limit in the first method. This approach, however, has a significant challenge in obtaining cost-emission trade-off relationships. The second method considers emission as an additional objective to the cost. Here, this issue is turned into a single-objective problem by linearly combining or optimizing both goals. In the last method, both goals are optimized concurrently in solving the CEED issue. Traditional optimization methods were used to tackle the ED problem successfully. However, they cannot discover appropriate solutions for medium or large CEED problems. Deploying metaheuristic optimization algorithms to overcome these limitations has been approved. In this problem, the optimization variables (x) include the generator's active power, and the dependent variables (y) include the slack power [111]. The objective function for this problem can be defined as follows [112]:

$$F_{CEED} = [w \cdot F_{ED} + (1 - w)\beta \cdot F_E] \tag{17}$$

where w is a constant [0, 1], and β is a scaling factor.

This objective function is submitted to the following constraints:

$$\begin{array}{l} \sum_{i=1}^{ng} PG_i - P_{load} - P_{loss} = 0 \\ PG_i^{\min} \le PG_i \le PG_i^{\max},\ i = 1 \cdots ng \end{array} \tag{18}$$

Many metaheuristic algorithms have been developed recently to address the complicated restrictions of this optimization issue. Many metaheuristic optimization algorithms have been used to solve ED/CEED. Applications of metaheuristic optimization algorithms for resolving the CEED problem are shown in Table 4. This PSO is the most used MOA to solve this problem.

Table 4. List of metaheuristic optimization algorithms for the CEED problem.

Ref	Algorithm	Description and Objectives
[113]	Genetic algorithm (GA) Evolutionary programming (EP) Particle swarm optimization (PSO) Differential evolution (DE)	Solve CEED for the IEEE 30-bus and 15-unit systems.
[114]	Pareto-based, multi-objective evolutionary algorithms (MOEA)	Solve CEED for the IEEE 30-bus and 6-unit systems.
[115]	Hybrid evolutionary algorithm (HEA)	Solve CEED problems for the IEEE 57 and 118-bus systems.
[116]	Improved particle swarm optimization (IPSO)	Used three ED problems applied to the large-scale power system in Korea.
[117]	PSO with smart inertia factor (PSO-SIF)	Used 6, 15, 20, and 40 units testing systems.
[118]	Improved COOT optimization Algorithm (iCOOT)	Reduce the generating cost, pollutant emissions, and satisfaction weight coefficient of the unit.
[119]	Hybrid gravitational search algorithm and random forest regression (GSA-RFR)	Solve the CEED for combined cooling, heating, and power (CCHP) and power-to-gas (P2G)-based microgrid.
[120]	Artificial bee colony (ABC)	Assess the combined cost and emission targets to decrease losses and raise transmission line efficiency.
[121]	Adaptive Bat Algorithm	Resolve large-scale ED with reduced execution time
[122]	Artificial ecosystem optimization (AEO)	Reduce the economic charges as well as the three harmful gas emissions of sulfur dioxide (SO_2), nitrous oxide (N_2O), and carbon dioxide (CO_2).

Table 4. *Cont.*

Ref	Algorithm	Description and Objectives
[123]	Spiral optimization algorithm (SOA)	Reduce costs and emissions while meeting load requirements and operating restrictions.
[124]	Hybrid PSO-FA	Reduce costs and emissions while meeting load requirements and operating restrictions.
[125]	Flower pollination algorithm (FPA)	Solve the CEED problem while taking into account the environmental consequences of fossil-fueled power stations' emissions of gaseous pollutants.
[126]	Levy-based glowworm swarm optimization (LGSO) Grey wolf optimization (GWO) Whale optimization algorithm (WOA) Dragonfly algorithm (DA) Glowworm swarm optimization (GSO)	The LGSO provided the best solution by choosing the generation of renewable energy sources.

3.4. Optimal Power Flow in Distribution Networks

Large-scale, extremely complex, linked systems make up modern electric power systems and require decisions about resource generation, transmission, and distribution over various time horizons. Fuel cells, diesel generators, and microturbines are among the dispatchable DG units that may be coupled to the distribution system at any point. They can be linked via a machine and/or power electronic converter. Using synchronous or asynchronous machines requires the introduction of constant active/reactive power (P/Q) or active power and voltage amplitude (PV) control modes [127,128]. The active distribution network can be kept safe, stable, and cost-effective only by efficiently coordinating the operation of DG units, voltage control, and reactive power compensation. This can be achieved by solving an OPF problem. The OPF suffers common issues with all problems represented by nonlinear power flow limitations, which can alter the robustness, scalability, and availability of the accommodated DER [129]. Optimizing the OPF can decrease fuel costs, enhance voltage profiles and Var/Volt harmony, and minimize power losses by optimizing control variable setups while meeting different distribution network operating restrictions [130]. The set of optimization variables includes the active power of the dispatchable sources (*PD*), their terminal voltages (*V*), transformer tap setting (*T*), and the Var compensator output (*QC*). On the other hand, the dependent variables include the active grid power (P_{grid}), load voltage (V*L*), reactive generator power (*QD*), and branch flow (*Sl*). They can be presented as follows

$$\begin{aligned} x &= \left[PG_1 \ldots PG_{ndg}, V_0, VG_1 \ldots VG_{ndg}, T_1 \ldots T_{nt}, QC_1 \ldots QC_{nc}\right] \\ y &= \left[P_{grid}, VL_1 \ldots VL_{nl}, QG_1 \ldots QG_{ndg}, Sl_1 \ldots Sl_{ntl}\right] \end{aligned} \tag{19}$$

where *ndg* is the number of dispatchable sources (without including the renewable sources), and V_0 is the primary bus voltage.

If the objective functions express the operating cost, it can be described based on Equation (2) as follows:

$$\min F(x,y) = \min\left[EM\left(P_{grid}\right) + \sum_{i=1}^{ndg}\left(PD_i^{\,2} \cdot a_i + PD_i \cdot b_i + c_i\right)\right] \tag{20}$$

where *EM* is the electricity market prices.

The objective function can include the power losses as a multi-objective function by adding the losses term to Equation (15). The multi-objective function can then be formulated as follows:

$$\min F(x,y) = \min\left[EM\left(P_{grid}\right) + \sum_{i=1}^{ndg}\left(PD_i^{\,2} \cdot a_i + PD_i \cdot b_i + c_i\right) + w\sum_{i=1}^{nb} P_{loss\_i}\right] \tag{21}$$

where w is a penalty factor.

The objective function is submitted to several equality constraints, such as

$$\sum_{i=1}^{ndg} PG_i + \sum_{i=1}^{nrg} PG_i + P_{grid} - P_{load} - P_{loss} = 0 \tag{22}$$

where *nrg* is the number of renewable generators, the inequality constraints are similar to the OPF case.

The nonlinear and nonconvex power flow restrictions of the OPF are linearized in the literature using a generalized linear-constrained optimal power flow (GLOPF) model based on the first-order Taylor series approximation method [131]. This linearized model allows for the numerical optimization of the OPF problem. However, the approximations used in the linearization process can reduce the model fidelity. In addition, because of the various random disturbances or uncertain factors in the loads, the network configurations, and renewable production, the traditional optimization methods cannot provide suitable performance. For this reason, metaheuristic optimization algorithms have been used widely to resolve the OPF. The objective function might include all the DG units, including the renewable and nonrenewable sources. For distribution networks to operate economically, securely, and dependably, the OPF is a crucial instrument. Table 5 presents a set of the metaheuristic algorithms utilized to solve the OPF.

Table 5. List of metaheuristic optimization algorithms for the OPF problem in distribution networks.

Ref	Algorithm	Description and Objectives
[132]	Genetic algorithm (GA)	DG units include fuel cells (FCs), microturbines (MTs), diesel generators (DGs), photovoltaic systems (PVs), and wind turbines (WTs).
[133]	Genetic algorithm (GA)	Resolving the OPF considering the spatial electrothermal coupling effect.
[134]	Particle swarm optimization (PSO)	Use the PSO to determine each DG unit's active and reactive power and the tap of tap-changer transformers to reduce the cost, considering various physical and technical restrictions.
[135]	Gravitational search algorithm (GSA)	The GSA successfully resolved the OPF problem on two distribution systems, and its results were compared to those obtained using the GA method.
[136]	Improved GSA	DGs with unpredictable power outputs are included in the distribution networks' optimum reactive power flow issue-solving.
[137]	Spotted hyena optimizer (SHO)	Reducing the overshoot/undershoot peaks and time response of a power system with various DERs.

3.5. Optimal Volt/Var Controlling in the Distribution Power Network

VD levels that exceed the permitted limits can cause abnormal performance, reduced efficiency, and, in severe circumstances, breakdown. For this reason, the voltage magnitude is a crucial power quality factor. The voltage must be within acceptable bounds at every point in the distribution power network. The permitted VD limits are expressed as a percentage of the rated voltage (standardized between $\pm 5\%$ or $\pm 10\%$ for medium-voltage (MV) and low-voltage (LV) power grids) [138]. Various voltage control devices are used to keep the voltage within permitted limits under varying load levels. Voltage is usually controlled by altering transformers' transmission ratio and correcting for reactive power. This control process involves the Static Var Compensators (SVCs), which can adjust reactive power, incorporated with capacitors with fixed capacities, and are known as reactive power compensation devices [112]. Underload tap-changing transformers (ULTCTs) are also involved in MV/HV power grids, whereas Off-voltage tap-changing transformers (OVTCTs) are required in MV/LV power grids [112].

Optimizing the Volt/Var control in distribution networks is considered a constrained optimization problem for distribution networks that include the ULTCT, SVCs, shunt capacitor banks, and DG generators. The control variables may consist of

- VRs, OVTCTs, and ULTCTs tap-changer settings;
- voltage magnitudes in PV buses;
- capacitors and SVCs' reactive powers.

The load buses' voltages are the dependent variables that define the distribution network's operation state. The objectives function may be VD minimization [139,140], total power loss minimization [141,142], operating costs minimization [143–147], number of switching operations minimization [148,149], harmonic distortion minimization [150–152], and voltage stability [153]. Because distribution networks frequently include a significant number of nodes and branches based on the network's topology, there are a considerable number of control factors to consider in the objective function. These factors must be considered while developing an effective model for optimal voltage management. The Volt/Var control (VVC) problem has been successfully solved using metaheuristic optimization algorithms. Usually, the VVC problem can be expressed as a multi-objective function as follows (Optimal Volt/VAR control in distribution systems with prosumer DERs):

$$\begin{aligned} F_1 &= \sum_{i=1}^{T} \beta_i P_{loos}^i \\ F_2 &= \sum_{i=1}^{T} \left(\begin{array}{l} \sum_{m=1}^{Ncb} \alpha_{cb} \left| q_m^t - q_m^{t-1} \right| + \sum_{j=1}^{Noltc} \alpha_{oltc} \left| T_j^t - T_j^{t-1} \right| \\ + \sum_{r=1}^{\mathrm{Reg}} \alpha_{\mathrm{Reg}} \left| R_r^t - R_r^{t-1} \right| \end{array} \right) \end{aligned} \quad (23)$$

where F_1 minimizes the power loss and F_2 minimizes the cost of adjusting voltage control assets for the entire time horizon, N_{cb} is the number of capacitor banks, N_{oltc} is the transformers' number with on-load tap changers, N_{Reg} is the voltage regulators' number, α_{cb} is the capacitor banks' adjustment cost, α_{oltc} is the OLTC transformers' adjustment cost, α_{Reg} is the voltage regulators' adjustment cost, q_m is of the mth capacitor bank' status, T_j is the jth OLTC transformer's status, and R_r is the rth voltage regulator status. Each variable must be limited within its upper and lower limits.

Some of these algorithms are listed in Table 6. This GA is the MOA used most frequently to solve this problem, followed by the PSO.

Table 6. List of metaheuristic optimization algorithms for the VVC problem.

Ref	Algorithm	Description and Objectives
[154]	Genetic algorithm (GA)	Based on the day-ahead load projection, create optimal dispatch schedules for on-load tap changer (OLTC) settings at substations and all shunt capacitor switching to minimize the loss and enhance the voltage profile.
[155]	Genetic algorithm (GA)	Reduce the operation numbers of ULTC and switching capacitors to minimize the loss and enhance the voltage profile for 24 h.
[156]	Genetic algorithm (GA)	GA controls the load ratio of the transformer, the step voltage regulator (SVR), the shunt capacitor, the reactor, and the static Var compensator.
[148]	Genetic algorithm (GA)	Minimal power losses and capacitor banks' switching are the goals of the proposed day-ahead coordinated reactive power dispatch technique while forecasting the DG errors to assess their reactive power capability.
[151]	Genetic algorithm (GA)	The PV solar reactive power is an additional control variable for substation capacitors, feeder capacitors, and OLTC tap positions.
[157]	Evolutionary programming (EP)	Microgeneration shedding is included to enhance the Volt/Var solving performance.
[158]	Particle swarm optimization (PSO)	The distribution networks are feeder capacitors, paired substation capacitors, and OLTC.

Table 6. *Cont.*

Ref	Algorithm	Description and Objectives
[145]	Fuzzy adaptive PSO (FAPSO)	Find the best active and reactive power distribution for the DG units, including the capacitor banks and the tap settings for the transformers, for 24 h.
[147]	Particle swarm optimization (PSO)	Eliminate the active power loss, the VD, and the reactive power compensation device's capacity (or reduce its investment cost).
[146]	Fuzzy adaptive PSO (FAPSO)	Minimize operation cost of transformers and capacitors and power loss while meeting the system constraints.
[136]	Improved gravitational search algorithm (IGSA)	Active network loss minimization in the IEEE-33 node standard test system.
[159]	modified Teaching-Learning Algorithm (mTLA)	Solve the Volt/Var problem considering the loads and generated power uncertainties.
[160]	Bacterial Foraging Algorithm (BFA)	Solve the Volt/Var problem for several DGs as a weighted combination of a single objective, and then determine the best Pareto-front for different combinations of objective functions.
[161]	Gravitational Search Algorithm (GSA)	Optimal capacitor power control to reduce power losses and the reactive power cost generated by capacitors.

3.6. Optimizing the Size and Placement of DGs

Recent updates to the distribution network structure have opened up possibilities for a wide range of technical features, including integrating distributed generations (DGs). Inadequate DG unit sizing and placement (S&P) can result in excessive power losses, poor voltage profiles, and harmonic propagations [162]. Therefore, determining the optimal size and location of DG units is required. DGs may be classified into two groups based on their nature [163]. The first group includes the DGs with weather or location dependability, such as RESs. Geographic, hydrological, and meteorological factors are the first group's principal factors in location and size determination. Optimizing the connection point is feasible by specifying the collection of buses to which the DG will be linked. The second group consists of those DGs that may be linked in a distribution network at any point and have dispatchable power generation, such as microturbines, fuel cells, and diesel generators. The locations technique determines the change in a dispersed network's total power loss caused by a change in bus injection power. This process involves active and reactive power losses P and Q. As a result, the power loss variations are stated as a function of the Jacobian matrix (J) as follows [2]:

$$\begin{bmatrix} \frac{\partial P_{loss}}{\partial P} \\ \frac{\partial P_{loss}}{\partial Q} \end{bmatrix} = J^{-1} \begin{bmatrix} \frac{\partial P_{loss}}{\partial \theta} \\ \frac{\partial P_{loss}}{\partial V} \end{bmatrix} \tag{24}$$

$$J =^{-1} \begin{bmatrix} \frac{\partial \Delta P}{\partial \theta} & \frac{\partial \Delta P}{\partial V} \\ \frac{\partial \Delta Q}{\partial \theta} & \frac{\partial \Delta Q}{\partial V} \end{bmatrix} \tag{25}$$

The bus location coefficients (BLCs) express the DG linking favorability. The BLCs can be defined as:

$$\begin{aligned} BLCi &= w_i \frac{\partial P_{loss}}{\partial P_i} + (1 - w_i) \frac{\partial P_{loss}}{\partial Q_i} \\ w_i &= 1 - \frac{1}{(r_i/x_i) + 1} \end{aligned} \tag{26}$$

where x_i and r_i denote the reactance and resistance in the ith branch.

The objective function can be formulated to minimize the total power losses. This sizing problem is related to the DG operation and planning. The operation problem seeks to determine the ideal DG operation in a given static network mode in order to reduce power loss. The planning problem aims to choose installed electricity for DGs that will be connected to predetermined locations.

In published research, a variety of methods for choosing the best location and size of DGs are offered. They include analytical [164–166], linear [167], and quadratic programming [168] methods. Recently, metaheuristic optimization algorithms have gained more popularity in the optimal sizing and placement of DGs. Table 7 presents a set of these algorithms applied to resolve this problem. Various GA and PSO versions have been widely used to solve this problem.

Table 7. List of metaheuristic optimization algorithms optimal S&P of DGs.

Ref	Algorithm	Description and Objectives
[169]	Genetic algorithm (GA)	The best allocation of several DG types is established using GA to minimize total mean daily active power losses.
[170]	Genetic algorithm (GA)	Optimal sizing and placement of DGs considering power quality improvement.
[171]	GA-based tabu search (GA-TS)	Determine the best position of DG units in a distribution system as the independent private sector.
[172]	Non-dominated sorting GA (NSGAII)	Solve this problem as a multi-objective probabilistic optimization problem that includes total costs, power losses, and investment charges.
[173]	An analytical method with GA	The objective function includes the minimization of the distribution network power loss.
[174]	Particle swarm optimization (PSO)	PSO is used to handle the problem of optimal DG unit placement while accounting for load changes in the distribution network.
[175]	Multiobjective PSO (MOPSO)	Determine the best position and size of DGs and shunt capacitor banks in distribution networks while considering load randomness.
[176]	Improved MOPSO (IMOPSO)	Determine the best location and size for DG units in the distribution network.
[177]	Multiobjective PSO (MOPSO)	Determine the best DG size and location by considering several metrics, such as active and reactive power losses, VD, and reliability.
[178]	Particle swarm optimization (PSO)	Consider the time-varying features of electrical load demand to calculate DGs' appropriate size and position to minimize yearly power loss.
[179]	Particle swarm optimization (PSO)	Determine the appropriate position and size of various DG units by considering factors, such as total power losses, voltage profile enhancement, and greenhouse gas emissions.
[180]	Improved Gravitational Search Algorithm (IGSA)	Find DG's appropriate location and sizing in a radial distribution network to reduce power losses, harmonic distortion, and VD.
[181]	Gravitational Search Algorithm (GSA)	Enhance nodal pricing and voltage profiles in the distribution network using the GSA.
[182]	Backtracking search algorithm (BSA)	In a radial distribution network, optimal sizing and location of DGs, capacitor banks, and a thyristor-controlled series compensator.
[183]	Fuzzy-BSA	Increasing operational performance, reducing the loss, and enhancing the voltage profile goals are included in the objective function. The combined power factor and network reactive power loss decrease are also included.
[184]	Hybrid ACO–ABC	Reducing electrical energy costs, power losses, and total emissions from substations and resources enhances voltage stability.
[185]	Gray wolf optimizer (GWO)	Reduce reactive power losses and enhance distribution system voltage profiles while remaining within power system restrictions.
[186]	Bacterial foraging optimization (BFO)	Reduce power loss and enhance voltage profile of radial distribution network on 12-bus, 34-bus, and 69-bus radial distribution systems with 11, 33, and 68 sections, respectively.

3.7. Unit Commitment

Unit commitment (UC) is regarded as one of the essential duties in the effective, trustworthy, and ideal planning of the power systems' short-term operation. Commitment/Decommitment (ON/OFF) schedules and economic dispatch of committed units are the two phases in the UC problem. The start-up and shut-down timetables of each unit employed to fulfill anticipated demand over a short period of time are determined by solving the UC issue in a power system [187]. The problem comprises both continuous and integer variables, as well as a complex collection of unit-related constraints, such as minimum up- and down-timings and start-up behavior. Usually, stochastic programming and mathematics have been used to solve this problem [188,189]. However, using metaheuristic optimization algorithms to solve this problem has received a great deal of attention in the last few years. The reduction of overall production costs over the time horizon is the ultimate objective of the UC issue. The total costs include [190]:

- Start-up costs; these costs are described as an exponential (for cooling) or linear (for banking) function of the number of hours the machine has been down.
- Shut-clown costs; these expenses are specified as a set sum for each unit per shutdown.
- Fuel costs; however, using multiple fuels for flame stability while the machine is operating at low output levels might make this aspect more complicated.

The UC problem may be expressed mathematically as follows:

$$F_{UC} = \sum_{i=1}^{Ng} \sum_{t=1}^{T} \left(I_i(t) F_i(P_i(t)) + S_i(t)(1 - I_i(t-1)) I_i(t) \right) \tag{27}$$

where Ng expresses the generators' number, T symbols the overall scheduling hours, $P_i(t)$ is the ith unit power generated at instant t, $I_i(t)$ represents the switching status (ON/OFF) of ith unit at instant t, $F_i(P_i(t))$ is the ith unit fuel cost which is given in Equation (27), $S_i(t)$ is the ith unit start-up cost, which is presented as

$$S_i(t) = \begin{cases} Sh_i & if\ T_{i,off}(t) \leq T_{i,Down} + T_{i,cold} \\ Sc_i & if\ T_{i,off}(t) > T_{i,Down} + T_{i,cold} \end{cases} \tag{28}$$

where Sh_i and Sc_i are the hot and cold start-up costs, $T_{i,off}(t)$ is the duration of ith unit's continuous inactivity, $T_{i,Down}$ is the minimum downtime of ith unit, and $T_{i,cold}$ is the cold start-up time of the ith unit.

The following restrictions must be met throughout the optimization process [190]:

- Power balance.
- System reserve requirements.
- Initial conditions.
- High and low production limits.
- Unit minimum-up and minimum-down times.
- Rate limits.
- Unit start-up and shut-down ramps.
- Flame stabilization using dual or alternate fuel.

Metaheuristic optimization algorithms have been used widely for solving this problem. Table 8 presents a set of MOAs that are used to solve the UC problem.

Table 8. List of metaheuristic optimization algorithms used to UC problem.

Ref	Algorithm	Description and Objectives
[190]	Genetic algorithm (GA)	Provide enhanced binary coding performance for each unit on/off switching states.
[191]	Evolutionary algorithm (EA)	A comprehensive review of the UC problem using evolutionary optimization algorithms
[192]	Particle swarm optimization (PSO)	Use three versions of PSO algorithms: Binary PSO, Improved binary PSO, and PSO with Lagrangian relaxation for unit commitment problems.
[193]	novel binary ant colony optimization (NBACO)	Consider all possible solution sets as well as drawbacks, such as large memory size and a long execution time while solving the UC problem.
[194]	Hybrid Taguchi-ant colony system (HTACS)	Better UC solutions are rapidly chosen to reflect possible UC schedules.

4. Conclusions

This paper provided an extensive study relating the use of metaheuristic optimization techniques to solve power system problems in order to guarantee sustainable environments. As power system topologies and sizes expand, so do the associated concerns. These issues can include optimizing power flow in transmission and distribution systems, optimizing reactive power dispatching, optimally combining economic and emission dispatching, optimizing Volt/Var regulating in the distribution power network, and optimizing DG scale and location and unit commitment. The significant goal of this study is to examine the application of numerous metaheuristic optimization methods to power system challenges. These difficulties and their restrictions can be described mathematically as optimization problems that can be addressed using optimization techniques. Metaheuristic optimization algorithms represent methods for addressing complicated optimization problems that are mathematically grounded. These algorithms are intended to locate or provide sufficiently feasible solutions to a given problem. In the beginning, this research examined the fundamental concepts of metaheuristic optimization algorithms as well as their classifications. The seven problems concerning electricity systems were then presented and explored. For each task, a list of various metaheuristic optimization strategies was provided. According to the results, employing the metaheuristic optimization algorithm to tackle the performance of current power systems is an appealing issue for academic researchers and industry patterns because of their exceptional ability to successfully manage these challenges. Based on the achieved results, the particle swarm optimization (PSO) and the genetic algorithm (GA) are the most used metaheuristic optimization algorithms due to several reasons, such as the date of their first utilization, and their simplicity to understand and to implement. However, due to the recent progress in these algorithms, newer algorithms can replace them. For example, the salp swarm algorithm (SSA) can be implemented more easily with higher performance and limited camping time. In terms of accuracy, the bald eagle search algorithm (BES) can generate excellent results but requires more computing time. So, the choice of an appropriate algorithm depends on the nature of the problem and the accuracy of the desired results.

With raised interest in AI in the last months, they may replace the current solving algorithms (including the metaheuristic algorithms). However, the metaheuristic algorithms are increasingly enhanced, so merging them with existing algorithms can provide enhanced performance for each problem.

Author Contributions: A.M.N.: Supervision, Methodology, Conceptualization, Investigation, Software, Formal analysis, Writing—review and editing. M.A.A.: Conceptualization, Software, Formal analysis, H.M.M.: Investigation, Visualization, A.B.: Writing—review and editing. All authors have read and agreed to the published version of the manuscript.

Funding: This study was sponsored by the Prince Sattam bin Abdulaziz University via project number 2023/RV/016.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Acknowledgments: This study was sponsored by the Prince Sattam bin Abdulaziz University via project number 2023/RV/016.

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

References

1. De Leon-Aldaco, S.E.; Calleja, H.; Aguayo Alquicira, J. Metaheuristic Optimization Methods Applied to Power Converters: A Review. *IEEE Trans. Power Electron.* **2015**, *30*, 6791–6803. [CrossRef]
2. Dantzig, G.B. Linear Programming. *Oper. Res.* **2002**, *50*, 42–47. [CrossRef]
3. Bertsekas, D.P. Nonlinear Programming. *J. Oper. Res. Soc.* **1997**, *48*, 334. [CrossRef]

4. Bellman, R. Dynamic Programming. *Science* **1966**, *153*, 34–37. [CrossRef]
5. Fletcher, R. *Practical Methods of Optimization*; John Wiley & Sons, Ltd.: Chichester, UK, 2000; ISBN 9781118723203.
6. Box, F. A Heuristic Technique for Assigning Frequencies to Mobile Radio Nets. *IEEE Trans. Veh. Technol.* **1978**, *27*, 57–64. [CrossRef]
7. Devarapalli, R.; Bhattacharyya, B.; Sinha, N.K. An Intelligent EGWO-SCA-CS Algorithm for PSS Parameter Tuning under System Uncertainties. *Int. J. Intell. Syst.* **2020**, *35*, 1520–1569. [CrossRef]
8. Wolpert, D.H.; Macready, W.G. No Free Lunch Theorems for Optimization. *IEEE Trans. Evol. Comput.* **1995**, *1*, 67–82. [CrossRef]
9. Tsai, C.-W.; Chiang, M.-C.; Ksentini, A.; Chen, M. Metaheuristic Algorithms for Healthcare: Open Issues and Challenges. *Comput. Electr. Eng.* **2016**, *53*, 421–434. [CrossRef]
10. Shah, P.; Sekhar, R.; Kulkarni, A.J.; Siarry, P. *Metaheuristic Algorithms in Industry 4.0*; CRC Press: Boca Raton, FL, USA, 2021; ISBN 9781003143505.
11. Dai, Y.; Zhou, X.; Chu, X.; Li, C.; Su, Z.; Zhu, Z.; Cui, P.; Qi, J.; Wang, Y. Effect of Entrainer Thermodynamic Properties on the Separation of Ternary Mixtures Containing Two Minimum Boiling Azeotropes by Extractive Distillation. *Ind. Eng. Chem. Res.* **2022**, *61*, 15273–15288. [CrossRef]
12. Wang, Y.; Bu, G.; Wang, Y.; Zhao, T.; Zhang, Z.; Zhu, Z. Application of a Simulated Annealing Algorithm to Design and Optimize a Pressure-Swing Distillation Process. *Comput. Chem. Eng.* **2016**, *95*, 97–107. [CrossRef]
13. Byles, D.; Mohagheghi, S. Sustainable Power Grid Expansion: Life Cycle Assessment, Modeling Approaches, Challenges, and Opportunities. *Sustainability* **2023**, *15*, 8788. [CrossRef]
14. Massoud Amin, S.; Wollenberg, B.F. Toward a Smart Grid: Power Delivery for the 21st Century. *IEEE Power Energy Mag.* **2005**, *3*, 34–41. [CrossRef]
15. Agustriyanto, R.; Zhang, J. Obtaining the Worst Case RGA and RDGA for Uncertain Systems via Optimization. *Proc. Am. Control Conf.* **2007**, 5360–5365. [CrossRef]
16. Han, Q.; Wen, M. An Uncertain Optimization Model for Repairable Inventory System. In *Proceedings of the 2014 Prognostics and System Health Management Conference (PHM-2014 Hunan), Zhangjiajie, China, 24–27 August 2014*; IEEE: Piscataway, NJ, USA, 2014; pp. 378–382.
17. Fu, X.; Guo, Q.; Sun, H. Statistical Machine Learning Model for Stochastic Optimal Planning of Distribution Networks Considering a Dynamic Correlation and Dimension Reduction. *IEEE Trans. Smart Grid* **2020**, *11*, 2904–2917. [CrossRef]
18. Fu, X. Statistical Machine Learning Model for Capacitor Planning Considering Uncertainties in Photovoltaic Power. *Prot. Control Mod. Power Syst.* **2022**, *7*, 5. [CrossRef]
19. Lee k, Y.; EI-Sharkawi, M. *Modern Heuristic Optimization Techniques*; Lee, K.Y., El-Sharkawi, M.A., Eds.; John Wiley & Sons, Inc.: Hoboken, NJ, USA, 2008; ISBN 9780470225868.
20. Rezk, H.; Olabi, A.G.; Wilberforce, T.; Sayed, E.T. A Comprehensive Review and Application of Metaheuristics in Solving the Optimal Parameter Identification Problems. *Sustainability* **2023**, *15*, 5732. [CrossRef]
21. 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. [CrossRef]
22. Ganesan, V.; Sobhana, M.; Anuradha, G.; Yellamma, P.; Devi, O.R.; Prakash, K.B.; Naren, J. Quantum Inspired Meta-Heuristic Approach for Optimization of Genetic Algorithm. *Comput. Electr. Eng.* **2021**, *94*, 107356. [CrossRef]
23. Lazar, A. Heuristic Knowledge Discovery for Archaeological Data Using Genetic Algorithms and Rough Sets. In *Heuristic and Optimization for Knowledge Discovery*; IGI Global: Hershey, PA, USA, 2002; Volume 2, pp. 263–278.
24. Yang, X. *Nature-Inspired Metaheuristic Algorithms*, 2nd ed.; Luniver Press: Bristol, 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. Vinod Chandra, S.S.; Anand, H.S. Nature Inspired Meta Heuristic Algorithms for Optimization Problems. *Computing* **2022**, *104*, 251–269. [CrossRef]
27. Abdullah, H.M.; Park, S.; Seong, K.; Lee, S. Hybrid Renewable Energy System Design: A Machine Learning Approach for Optimal Sizing with Net-Metering Costs. *Sustainability* **2023**, *15*, 8538. [CrossRef]
28. Justin, S.; Saleh, W.; Lashin, M.M.A.; Albalawi, H.M. Design of Metaheuristic Optimization with Deep-Learning-Assisted Solar-Operated On-Board Smart Charging Station for Mass Transport Passenger Vehicle. *Sustainability* **2023**, *15*, 7845. [CrossRef]
29. Alshammari, A.; Chabaan, R.C. Metaheruistic Optimization Based Ensemble Machine Learning Model for Designing Detection Coil with Prediction of Electric Vehicle Charging Time. *Sustainability* **2023**, *15*, 6684. [CrossRef]
30. Boussaïd, I.; Lepagnot, J.; Siarry, P. A Survey on Optimization Metaheuristics. *Inf. Sci.* **2013**, *237*, 82–117. [CrossRef]
31. Dreo, J.; Petrowsdki, A.; Siarry, P.; Taillard, E.; Chatterjee, A. *Metaheuristics for Hard Optimization: Methods and Case Studies*; Springer: Cham, Switzerland, 2006; ISBN 978-3-540-30966-6.
32. Knypiński, Ł. Adaptation of the Penalty Function Method to Genetic Algorithm in Electromagnetic Devices Designing. *COMPEL-Int. J. Comput. Math. Electr. Electron. Eng.* **2019**, *38*, 1285–1294. [CrossRef]
33. 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, 16–18 November 2005*; IEEE: Piscataway, NJ, USA, 2005; Volume 2005, p. 6.
34. Baretich, M.F. Electrical Power. In *Clinical Engineering Handbook*; Elsevier: Amsterdam, The Netherlands, 2020; pp. 667–669.

35. Da Silva Filho, J.I.; Shozo, A.; Pompeo Ferrara, L.F.; Conceicao, M.; de Melo Camargo, J.; Vilanova, D.; dos Santos, M.R.; Rocco, A. Electric Power System Operation Decision Support by Expert System Built with Paraconsistent Annotated Logic. In *Advances in Expert Systems*; InTech: Rijeka, Croatia, 2012.
36. Cain, M.; O'Neill, R.; Castillo, A. History of Optimal Power Flow and Formulations. *Fed. Energy Regul. Comm.* **2012**, *1*, 1–36.
37. Kargarian, A.; Mohammadi, J.; Guo, J.; Chakrabarti, S.; Barati, M.; Hug, G.; Kar, S.; Baldick, R. Toward Distributed/Decentralized DC Optimal Power Flow Implementation in Future Electric Power Systems. *IEEE Trans. Smart Grid* **2018**, *9*, 2574–2594. [CrossRef]
38. Dommel, H.W.; Tinney, W.F. Optimal Power Flow Solutions. *IEEE Trans. Power Appar. Syst.* **1968**, *PAS-87*, 1866–1876. [CrossRef]
39. 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]
40. Abou El Ela, A.A.; Abido, M.A.; Spea, S.R. Optimal Power Flow Using Differential Evolution Algorithm. *Electr. Eng.* **2009**, *91*, 69–78. [CrossRef]
41. Abido, M.A. Optimal Power Flow Using Particle Swarm Optimization. *Int. J. Electr. Power Energy Syst.* **2002**, *24*, 563–571. [CrossRef]
42. Lai, L.L.; Ma, J.T.; Yokoyama, R.; Zhao, M. Improved Genetic Algorithms for Optimal Power Flow under Both Normal and Contingent Operation States. *Int. J. Electr. Power Energy Syst.* **1997**, *19*, 287–292. [CrossRef]
43. Bakirtzis, A.G.; Biskas, P.N.; Zoumas, C.E.; Petridis, V. Optimal Power Flow by Enhanced Genetic Algorithm. *IEEE Trans. Power Syst.* **2002**, *17*, 229–236. [CrossRef]
44. Banu, R.N.; Devaraj, D. Genetic Algorithm Approach for Optimal Power Flow with FACTS Devices. In *Proceedings of the 2008 4th International IEEE Conference Intelligent Systems, Varna, Bulgaria, 6–8 September 2008*; IEEE: Piscataway, NJ, USA, 2008; Volume 2, pp. 23-11–23-16.
45. Mahdad, B.; Bouktir, T.; Srairi, K.; EL Benbouzid, M. Dynamic Strategy Based Fast Decomposed GA Coordinated with FACTS Devices to Enhance the Optimal Power Flow. *Energy Convers. Manag.* **2010**, *51*, 1370–1380. [CrossRef]
46. Attia, A.-F.; Al-Turki, Y.A.; Abusorrah, A.M. Optimal Power Flow Using Adapted Genetic Algorithm with Adjusting Population Size. *Electr. Power Compon. Syst.* **2012**, *40*, 1285–1299. [CrossRef]
47. Saravanan, T.; Saritha, G.; Srinivasan, V. Optimal Power Flow Using Particle Swarm Optimization. *Middle-East J. Sci. Res.* **2014**, *20*, 1554–1560. [CrossRef]
48. Vo, D.N.; Schegner, P. An Improved Particle Swarm Optimization for Optimal Power Flow. In *Meta-Heuristics Optimization Algorithms in Engineering, Business, Economics, and Finance*; IGI Global: Hershey, PA, USA, 2013; pp. 1–40. ISBN 9781466620865.
49. Wang, C.-R.; Yuan, H.-J.; Huang, Z.-Q.; Zhang, J.-W.; Sun, C.-J. A Modified Particle Swarm Optimization Algorithm and Its Application in Optimal Power Flow Problem. In *Proceedings of the 2005 International Conference on Machine Learning and Cybernetics, Guangzhou, China, 18–21 August 2005*; IEEE: Piscataway, NJ, USA, 2005; Volume 5, pp. 2885–2889.
50. Yumbla, P.E.O.; Ramirez, J.M.; Coello Coello, C.A. Optimal Power Flow Subject to Security Constraints Solved with a Particle Swarm Optimizer. *IEEE Trans. Power Syst.* **2008**, *23*, 33–40. [CrossRef]
51. Swaroopan, N.M.J.; Somasundaram, P. Optimal Power Flow for Security Enhancement Using Fuzzified Particle Swarm Optimization. In *Proceedings of the International Conference on Sustainable Energy and Intelligent Systems (SEISCON 2011), Chennai, India, 20–22 July 2011*; IET: London, UK, 2011; Volume 2011, pp. 474–479.
52. Niknam, T.; Narimani, M.R.; Aghaei, J.; Azizipanah-Abarghooee, R. Improved Particle Swarm Optimisation for Multi-Objective Optimal Power Flow Considering the Cost, Loss, Emission and Voltage Stability Index. *IET Gener. Transm. Distrib.* **2012**, *6*, 515–527. [CrossRef]
53. Chang, Y.-C.; Lee, T.-Y.; Chen, C.-L.; Jan, R.-M. Optimal Power Flow of a Wind-Thermal Generation System. *Int. J. Electr. Power Energy Syst.* **2014**, *55*, 312–320. [CrossRef]
54. Basu, M. Multi-Objective Optimal Power Flow with FACTS Devices. *Energy Convers. Manag.* **2011**, *52*, 903–910. [CrossRef]
55. Basu, M. Optimal Power Flow with FACTS Devices Using Differential Evolution. *Int. J. Electr. Power Energy Syst.* **2008**, *30*, 150–156. [CrossRef]
56. Varadarajan, M.; Swarup, K.S. Solving Multi-Objective Optimal Power Flow Using Differential Evolution. *IET Gener. Transm. Distrib.* **2008**, *2*, 720. [CrossRef]
57. Amjady, N.; Sharifzadeh, H. Security Constrained Optimal Power Flow Considering Detailed Generator Model by a New Robust Differential Evolution Algorithm. *Electr. Power Syst. Res.* **2011**, *81*, 740–749. [CrossRef]
58. Sayah, S.; Zehar, K. Modified Differential Evolution Algorithm for Optimal Power Flow with Non-Smooth Cost Functions. *Energy Convers. Manag.* **2008**, *49*, 3036–3042. [CrossRef]
59. Shaheen, A.M.; El-Sehiemy, R.A.; Farrag, S.M. Solving Multi-objective Optimal Power Flow Problem via Forced Initialised Differential Evolution Algorithm. *IET Gener. Transm. Distrib.* **2016**, *10*, 1634–1647. [CrossRef]
60. Duman, S.; Güvenç, U.; Sönmez, Y.; Yörükeren, N. Optimal Power Flow Using Gravitational Search Algorithm. *Energy Convers. Manag.* **2012**, *59*, 86–95. [CrossRef]
61. Bhattacharya, A.; Roy, P.K. Solution of Multi-Objective Optimal Power Flow Using Gravitational Search Algorithm. *IET Gener. Transm. Distrib.* **2012**, *6*, 751. [CrossRef]
62. Jahan, M.S.; Amjady, N. Solution of Large-Scale Security Constrained Optimal Power Flow by a New Bi-Level Optimisation Approach Based on Enhanced Gravitational Search Algorithm. *IET Gener. Transm. Distrib.* **2013**, *7*, 1481–1491. [CrossRef]

63. Allaoua, B.; Laoufi, A. Optimal Power Flow Solution Using Ant Manners for Electrical Network. *Adv. Electr. Comput. Eng.* **2009**, *9*, 34–40. [CrossRef]
64. Allaoua, B.; Laoufi, A. Collective Intelligence for Optimal Power Flow Solution Using Ant Colony Optimization. *Leonardo Electron. J. Pract. Technol.* **2008**, *7*, 088–105.
65. Gasbaoui, B.; Allaoua, B. Ant Colony Optimization Applied on Combinatorial Problem for Optimal Power Flow Solution. *Leonardo J. Sci.* **2009**, *14*, 1–17.
66. Joshi, S.K.; Ghanchi, V.H. Solution of Optimal Power Flow Subject to Security Constraints by an Ant Colony Optimization. In *Proceedings of the Third International Conference on Computational Intelligence and Information Technology (CIIT 2013), Mumbai, India, 18–19 October 2013*; Institution of Engineering and Technology: London, UK, 2013; Volume 2013, pp. 590–597.
67. Kılıç, U. Backtracking Search Algorithm-Based Optimal Power Flow with Valve Point Effect and Prohibited Zones. *Electr. Eng.* **2015**, *97*, 101–110. [CrossRef]
68. Bouchekara, H.R.E.H.; Chaib, A.E.; Abido, M.A.; El-Sehiemy, R.A. Optimal Power Flow Using an Improved Colliding Bodies Optimization Algorithm. *Appl. Soft Comput.* **2016**, *42*, 119–131. [CrossRef]
69. Bouchekara, H.R.E.H. Optimal Power Flow Using Black-Hole-Based Optimization Approach. *Appl. Soft Comput.* **2014**, *24*, 879–888. [CrossRef]
70. Mahdad, B.; Srairi, K. Blackout Risk Prevention in a Smart Grid Based Flexible Optimal Strategy Using Grey Wolf-Pattern Search Algorithms. *Energy Convers. Manag.* **2015**, *98*, 411–429. [CrossRef]
71. Herbadji, O. Optimal Power Flow Using Firefly Algorithm with Consideration of FACTS Devices "UPFC". *Int. J. Electr. Eng. Inform.* **2015**, *7*, 12–28. [CrossRef]
72. Balasubbareddy, M.; Sivanagaraju, S.; Suresh, C.V. Multi-Objective Optimization in the Presence of Practical Constraints Using Non-Dominated Sorting Hybrid Cuckoo Search Algorithm. *Eng. Sci. Technol. Int. J.* **2015**, *18*, 603–615. [CrossRef]
73. Mohamed, A.-A.A.A.; Mohamed, Y.S.; El-Gaafary, A.A.M.; Hemeida, A.M. Optimal Power Flow Using Moth Swarm Algorithm. *Electr. Power Syst. Res.* **2017**, *142*, 190–206. [CrossRef]
74. Roy, P.K.; Paul, C. Optimal Power Flow Using Krill Herd Algorithm. *Int. Trans. Electr. Energy Syst.* **2015**, *25*, 1397–1419. [CrossRef]
75. Mukherjee, A.; Mukherjee, V. Solution of Optimal Power Flow with FACTS Devices Using a Novel Oppositional Krill Herd Algorithm. *Int. J. Electr. Power Energy Syst.* **2016**, *78*, 700–714. [CrossRef]
76. Mukherjee, A.; Roy, P.K.; Mukherjee, V. Transient Stability Constrained Optimal Power Flow Using Oppositional Krill Herd Algorithm. *Int. J. Electr. Power Energy Syst.* **2016**, *83*, 283–297. [CrossRef]
77. Rahiminejad, A.; Alimardani, A.; Vahidi, B.; Hosseinian, S.H. Shuffled Frog Leaping Algorithm Optimization for AC--DC Optimal Power Flow Dispatch. *TURKISH J. Electr. Eng. Comput. Sci.* **2014**, *22*, 874–892. [CrossRef]
78. Vahedi, H.; Hosseini, S.H.; Noroozian, R. Bacterial Foraging Algorithm for Security Constrained Optimal Power Flow. In *Proceedings of the 2010 7th International Conference on the European Energy Market, Madrid, Spain, 23–25 June 2010*; IEEE: Piscataway, NJ, USA, 2010; pp. 1–6.
79. Panda, A.; Tripathy, M. Security Constrained Optimal Power Flow Solution of Wind-Thermal Generation System Using Modified Bacteria Foraging Algorithm. *Energy* **2015**, *93*, 816–827. [CrossRef]
80. Mahdad, B.; Srairi, K. A New Interactive Sine Cosine Algorithm for Loading Margin Stability Improvement under Contingency. *Electr. Eng.* **2018**, *100*, 913–933. [CrossRef]
81. Warid, W.; Hizam, H.; Mariun, N.; Abdul-Wahab, N. Optimal Power Flow Using the Jaya Algorithm. *Energies* **2016**, *9*, 678. [CrossRef]
82. Devarapalli, R.; Sinha, N.K.; Rao, B.V.; Knypinski, L.; Lakshmi, N.J.N.; Márquez, F.P.G. Allocation of Real Power Generation Based on Computing over All Generation Cost: An Approach of Salp Swarm Algorithm. *Arch. Electr. Eng.* **2021**, *70*, 337–349. [CrossRef]
83. Khan, M.H.; Ulasyar, A.; Khattak, A.; Zad, H.S.; Alsharef, M.; Alahmadi, A.A.; Ullah, N. Optimal Sizing and Allocation of Distributed Generation in the Radial Power Distribution System Using Honey Badger Algorithm. *Energies* **2022**, *15*, 5891. [CrossRef]
84. Truong, K.H.; Nallagownden, P.; Elamvazuthi, I.; Vo, D.N. A Quasi-Oppositional-Chaotic Symbiotic Organisms Search Algorithm for Optimal Allocation of DG in Radial Distribution Networks. *Appl. Soft Comput. J.* **2020**, *88*, 106067. [CrossRef]
85. Radosavljević, J.; Jevtić, M.; Milovanović, M. A Solution to the ORPD Problem and Critical Analysis of the Results. *Electr. Eng.* **2018**, *100*, 253–265. [CrossRef]
86. Radosavljevic, J.; Jevtic, M. Solution of Optimal Reactive Power Dispatch by a Hybrid GSA-SQP Algorithm. *Elektron. Ir Elektrotechnika* **2016**, *22*, 3–6. [CrossRef]
87. Robbins, B.A.; Domínguez-García, A.D. Optimal Reactive Power Dispatch for Voltage Regulation in Unbalanced Distribution Systems. *IEEE Trans. Power Syst.* **2016**, *31*, 2903–2913. [CrossRef]
88. Vlachogiannis, J.G.; Lee, K.Y. Quantum-Inspired Evolutionary Algorithm for Real and Reactive Power Dispatch. *IEEE Trans. Power Syst.* **2008**, *23*, 1627–1636. [CrossRef]
89. Gangotri, K.M.; Bhimwal, M.K. Genetic Algorithm Based Reactive Power Dispatch for Voltage Stability Improvement. *Int. J. Electr. Power Energy Syst.* **2010**, *32*, 1151–1156.
90. Muhammad, Y.; Khan, R.; Raja, M.A.Z.; Ullah, F.; Chaudhary, N.I.; He, Y. Solution of Optimal Reactive Power Dispatch with FACTS Devices: A Survey. *Energy Rep.* **2020**, *6*, 2211–2229. [CrossRef]

91. Saddique, M.S.; Bhatti, A.R.; Haroon, S.S.; Sattar, M.K.; Amin, S.; Sajjad, I.A.; ul Haq, S.S.; Awan, A.B.; Rasheed, N. Solution to Optimal Reactive Power Dispatch in Transmission System Using Meta-Heuristic Techniques—Status and Technological Review. *Electr. Power Syst. Res.* **2020**, *178*, 106031. [CrossRef]
92. Yoshida, H.; Kawata, K.; Fukuyama, Y.; Takayama, S.; Nakanishi, Y. A Particle Swarm Optimization for Reactive Power and Voltage Control Considering Voltage Security Assessment. *IEEE Trans. Power Syst.* **2000**, *15*, 1232–1239. [CrossRef]
93. Zhao, B.; Guo, C.X.; Cao, Y.J. A Multiagent-Based Particle Swarm Optimization Approach for Optimal Reactive Power Dispatch. *IEEE Trans. Power Syst.* **2005**, *20*, 1070–1078. [CrossRef]
94. Mahadevan, K.; Kannan, P.S. Comprehensive Learning Particle Swarm Optimization for Reactive Power Dispatch. *Appl. Soft Comput. J.* **2010**, *10*, 641–652. [CrossRef]
95. El Ela, A.A.A.; Abido, M.A.; Spea, S.R. Differential Evolution Algorithm for Optimal Reactive Power Dispatch. *Electr. Power Syst. Res.* **2011**, *81*, 458–464. [CrossRef]
96. Basu, M. Quasi-Oppositional Differential Evolution for Optimal Reactive Power Dispatch. *Int. J. Electr. Power Energy Syst.* **2016**, *78*, 29–40. [CrossRef]
97. Sakr, W.S.; EL-Sehiemy, R.A.; Azmy, A.M. Adaptive Differential Evolution Algorithm for Efficient Reactive Power Management. *Appl. Soft Comput. J.* **2017**, *53*, 336–351. [CrossRef]
98. Subbaraj, P.; Rajnarayanan, P.N. Optimal Reactive Power Dispatch Using Self-Adaptive Real Coded Genetic Algorithm. *Electr. Power Syst. Res.* **2009**, *79*, 374–381. [CrossRef]
99. Bhattacharya, A.; Chattopadhyay, P.K. Solution of Optimal Reactive Power Flow Using Biogeography-Based Optimization. *World Acad. Sci. Eng. Technol.* **2009**, *39*, 852–860.
100. Duman, S.; Sönmez, Y.; Güvenç, U.; Yörükeren, N. Optimal Reactive Power Dispatch Using a Gravitational Search Algorithm. *IET Gener. Transm. Distrib.* **2012**, *6*, 563–576. [CrossRef]
101. Shaw, B.; Mukherjee, V.; Ghoshal, S.P. Solution of Reactive Power Dispatch of Power Systems by an Opposition-Based Gravitational Search Algorithm. *Int. J. Electr. Power Energy Syst.* **2014**, *55*, 29–40. [CrossRef]
102. Mukherjee, A.; Mukherjee, V. Solution of Optimal Reactive Power Dispatch by Chaotic Krill Herd Algorithm. *IET Gener. Transm. Distrib.* **2015**, *9*, 2351–2362. [CrossRef]
103. Khazali, A.H.; Kalantar, M. Optimal Reactive Power Dispatch Based on Harmony Search Algorithm. *Int. J. Electr. Power Energy Syst.* **2011**, *33*, 684–692. [CrossRef]
104. Mandal, B.; Roy, P.K. Optimal Reactive Power Dispatch Using Quasi-Oppositional Teaching Learning Based Optimization. *Int. J. Electr. Power Energy Syst.* **2013**, *53*, 123–134. [CrossRef]
105. Abou El-Ela, A.A.; Kinawy, A.M.; El-Sehiemy, R.A.; Mouwafi, M.T. Optimal Reactive Power Dispatch Using Ant Colony Optimization Algorithm. *Electr. Eng.* **2011**, *93*, 103–116. [CrossRef]
106. Sulaiman, M.H.; Mustaffa, Z.; Mohamed, M.R.; Aliman, O. Using the Gray Wolf Optimizer for Solving Optimal Reactive Power Dispatch Problem. *Appl. Soft Comput. J.* **2015**, *32*, 286–292. [CrossRef]
107. Rajan, A.; Malakar, T. Exchange Market Algorithm Based Optimum Reactive Power Dispatch. *Appl. Soft Comput. J.* **2016**, *43*, 320–336. [CrossRef]
108. Rajan, A.; Malakar, T. Optimal Reactive Power Dispatch Using Hybrid Nelder-Mead Simplex Based Firefly Algorithm. *Int. J. Electr. Power Energy Syst.* **2015**, *66*, 9–24. [CrossRef]
109. Kulkarni, P.S.; Kothari, A.G.; Kothari, D.P. Combined Economic and Emission Dispatch Using Improved Backpropagation Neural Network. *Electr. Mach. Power Syst.* **2000**, *28*, 31–44. [CrossRef]
110. Radosavljević, J. A Solution to the Combined Economic and Emission Dispatch Using Hybrid PSOGSA Algorithm. *Appl. Artif. Intell.* **2016**, *30*, 445–474. [CrossRef]
111. Mahdi, F.P.; Vasant, P.; Kallimani, V.; Watada, J.; Fai, P.Y.S.; Abdullah-Al-Wadud, M. A Holistic Review on Optimization Strategies for Combined Economic Emission Dispatch Problem. *Renew. Sustain. Energy Rev.* **2018**, *81*, 3006–3020. [CrossRef]
112. Radosavljevic, J. *Metaheuristic Optimization in Power Engineering*; Institution of Engineering and Technology: London, UK, 2018; ISBN 978-1-78561-547-4.
113. Jacob Raglend, I.; Veeravalli, S.; Sailaja, K.; Sudheera, B.; Kothari, D.P. Comparison of AI Techniques to Solve Combined Economic Emission Dispatch Problem with Line Flow Constraints. *Int. J. Electr. Power Energy Syst.* **2010**, *32*, 592–598. [CrossRef]
114. Abido, M.A. Multiobjective Evolutionary Algorithms for Electric Power Dispatch Problem. *IEEE Trans. Evol. Comput.* **2006**, *10*, 315–329. [CrossRef]
115. Avvari, R.K.; DM, V.K. A New Hybrid Evolutionary Algorithm for Multi-Objective Optimal Power Flow in an Integrated WE, PV, and PEV Power System. *Electr. Power Syst. Res.* **2023**, *214*, 108870. [CrossRef]
116. Park, J.B.; Jeong, Y.W.; Shin, J.R.; Lee, K.Y. An Improved Particle Swarm Optimization for Nonconvex Economic Dispatch Problems. *IEEE Trans. Power Syst.* **2010**, *25*, 156–166. [CrossRef]
117. Ghorbani, N.; Vakili, S.; Babaei, E.; Sakhavati, A. Particle Swarm Optimization with Smart Inertia Factor for Solving Non-Convex Economic Load Dispatch Problems. *Int. Trans. Electr. Energy Syst.* **2014**, *24*, 1120–1133. [CrossRef]
118. Sheng, W.; Li, R.; Yan, T.; Tseng, M.-L.; Lou, J.; Li, L. A Hybrid Dynamic Economics Emissions Dispatch Model: Distributed Renewable Power Systems Based on Improved COOT Optimization Algorithm. *Renew. Energy* **2023**, *204*, 493–506. [CrossRef]

119. Nazir, M.S.; Almasoudi, F.M.; Abdalla, A.N.; Zhu, C.; Alatawi, K.S.S. Multi-Objective Optimal Dispatching of Combined Cooling, Heating and Power Using Hybrid Gravitational Search Algorithm and Random Forest Regression: Towards the Microgrid Orientation. *Energy Rep.* **2023**, *9*, 1926–1936. [CrossRef]
120. Maharana, H.S.; Dash, S.K. Quantum Behaved Artificial Bee Colony Based Conventional Controller for Optimum Dispatch. *Int. J. Electr. Comput. Eng.* **2023**, *13*, 1260. [CrossRef]
121. Pang, A.; Liang, H.; Lin, C.; Yao, L. A Surrogate-Assisted Adaptive Bat Algorithm for Large-Scale Economic Dispatch. *Energies* **2023**, *16*, 1011. [CrossRef]
122. Hassan, M.H.; Kamel, S.; Salih, S.Q.; Khurshaid, T.; Ebeed, M. Developing Chaotic Artificial Ecosystem-Based Optimization Algorithm for Combined Economic Emission Dispatch. *IEEE Access* **2021**, *9*, 51146–51165. [CrossRef]
123. Benasla, L.; Belmadani, A.; Rahli, M. Spiral Optimization Algorithm for Solving Combined Economic and Emission Dispatch. *Int. J. Electr. Power Energy Syst.* **2014**, *62*, 163–174. [CrossRef]
124. Arunachalam, S.; AgnesBhomila, T.; Ramesh Babu, M. Hybrid Particle Swarm Optimization Algorithm and Firefly Algorithm Based Combined Economic and Emission Dispatch Including Valve Point Effect. In Proceedings of the Swarm, Evolutionary, and Memetic Computing: 5th International Conference, SEMCCO 2014, Bhubaneswar, India, 18–20 December 2014; Volume 8947, pp. 647–660. [CrossRef]
125. Abdelaziz, A.Y.; Ali, E.S.; Abd Elazim, S.M. Implementation of Flower Pollination Algorithm for Solving Economic Load Dispatch and Combined Economic Emission Dispatch Problems in Power Systems. *Energy* **2016**, *101*, 506–518. [CrossRef]
126. Acharya, S.; Sivarajan, G.; Kumar, D.V.; Srikrishna, S. Modeling Combined Economic Emission Dispatch for Renewable Energy System via Levy-Based Glowworm Swarm Optimization. *Kybernetes* **2022**. [CrossRef]
127. Safigianni, A.S.; Koutroumpezis, G.N.; Poulios, V.C. Mixed Distributed Generation Technologies in a Medium Voltage Network. *Electr. Power Syst. Res.* **2013**, *96*, 75–80. [CrossRef]
128. Moghaddas-Tafreshi, S.M.; Mashhour, E. Distributed Generation Modeling for Power Flow Studies and a Three-Phase Unbalanced Power Flow Solution for Radial Distribution Systems Considering Distributed Generation. *Electr. Power Syst. Res.* **2009**, *79*, 680–686. [CrossRef]
129. Neto, A.B.; Barbosa, M.B.; Mota, L.M.; Lavorato, M.; de Carvalho, M.F.H. Optimal Power Flow Technique for Distribution System Considering Distributed Energy Resources (DER). *Energies* **2022**, *15*, 8507. [CrossRef]
130. Gabash, A.; Li, P. Active-Reactive Optimal Power Flow in Distribution Networks With Embedded Generation and Battery Storage. *IEEE Trans. Power Syst.* **2012**, *27*, 2026–2035. [CrossRef]
131. Li, B.; Wan, C.; Li, Y.; Jiang, Y.; Yu, P. Generalized Linear-constrained Optimal Power Flow for Distribution Networks. *IET Gener. Transm. Distrib.* **2023**, *17*, 1298–1309. [CrossRef]
132. Radosavljevic, J.; Jevtic, M.; Klimenta, D.; Arsic, N. Optimal Power Flow for Distribution Networks with Distributed Generation. *Serbian J. Electr. Eng.* **2015**, *12*, 145–170. [CrossRef]
133. Shu, J.; Guan, R.; Wu, L. Optimal Power Flow in Distribution Network Considering Spatial Electro-Thermal Coupling Effect. *IET Gener. Transm. Distrib.* **2017**, *11*, 1162–1169. [CrossRef]
134. Niknam, T. An Approach Based on Particle Swarm Optimization for Optimal Operation of Distribution Network Considering Distributed Generators. In *Proceedings of the IECON 2006—32nd Annual Conference on IEEE Industrial Electronics, Paris, France, 7–10 November 2006*; IEEE: Piscataway, NJ, USA, 2006; pp. 633–637.
135. Radosavljević, J.; Jevtic, M.; Arsić, N.; Klimenta, D. Optimal Power Flow for Distribution Networks Using Gravitational Search Algorithm. *Electr. Eng.* **2014**, *96*, 335–345. [CrossRef]
136. Wang, S.; Wang, N.; Wang, Q.; Yang, Y.; Huang, G. Reactive Power Optimization in Distribution Network by Using Improved Gravitational Search Algorithm. In *Proceedings of the 2015 5th International Conference on Electric Utility Deregulation and Restructuring and Power Technologies (DRPT), Changsha, China, 26–29 November 2015*; IEEE: Piscataway, NJ, USA, 2015; pp. 178–182.
137. Saha, A.; Dash, P.; Babu, N.R.; Chiranjeevi, T.; Dhananjaya, M.; Knypiński, Ł. Dynamic Stability Evaluation of an Integrated Biodiesel-Geothermal Power Plant-Based Power System with Spotted Hyena Optimized Cascade Controller. *Sustainability* **2022**, *14*, 14842. [CrossRef]
138. Mahmud, M.A.; Hossain, M.J.; Pota, H.R. Voltage Variation on Distribution Networks with Distributed Generation: Worst Case Scenario. *IEEE Syst. J.* **2014**, *8*, 1096–1103. [CrossRef]
139. Castro, J.R.; Saad, M.; Lefebvre, S.; Asber, D.; Lenoir, L. Optimal Voltage Control in Distribution Network in the Presence of DGs. *Int. J. Electr. Power Energy Syst.* **2016**, *78*, 239–247. [CrossRef]
140. Viawan, F.A.; Sannino, A.; Daalder, J. Voltage Control with On-Load Tap Changers in Medium Voltage Feeders in Presence of Distributed Generation. *Electr. Power Syst. Res.* **2007**, *77*, 1314–1322. [CrossRef]
141. Viawan, F.A.; Karlsson, D. Combined Local and Remote Voltage and Reactive Power Control in the Presence of Induction Machine Distributed Generation. *IEEE Trans. Power Syst.* **2007**, *22*, 2003–2012. [CrossRef]
142. Hong, Y.Y.; Luo, Y.F. Optimal VAR Control Considering Wind Farms Using Probabilistic Load-Flow and Gray-Based Genetic Algorithms. *IEEE Trans. Power Deliv.* **2009**, *24*, 1441–1449. [CrossRef]
143. Villacci, D.; Bontempi, G.; Vaccaro, A. An Adaptive Local Learning-Based Methodology for Voltage Regulation in Distribution Networks with Dispersed Generation. *IEEE Trans. Power Syst.* **2006**, *21*, 1131–1140. [CrossRef]
144. Galdi, V.; Vaccaro, A.; Villacci, D. Voltage Regulation in MV Networks with Dispersed Generations by a Neural-Based Multiobjective Methodology. *Electr. Power Syst. Res.* **2008**, *78*, 785–793. [CrossRef]

145. Niknam, T.; Firouzi, B.B.; Ostadi, A. A New Fuzzy Adaptive Particle Swarm Optimization for Daily Volt/Var Control in Distribution Networks Considering Distributed Generators. *Appl. Energy* **2010**, *87*, 1919–1928. [CrossRef]
146. Chen, S.; Hu, W.; Su, C.; Zhang, X.; Chen, Z. Optimal Reactive Power and Voltage Control in Distribution Networks with Distributed Generators by Fuzzy Adaptive Hybrid Particle Swarm Optimisation Method. *IET Gener. Transm. Distrib.* **2015**, *9*, 1096–1103. [CrossRef]
147. Cheng, S.; Chen, M.Y. Multi-Objective Reactive Power Optimization Strategy for Distribution System with Penetration of Distributed Generation. *Int. J. Electr. Power Energy Syst.* **2014**, *62*, 221–228. [CrossRef]
148. Zhang, L.; Tang, W.; Liang, J.; Cong, P.; Cai, Y. Coordinated Day-Ahead Reactive Power Dispatch in Distribution Network Based on Real Power Forecast Errors. *IEEE Trans. Power Syst.* **2016**, *31*, 2472–2480. [CrossRef]
149. Daratha, N.; Das, B.; Sharma, J. Robust Voltage Regulation in Unbalanced Radial Distribution System under Uncertainty of Distributed Generation and Loads. *Int. J. Electr. Power Energy Syst.* **2015**, *73*, 516–527. [CrossRef]
150. Ulinuha, A.; Masoum, M.A.S.; Islam, S. Hybrid Genetic-Fuzzy Algorithm for Volt/Var/Total Harmonic Distortion Control of Distribution Systems with High Penetration of Non-Linear Loads. *IET Gener. Transm. Distrib.* **2011**, *5*, 425–439. [CrossRef]
151. Jashfar, S.; Esmaeili, S. Volt/Var/THD Control in Distribution Networks Considering Reactive Power Capability of Solar Energy Conversion. *Int. J. Electr. Power Energy Syst.* **2014**, *60*, 221–233. [CrossRef]
152. Jashfar, S.; Hosseini-Biyouki, M.M.; Esmaeili, S. A Stochastic Programming to Volt/VAR/Total Harmonic Distortion Control in Distribution Networks Including Wind Turbines. *Electr. Power Components Syst.* **2015**, *43*, 733–746. [CrossRef]
153. Seelig, B.H.T.; de Souza, L.J.; Prada, R.B. Voltage Control in Heavily Loaded Networks. *Int. Trans. Electr. Energy Syst.* **2015**, *25*, 3275–3287. [CrossRef]
154. Hu, Z.; Wang, X.; Chen, H.; Taylor, G.A. Volt/VAr Control in Distribution Systems Using a Time-Interval Based Approach. *IEEE Proc.-Gener. Transm. Distrib.* **2003**, *150*, 548. [CrossRef]
155. Park, J.Y.; Nam, S.R.; Park, J.K. Control of a ULTC Considering the Dispatch Schedule of Capacitors in a Distribution System. *IEEE Trans. Power Syst.* **2007**, *22*, 755–761. [CrossRef]
156. Senjyu, T.; Miyazato, Y.; Yona, A.; Urasaki, N.; Funabashi, T. Optimal Distribution Voltage Control and Coordination with Distributed Generation. *IEEE Trans. Power Deliv.* **2008**, *23*, 1236–1242. [CrossRef]
157. Madureira, A.G.; Peças Lopes, J.A. Coordinated Voltage Support in Distribution Networks with Distributed Generation and Microgrids. *IET Renew. Power Gener.* **2009**, *3*, 439–454. [CrossRef]
158. Mokgonyana, L.; Zhang, J.; Zhang, L.; Xia, X. Coordinated Two-Stage Volt/Var Management in Distribution Networks. *Electr. Power Syst. Res.* **2016**, *141*, 157–164. [CrossRef]
159. Niknam, T.; Zare, M.; Aghaei, J. Scenario-Based Multiobjective Volt/Var Control in Distribution Networks Including Renewable Energy Sources. *IEEE Trans. Power Deliv.* **2012**, *27*, 2004–2019. [CrossRef]
160. Zare, M.; Niknam, T. A New Multi-Objective for Environmental and Economic Management of Volt/Var Control Considering Renewable Energy Resources. *Energy* **2013**, *55*, 236–252. [CrossRef]
161. Mohamed Shuaib, Y.; Surya Kalavathi, M.; Christober Asir Rajan, C. Optimal Capacitor Placement in Radial Distribution System Using Gravitational Search Algorithm. *Int. J. Electr. Power Energy Syst.* **2015**, *64*, 384–397. [CrossRef]
162. Abdul Kadir, A.F.; Mohamed, A.; Shareef, H.; Che Wanik, M.Z. Optimal Placement and Sizing of Distributed Generations in Distribution Systems for Minimizing Losses and THD$_{v}$ Using Evolutionary Programming. *TURKISH J. Electr. Eng. Comput. Sci.* **2013**, *21*, 2269–2282. [CrossRef]
163. Khoa, T.Q.D.; Binh, P.T.T.; Tran, H.B. Optimizing Location and Sizing of Distributed Generation in Distribution Systems. In *Proceedings of the 2006 IEEE PES Power Systems Conference and Exposition, Atlanta, GA, USA, 1 November 2006*; IEEE: Piscataway, NJ, USA, 2006; pp. 725–732.
164. Elsaiah, S.; Benidris, M.; Mitra, J. Analytical Approach for Placement and Sizing of Distributed Generation on Distribution Systems. *IET Gener. Transm. Distrib.* **2014**, *8*, 1039–1049. [CrossRef]
165. Gopiya Naik, S.N.; Khatod, D.K.; Sharma, M.P. Analytical Approach for Optimal Siting and Sizing of Distributed Generation in Radial Distribution Networks. *IET Gener. Transm. Distrib.* **2015**, *9*, 209–220. [CrossRef]
166. Viral, R.; Khatod, D.K. An Analytical Approach for Sizing and Siting of DGs in Balanced Radial Distribution Networks for Loss Minimization. *Int. J. Electr. Power Energy Syst.* **2015**, *67*, 191–201. [CrossRef]
167. Keane, A.; O'Malley, M. Optimal Allocation of Embedded Generation on Distribution Networks. *IEEE Trans. Power Syst.* **2005**, *20*, 1640–1646. [CrossRef]
168. Le, A.D.T.; Kashem, M.A.; Negnevitsky, M.; Ledwich, G. Optimal Distributed Generation Parameters for Reducing Losses with Economic Consideration. In *Proceedings of the 2007 IEEE Power Engineering Society General Meeting, Tampa, FL, USA, 24–28 June 2007*; IEEE: Piscataway, NJ, USA, 2007; pp. 1–8.
169. Prenc, R.; Škrlec, D.; Komen, V. Distributed Generation Allocation Based on Average Daily Load and Power Production Curves. *Int. J. Electr. Power Energy Syst.* **2013**, *53*, 612–622. [CrossRef]
170. Savić, A.; Ðurišić, Ž. Optimal Sizing and Location of SVC Devices for Improvement of Voltage Profile in Distribution Network with Dispersed Photovoltaic and Wind Power Plants. *Appl. Energy* **2014**, *134*, 114–124. [CrossRef]
171. Mohammadi, M.; Nafar, M. Optimal Placement of Multitypes DG as Independent Private Sector under Pool/Hybrid Power Market Using GA-Based Tabu Search Method. *Int. J. Electr. Power Energy Syst.* **2013**, *51*, 43–53. [CrossRef]

172. Dehghanian, P.; Hosseini, S.H.; Moeini-Aghtaie, M.; Arabali, A. Optimal Siting of DG Units in Power Systems from a Probabilistic Multi-Objective Optimization Perspective. *Int. J. Electr. Power Energy Syst.* **2013**, *51*, 14–26. [CrossRef]
173. Vatani, M.; Alkaran, D.S.; Sanjari, M.J.; Gharehpetian, G.B. Multiple Distributed Generation Units Allocation in Distribution Network for Loss Reduction Based on a Combination of Analytical and Genetic Algorithm Methods. *IET Gener. Transm. Distrib.* **2016**, *10*, 66–72. [CrossRef]
174. Gkaidatzis, P.A.; Bouhouras, A.S.; Doukas, D.I.; Sgouras, K.I.; Labridis, D.P. Load Variations Impact on Optimal DG Placement Problem Concerning Energy Loss Reduction. *Electr. Power Syst. Res.* **2017**, *152*, 36–47. [CrossRef]
175. Zeinalzadeh, A.; Mohammadi, Y.; Moradi, M.H. Optimal Multi Objective Placement and Sizing of Multiple DGs and Shunt Capacitor Banks Simultaneously Considering Load Uncertainty via MOPSO Approach. *Int. J. Electr. Power Energy Syst.* **2015**, *67*, 336–349. [CrossRef]
176. Cheng, S.; Chen, M.-Y.; Fleming, P.J. Improved Multi-Objective Particle Swarm Optimization with Preference Strategy for Optimal DG Integration into the Distribution System. *Neurocomputing* **2015**, *148*, 23–29. [CrossRef]
177. Bohre, A.K.; Agnihotri, G.; Dubey, M. Optimal Sizing and Sitting of DG with Load Models Using Soft Computing Techniques in Practical Distribution System. *IET Gener. Transm. Distrib.* **2016**, *10*, 2606–2621. [CrossRef]
178. Kumawat, M.; Gupta, N.; Jain, N.; Bansal, R.C. Swarm-Intelligence-Based Optimal Planning of Distributed Generators in Distribution Network for Minimizing Energy Loss. *Electr. Power Components Syst.* **2017**, *45*, 589–600. [CrossRef]
179. Sharma, D.; Kumar Yadav, N.; Gunjan; Bala, A. Impact of Distributed Generation on Voltage Profile Using Different Optimization Techniques. In *Proceedings of the 2016 International Conference on Control, Computing, Communication and Materials (ICCCCM), Allahabad, India, 21–22 October 2016*; IEEE: Piscataway, NJ, USA, 2016; pp. 1–6.
180. Fazliana Abdul Kadir, A.; Mohamed, A.; Shareef, H.; Asrul Ibrahim, A.; Khatib, T.; Elmenreich, W. An Improved Gravitational Search Algorithm for Optimal Placement and Sizing of Renewable Distributed Generation Units in a Distribution System for Power Quality Enhancement. *J. Renew. Sustain. Energy* **2014**, *6*, 033112. [CrossRef]
181. Sarkar, B.K.; Chakrabarti, A. OPF Governed Determination of Location and Size of Distribution Generators Using Gravitational Search Algorithm. In *Proceedings of the 2016 2nd International Conference on Control, Instrumentation, Energy & Communication (CIEC), Kolkata, India, 28–30 January 2016*; IEEE: Piscataway, NJ, USA, 2016; pp. 446–450.
182. Fadel, W.; Kilic, U.; Taskin, S. Placement of Dg, Cb, and Tcsc in Radial Distribution System for Power Loss Minimization Using Back-Tracking Search Algorithm. *Electr. Eng.* **2017**, *99*, 791–802. [CrossRef]
183. El-Fergany, A. Optimal Allocation of Multi-Type Distributed Generators Using Backtracking Search Optimization Algorithm. *Int. J. Electr. Power Energy Syst.* **2015**, *64*, 1197–1205. [CrossRef]
184. Kefayat, M.; Lashkar Ara, A.; Nabavi Niaki, S.A. A Hybrid of Ant Colony Optimization and Artificial Bee Colony Algorithm for Probabilistic Optimal Placement and Sizing of Distributed Energy Resources. *Energy Convers. Manag.* **2015**, *92*, 149–161. [CrossRef]
185. Sultana, U.; Khairuddin, A.B.; Mokhtar, A.S.; Zareen, N.; Sultana, B. Grey Wolf Optimizer Based Placement and Sizing of Multiple Distributed Generation in the Distribution System. *Energy* **2016**, *111*, 525–536. [CrossRef]
186. Devi, S.; Geethanjali, M. Application of Modified Bacterial Foraging Optimization Algorithm for Optimal Placement and Sizing of Distributed Generation. *Expert Syst. Appl.* **2014**, *41*, 2772–2781. [CrossRef]
187. 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]
188. Zheng, Q.P.; Wang, J.; Liu, A.L. Stochastic Optimization for Unit Commitment—A Review. *IEEE Trans. Power Syst.* **2015**, *30*, 1913–1924. [CrossRef]
189. 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]
190. 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]
191. 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]
192. 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*; IEEE: Piscataway, NJ, USA, 2010; pp. 642–647.
193. 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]
194. 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]