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Review

Multi-Objective Optimization of Load Flow in Power Systems: An Overview

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Abstract

The expanding complexity of power systems—driven by the motivation to reduce their carbon footprint by integrating renewable energy sources (RESs) in the grid, the increasing energy demand, grid scalability, and the necessity for reliable and sustainable operation—has made the optimal power flow (OPF) problem the main issue in power systems. Hence, the concept of muti-objective optimal power flow (MOOPF) in power systems has become a crucial tool for power system management and planning. This article provides an overview of recent optimization techniques in power systems that have MOOPF as their central problem, as well as their applications in power systems, with the purpose of identifying significant approaches, challenges and trends when it comes to large-scale probabilistic MOOPF. This overview was developed based on an in-depth analysis of MOOPF techniques, the classification of their applications, and the formulation of the problem in power systems. This overview contributes to the existing literature by highlighting the evolution of optimization techniques, and the need for robust, probabilistic hybrid optimization techniques that can address variability, uncertainty, reliability, and sustainability in power systems. These findings are significant because they emphasize the current transition towards more adaptive and intelligent optimization strategies, which are essential to developing sustainable, dependable, and effective power systems, especially as we move towards smart grids and low-carbon energy systems.

Keywords: dynamic system; multi-objective optimal power flow (MOOPF); optimization techniques; power systems; renewable energy sources (RESs)

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1. Introduction

The electric power grid is an ever-changing dynamic system. This system is intended to safely and consistently produce, transfer, and distribute electricity from power plants to consumers [1]. It is made up of power generation units, transmission and distribution systems, control and protection systems, and energy-consuming devices. Since its establishment in the late 19th century, the grid has experienced revolutionary transformations. Originally built for unidirectional power flow and centralized generation, it changed to accommodate expanding industrial and residential needs [2–4]. There is a need for more effective, adaptable, and intelligent grid management in line with the ever-growing demand for electricity. By 2035, this growth is expected to rise by 53% [5–11].

In the 21st century, a new phase has been reached in power systems, characterized by the integration of renewable energy sources (RESs) which is driven by environmental goals, decreasing technological costs, and accessibility to electricity in underdeveloped nations [12–14]. China, the EU, and the US have the largest installed solar PV capacity, with over 2.2 TW worldwide by the end of 2024, according to the International Renewable Energy Agency (IRENA) and about 19.2 GW for Africa and the Middle East. With a current installed capacity of 1.136 TW, wind energy comes in second position, with significant installations in Asia, North America, Europe and an expected installed capacity of 16 GW in Africa by 2025 [15,16].

Furthermore, grid dynamics are changing as a result of the integration of RESs. These sources have a major impact on grid stability and power quality. Due to their intermittent nature and time-varying output, their integration brings uncertainty and variability into the grid which can lead to voltage fluctuations, supply–demand imbalance, and excessive transmission losses, etc. [17–22]. It is therefore necessary to conduct studies aimed at examining and optimizing power systems in order to adapt to changes in the energy landscape and ensure the sustainability and resilience of the grid [23–30].

Applications of optimization techniques in power systems are motivated by the ongoing conflict between the growing complexity of the grid and the necessity for a cost-effective, reliable, and efficient power supply [3–7]. An evolution has been observed in power system configurations and optimization techniques used to address the management, operation, and planning of power systems, from basic cost-minimization problems with centralized structures to complex, multi-objective problems with interconnected networks and various power sources [31,32].

Optimization techniques in power systems started more than 45 years ago when the Optimal Power Flow (OPF) problem (which aims to identify the optimal state of operation for power systems) was developed, and they have since advanced through multiple chronological phases of problem formulation and solution approaches [33]. The development of optimization solutions across time can be approximately categorized into three periods as shown in Figure 1 [34–40]:

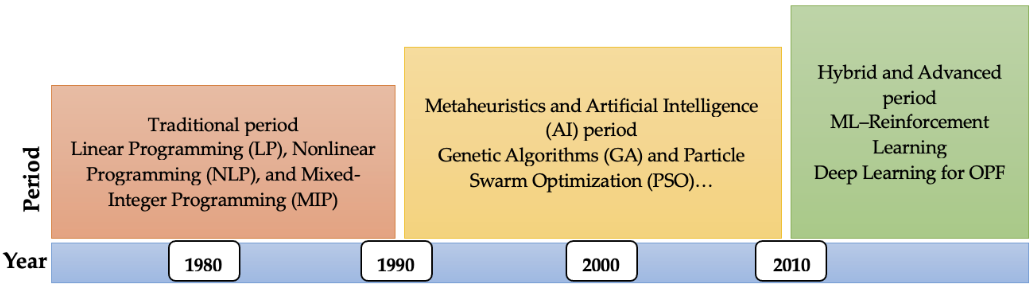

Figure 1. Evolutionary trajectory of optimization techniques in power systems.

In the traditional period, which spanned from before the 1980s to the early 1990s, traditional optimization methods including linear programming (LP), nonlinear programming (NLP), and mixed-integer programming (MIP) were considered the norm. For basic, deterministic situations, these techniques provided optimal solutions and were mathematically rigorous. However, the rise of deregulated markets and the grid's growing complexity made their weaknesses clear. In the Metaheuristics and Artificial Intelligence (AI) period, from the 1990s to the late 2000s, metaheuristics and AI based algorithms including Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) were popular. These algorithms were inspired by nature and were particularly good at searching large nonlinear search spaces for near-global solutions. Because of their resilience and adaptability, they were perfect for solving challenging, non-convex problems that traditional approaches were unable to solve. In the Modern or Hybrid and Advanced period, from the 2010s to present, managing the significant unpredictability brought by the widespread integration of renewable energy sources and smart grid technology has become the focus of most research studies. Nowadays, hybrid approaches that incorporate several approaches, robust optimization, and stochastic programming are examples of modern solutions. In an extremely uncertain environment, these strategies place a significant priority on resilience and real-time flexibility to guarantee that the grid stays steady, safe, and effective [4,21].

OPF comprises any optimization problem in a power system that aims to optimize power system operation while satisfying constraints. Several power system optimization issues are specific cases or extensions of OPF. This general structure includes dozens of optimization issues for power system planning and operation. In Figure 2, a wide range of optimization problems are shown, including long-term power system planning and maintenance scheduling to guarantee future capacity and reliability and short-term operational decisions like Unit Commitment and Economic Dispatch that minimize costs and maintain security [3,34]. In order to minimize losses and enhance voltage stability, optimization is essential for resolving particular network issues such as network reconfiguration and reactive source allocation [36–42]. Beyond technical and financial issues, applications such as pollution dispatch demonstrate how multi-objective optimization (MOO) is used to balance cost and environmental impact, guaranteeing that the grid in its entirety is not just secure and effective, but sustainable as well [41,42]. Figure 3 shows a quick view of the current state of power system optimization which emphasizes the fundamental operational and planning difficulties facing the transmission and generation industries as well as the management of the intricate distribution network. Power system optimization is moving away from deterministic algorithms, which perform well in the structured, high-accuracy requirements of generation and transmission at 53% of applications, and towards heuristic and hybrid approaches, which dominate the distribution network at 45% because they are better at handling non-linearity, non-convexity, and discrete variables while avoiding local optima. Heuristics and hybrids are more reliable for modern complex, uncertain systems, even though deterministic approaches are faster; at the same time, new AI-based techniques are demonstrating great promise for real-time, adaptive control, although their current use is constrained by the requirement for large amounts of data and processing power.

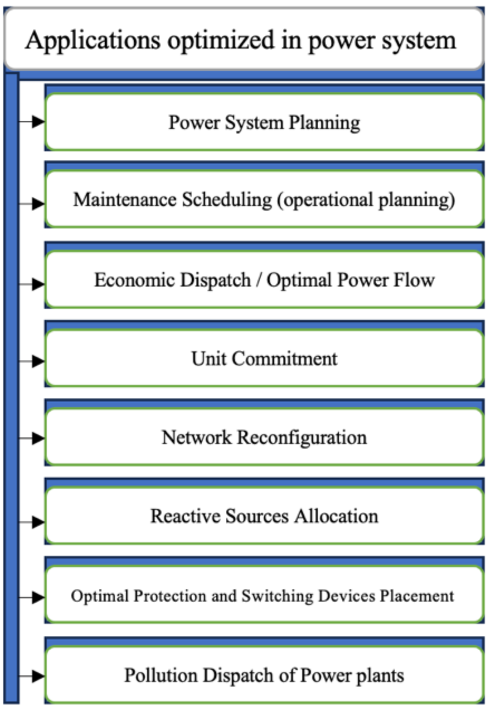

Figure 2. Optimization applications in power systems [36–42].

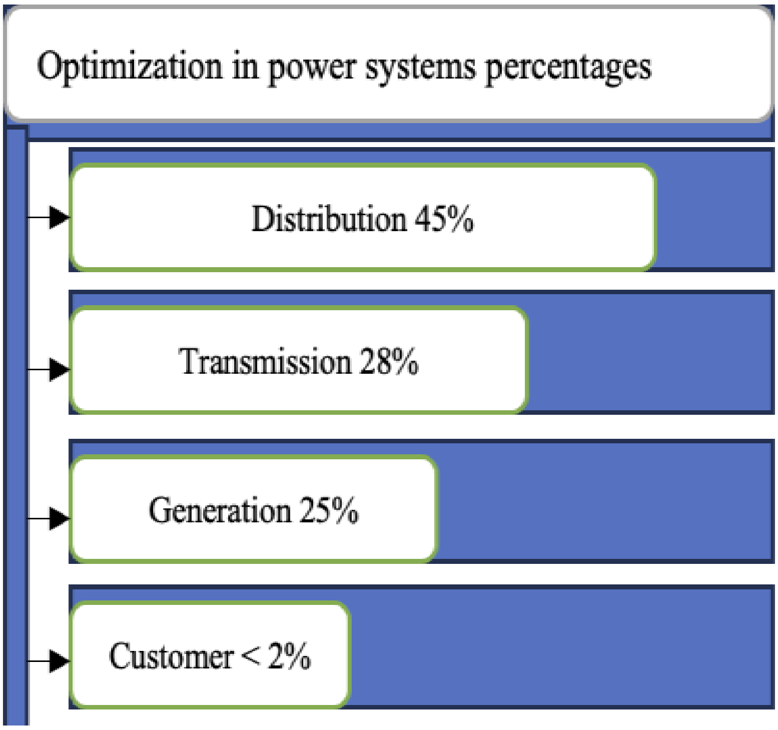

Figure 3. Optimization techniques in power systems percentages [43].

Power flow analysis is conducted to ascertain how power flows throughout the network under specific load and generation scenarios. It also gives important voltage information, such as phase and magnitude, at every grid node [44–47]. However, it is crucial to simplify the problem formulation and choose the most efficient optimization strategies [48,49].

As shown in Figure 4, this paper presents an in-depth review of MOOPF techniques by assessing critically what each proposed method has accomplished, as well as the classification of their applications, and the formulation of the problem in power systems. It critically examines how power system management, operation, and planning are addressed via optimization, but also how the problem is formulated. The study identifies trends in the use of MOO for power system issues such as RESs integration and OPF. This paper contributes to the current literature by emphasizing the evolution of optimization approaches and the need for robust, probabilistic hybrid optimization strategies that can handle variability, uncertainty, dependability, and sustainability in power systems. This study is in line with the global energy transition, which places a high priority on grid resilience, decarbonization, and RESs integration. It illustrates how distributed, intelligent systems that are rich in RE are replacing centralized, fossil fuel-based grids, necessitating the use of more sophisticated optimization methods. Optimization is a key facilitator for future power systems since it has a direct connection to the sustainability agenda. The following sections make up this paper: power system topologies are discussed in Section 2, classical and intelligent optimization techniques in power systems are covered in Sections 3 and 4, respectively, Section 5 covers Challenges and future directions in power systems and then comes the conclusion in Section 6.

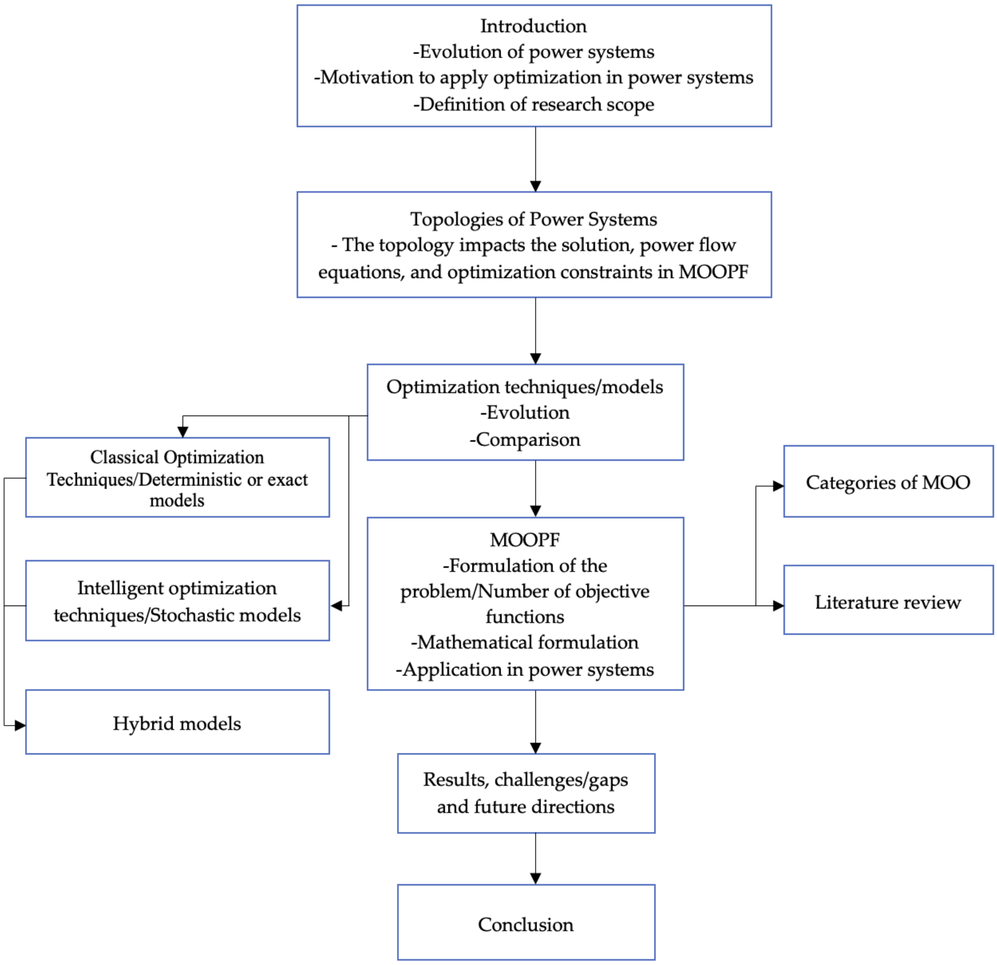

Figure 4. Overview of MOOPF in power system visual representation.

2. Topologies of Power Systems

The topology of power systems is the electrical or physical configuration of a power system's loads, transmission lines, and generators [50–53]. A variety of configurations, as illustrated below in Figure 5, can be used to organize power systems. Every kind of configuration has unique properties and operates in a variety of ways. As described in [54], the system's cost, adaptability, and dependability are determined by this configuration.

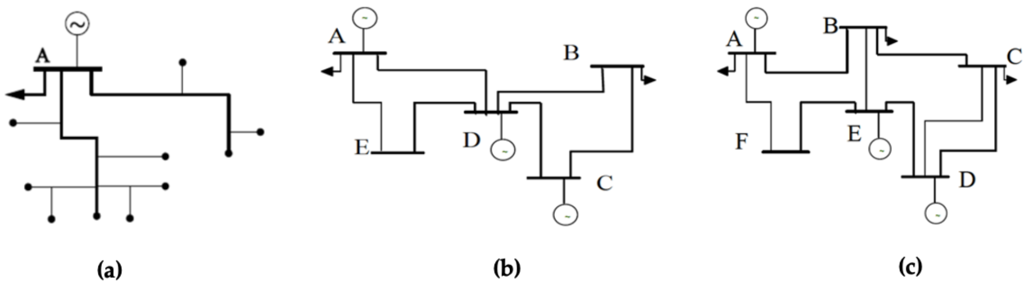

Figure 5. (**a**) Radial architecture, (**b**) Loop architecture, (**c**) Mesh architecture.

2.1. Radial or Star Networks

The most straightforward and typical configuration, particularly in distribution systems, is a radial structure as shown in Figure 5a. This arrangement creates no closed loops since feeders branch off from a single source of power, such as a substation, and provide electricity to loads as they go [55]. There is only one connection to the source for every load. Due to its affordability and ease of use, the radial configuration is frequently used for distribution networks, particularly in residential areas [56]. Its main drawback is that it is not very reliable because any defect on the feeder will cut off power to all downstream loads, leaving the system open to massive outages.

2.2. Loop Networks

A loop structure, as shown in Figure 5b, offers a closed path for power flow, which enhances the radial structure [57,58]. After leaving a substation, feeders travel around a service area before returning to the same substation or another one. Usually, a radial spur off the loop supplies each load. Individual loads are still served radially even when the loop itself offers two routes to the main supply. However, as opposed to the more straightforward radial structures, this increased reliability comes at the expense of being more costly and requiring more intricate protection measures.

2.3. Mesh or Connected Networks

A highly intricate and dependable configuration as illustrated in Figure 5c is a mesh topology, in which a grid is formed by connecting numerous generators and loads via a large number of transmission lines. Power can move between any two points in the system in a number of parallel ways [59]. This configuration is costly and intricate to construct, manage and safeguard. Sophisticated control and protection systems are necessary because of the intricate power flow pathways. For high-voltage transmission networks that serve as the foundation of a regional or national grid, this is the typical structure.

The feasible solution space, power flow equations, and optimization constraints in MOOPF studies are directly impacted by the electrical network topology. Thus, knowledge of network topology is essential for understanding how optimization algorithms are used and why some approaches work better in particular system configurations. Practicality, the most effective electrical network (power system) design is determined by the objective (dependability, cost, power quality, losses, etc.), but for modern power systems with transformers and distributed generation, mesh or connected network is typically the optimal architecture [51,52,59].

3. Optimization Techniques

In the realm of power systems, optimization approaches are crucial for enhancing the efficiency [60], reliability, and economic viability of electricity generation, distribution, and transmission [61–65]. The primary goal of an optimization problem, which is a mathematical model, is to minimize undesirable factors (such as cost, energy loss, errors, etc.) or maximize desirable factors (such as profit, quality, efficiency, etc.), subject to certain limitations [49,66–69]. However, a multi-objective problem with conflicting goals will never have a single optimal solution, but rather a collection of them [70].

Optimization issues can be tackled using a variety of traditional methods [71]. In the part that follows, we will examine the two primary aspects of optimization techniques in power systems: classical and intelligent optimization techniques [72–77], which are illustrated in Figure 6, and compared in Table 1. Classical models are particular computations produced by an algorithm that accepts a value or set of values as input and returns a value or set of values as output. Intelligent models are methods or procedures used to finish a task or find a solution [78,79].

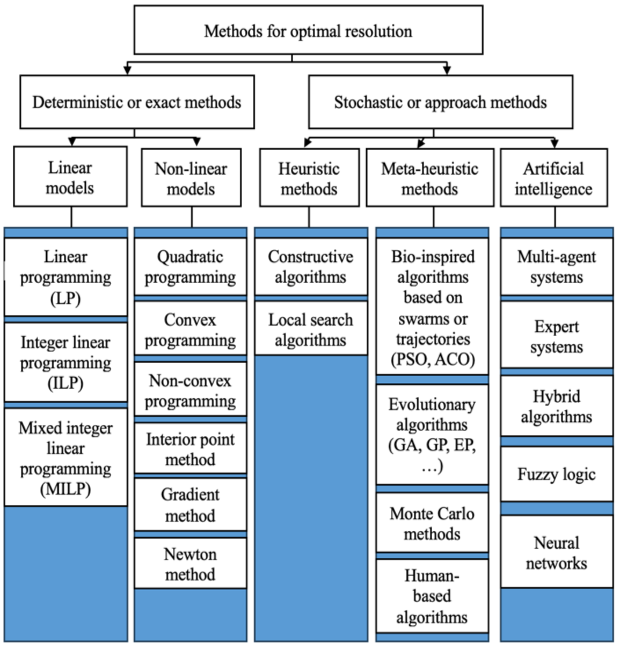

Figure 6. Methods to address optimization problems [72–77].

Table 1. Classical and intelligent optimization techniques comparison.

Feature	Classical Optimization	Intelligent Optimization
Method	Exact/Deterministic	Non-exact/Stochastic
Math model	Explicit mathematical model	Black-box models
Intricacy handling	Limited	High
Result	One optimal solution	Multiple (global optimum)
Speed	Fast (for basic models)	Slower (for iterative search)
Global search	Local minima propensity	Improved capability
Computation Time	Shorter (small, convex systems)	Higher (large, complex systems)
Convergence behavior	Quickly (convex)	Global/near-global solutions
Solution Quality	Exact/near-exact (convex, smooth)	High-quality
CFD/CFI (Constraint Feasibility Degree/Index)	CFD = 0 (satisfaction of constraints)	CFD > 0
Handling of CFD/CFI	Enforced rigidly (mathematically)	Flexible
Numerical Stability	High (Jacobian/Hessian well-conditioned)	Stable (Algorithmic adjustment)
Implementation Difficulty	Simpler	Difficult
Scalability	Effective (small, medium systems)	Adaptable (Large systems)

3.1. Classical Optimization Techniques

Conventional techniques created to address problems with clearly specified mathematical features are known as classical optimization techniques. They are deterministic, as shown in Figure 6, which means they will always yield the same outcome given a starting position. These techniques use calculus-based ideas like gradients and Hessians to methodically search for the best result [80].

A mathematical program is the fundamental building block for articulating and solving optimization problems using mathematical models [75]. Working with very simple mathematical equations may allow for the possibility of analytical solutions. In many real-world situations, the relationships involved are too complicated to allow for direct differentiation [81], hence alternative optimization processes are required to determine the optimal objective value and the associated values of independent variables.

There are several mathematical programs, often based on the particulars of the situation at hand. In this instance, the problem is regarded as Linear Programming (LP) if the variables in the problem (sometimes denoted by "x") allow both the objective function and the constraints to be characterized as linear functions [49]. However, when restrictions and/or the target functions exhibit non-linear features, the problem is categorized as Non-Linear Programming (NLP). Furthermore, variables are limited to believing that the "Integer" trait is applied only to integer values [69]. An example of a binary choice in a power system would be a transformer that is either in functioning mode (status = 1) or in a spare state (status = 0). When every variable satisfies this requirement to be an integer, the problem is known as integer programming (IP). However, only when some of the variables need integer values does Mixed Integer Programming (MIP) arise [82]. These variations in problem classification aid in choosing optimization strategies appropriate for the constraints and intrinsic complexity of the issue. Quadratic programming (QP) is an advanced form of NLP. The QP optimization model features linearly specified constraints and a quadratic objective function. QP is more accurate than LP-based techniques. The most commonly used objective function in power system optimization is the generation cost function, which is frequently quadratic. As a result, the QP solution to the power system optimization problem cannot be simplified using such an objective function [82]. Since it calculates the second-order partial derivatives of the power-flow equations in addition to other constraints (the Hessian), Newton's method, another type of NLP, is known as a second-order approach. Often, the prerequisites for optimality are the Kuhn–Tucker requirements [82,83].

3.2. Intelligent Optimization Techniques

Deterministic or exact optimization methods are rigorous, mathematical-based approaches, as explained in Sections 1 and 3.1, and they use known parameters. However, real-world problems frequently contain some unknown parameters [3]. Therefore, classical or exact optimization methods are limited because they are unable to handle integer-variable, variability, uncertainty, non-linearity and large-scale optimization problems [35–40,80,81]. Hence, the introduction of intelligent optimization techniques (stochastic). These approaches, as illustrated in Figure 6, are a class of algorithms that employ stochastic or heuristic ways to solve problems; they are also referred to as metaheuristics. They draw inspiration from biological or natural phenomena including physical annealing, swarm behavior, and evolution. They are intended to search a larger search space in order to identify a global or near-global optimum, and they do not require derivatives, in contrast to traditional approaches.

Optimization algorithms are computer programs used to solve the mathematical models developed during power system optimization. These algorithms search for the optimal solution within the parameters of the issue domain. There are two categories of algorithms: exact (deterministic) and not-exact (stochastic or approach methods), as seen in Figure 6. Even when exact algorithms find a global optimum, they frequently do not scale well to large problems [41,78]. For complicated power system problems, non-exact algorithms which fall into two categories—heuristic, and artificial intelligence (AI)—are most frequently employed in the literature.

Not-exact methods are often more scalable when handling large issues, allowing for precise characterization of the optimization problem. It is important to keep in mind that although these approaches look for fulfilling answers, they cannot ensure that the solution is feasible, near, or ideal. Nevertheless, certain modified heuristic techniques have come up and assert they can guarantee the best results [46].

Precise, conventional optimization methods often encounter issues that prevent them from solving the optimization problem in a timely way [44]. To avoid such circumstances, other methods that can detect high-quality, if not quite accurate, approximations to exact answers were created. These methods, referred to as heuristics, were initially primarily reliant on the knowledge and experience of specialists and were intended to explore the search space in a particularly useful way. Heuristics were initially employed by G. Polya in 1945 [84], and their use grew throughout the 1970s as new heuristics were created for specific issues in a range of technical and scientific fields, including electrical engineering. In essence, a heuristic is designed to provide better computational efficiency than conventional optimization methods at the expense of reduced precision.

Simple or basic heuristics and meta-heuristics are the two subclasses of heuristic [41]. In order to rapidly ascertain the control parameters for power system components such as transformers and generators without guaranteeing optimality, basic heuristics are commonly used in optimal power flow (OPF) and typically take the shape of constructive, local search algorithms [85]. Although simple heuristics can improve the solution for an issue rapidly and effectively, they have a high risk of becoming stuck in a local optimum.

Since they began in the mid-1980s, metaheuristic approaches to optimization problems have improved steadily, making it possible to address and solve a growing number of problems that were previously considered difficult or impossible to solve [86]. Meta-heuristics, which are a step up from simple heuristics, seek to find the optimal answer outside of a predetermined neighborhood. In OPF, meta-heuristic techniques are used to explore larger, complex solution spaces effectively than typical heuristics [87–92], such as evolutionary algorithms, Monte Carlo methods, human-based algorithms, etc. [45]. Many meta-heuristic methods are derived from biologic principles (nature-inspired, population-based algorithms) [93–96]. All of them, in essence, start with a point or set of points and go towards a better solution while being guided by heuristic, empirical, or logical rules and sensitivities [97–104]. These ideas are used to generate and categorize the search possibilities. In MOOPF, meta-heuristic algorithms are essential in solving problems efficiently by addressing multiple objectives simultaneously [3]. These algorithms balance exploration with exploitation by simulating a large number of control variable combinations, such as generator outputs, voltages, and tap settings, resulting in diverse, near-optimal solutions. Hence, the concept of Pareto optimality (Pareto front) as explained in Section 4 and illustrated by Figure 7 [14,78]. The purpose of the Pareto optimality is to find a set of trade-off optimal solutions (Pareto-optimal solutions), rather than one optimal solution [80,81]. As illustrated in Table 2, a power system operator has three objective functions—to minimize CO_2 emissions, generation cost and voltage deviation (VD). For such solutions, no objective function can be improved without first sacrificing at least one other objective function. For instance, in Table 2, the Pareto front illustrates that minimizing CO_2 emissions increases the generation cost, enabling decision-makers to choose their preferred point of operations based on policy considerations. The advantages of meta-heuristic algorithms are adaptability to change, and ability to handle integer-variable, non-linearity and large-scale optimization problems [3,41].

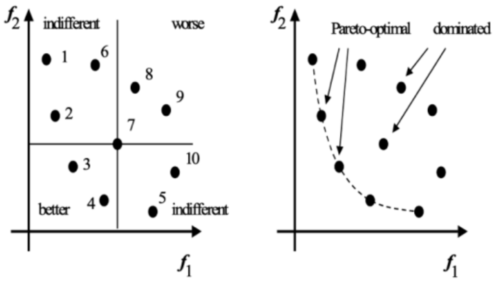

Figure 7. Illustration of the concept pareto optimality [78].

Table 2. An example of MOOPF solution based meta-heuristic algorithms (Pareto front).

Solution	CO_2 (kg/h)	Cost ($/h)	VD
1	400	900	0.016
2	300	950	0.014
3	200	1000	0.011

In OPF, AI techniques like machine learning and deep learning have grown in popularity [105]. By analyzing historical data, machine learning algorithms are able to predict the optimal power system configurations [106–111]. Because deep learning can handle complicated non-linear interactions, it is increasingly being used to solve OPF problems [112,113]. Because AI approaches may improve accuracy and automate power system management, they have potential when addressing large-scale, data-driven OPF operations [82]. For example, artificial neural networks (ANN) were based on a learning algorithm created by Hebb in 1949 that demonstrated how a network of neurons might exhibit learning behavior. ANNs are primarily categorized by their architecture (number of layers), learning regime, and topology (feed forward, connection pattern, or recurrent, etc.) [80].

However, the superiority of the heuristic approach in solving large-scale, complex, combinatorial, and nonlinear problems is supported by a vast number of models that have been published in scientific journals. Conversely, when the network size grows, exact techniques demand significantly more computing work [41,80,84]. To sum up, while accurate optimization techniques yield theoretically optimal outcomes, they may jeopardize modelling accuracy in power system settings, resulting in poor outcomes.

As explained in Section 1, a hybrid approach is possible and effective. The combination of deterministic and stochastic methods improves optimization results in power systems, resulting in more precise, faster, and dependable solutions. Deterministic approaches provide precision and speedy convergence, but stochastic approaches excel in exploring complex, nonlinear solution spaces [41,42]. Therefore, when employing hybrid approaches, stochastic algorithms identify the global optimum, and deterministic methods improve the results.

4. Multi-Objective Optimization in Power Systems

OPF is a set of optimization problems in power systems engineering. An optimization problem having many objective functions is referred to as multi-objective optimization. Unlike one objective with a single solution, multi-objective optimization (MOO) issues have a group or set of solutions that reflect trade-offs between objectives [78]. Subject to both operational and physical limitations, a MOOPF problem aims to concurrently optimize many competing objectives in power systems, as explained in Section 3.2. Multi-objective optimization techniques are intended to generate these trade-offs [114]. Resolving these compromises is essential because it provides the information and resources necessary for designers and operators to understand and weigh all their possibilities [46,78]. The following is a typical mathematical expression for a multi-objective optimization problem:

$$Min \backslash Max\ f_m(x) \tag{1}$$

Subject to

$$x_l \leq x \leq x_u$$
$$g(x) \leq 0$$
$$h(x) = 0$$

where x is an independent variable vector, $f_m(x)$ is a vector of objective functions, x_l and x_u are vectors of lower and upper bounds, respectively, and $h(x)$ and $g(x)$ are vectors of equality and inequality constraints. For every aim in the objective function vector, there are two alternative outcomes: minimization and maximization.

A complex MOO problem that considers the interests of multiple parties is the design, operation, and planning of a power system. These stakeholders, which include investors, network operators, end users, and regulators, each have unique goals that periodically clash. It is necessary to bring together several opposing goals, even within the same participating party. Consider the government's concurrent focus on economic and environmental challenges. Investors seek solutions that increase investment earnings while lowering construction expenses. Operators aim to achieve a balance between lowering operating expenses and preserving network stability. Power system optimization basically involves negotiating a complicated environment of many objectives and trade-offs in order to meet the needs and expectations of various stakeholders [81,82].

It is important to employ a concept other than optimal in order to solve a multi-objective optimization problem. Pareto-optimality is the most often used concept of optimality in multi-objective optimization [3,14,41,78,115,116]. The solution is considered non-dominated, Pareto optimal, Pareto efficient, or non-inferior if it is impossible to increase the value of any of the objective functions without lowering some of the other objective values. When the concept of Pareto optimality is applied, Figure 7 shows that solutions 3 and 4 "dominate" both solutions 7 and solutions 8 and 9, while solutions 8 and 9 are "dominated" by solution 7. All of the solutions in the entire set P that are not being dominated by any other solution comprise the set of non-dominated solutions [78]. Without further subjective preference information, there could be (perhaps infinite) numbers of Pareto optimal solutions that are all thought to be equally good [116]. The Pareto front of objectives is known as the Pareto front. Multi-objective optimization can therefore be said to have two true purposes [78]: (1) to find a set of solutions that are as close to the Pareto-optimal front as possible, and (2) to find a set of replies that are as diverse as possible. The following paragraphs examine and evaluate a number of important studies that have applied MOO to power system issues.

4.1. Categories of Multi-Objective Optimization Algorithm

MOO techniques can be divided into three major categories according to the manner preferences are expressed. Methods with preferences that have been expressed earlier, methods without preferences, and methods with preferences that have been presented later fall into these categories. A priori articulation provides the optimization approach with the prior knowledge about the preference or priority of different objective functions. An optimal solution is selected from the Pareto front, which is first acquired at a posterior articulation [116]. In addition to these three categories, MOO problems are also commonly solved using multi-objective evolutionary algorithms (MOEAs) [115–119]. Evolutionary algorithms (EAs) can also be applied to many types of challenges and search domains.

Additionally, data-driven methods like neural networks and reinforcement learning are being utilized to address MOO problems in power systems as a result of advancements in machine learning. These techniques reveal complex relationships between selection criteria and objectives, giving decision-makers valuable data. As a result, each of these five groups is briefly described in Figure 8 along with a few examples.

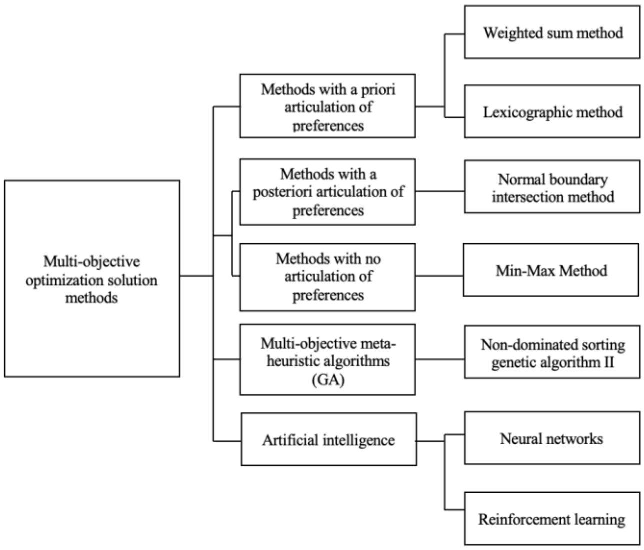

Figure 8. Categories of Multi-Objective Optimization Algorithm.

Since the methods listed in the three categories have different drawbacks, evolutionary algorithms (EAs) and AI-based algorithms are an excellent choice for solving multi-objective optimization issues [41].

4.2. Literature Review

MOO problems with hybrid and RES integration in power systems are addressed in [33–38], considering variabilities and uncertainties. In the first paper, a novel MOO technique that uses the Gravitational Search Algorithm (GSA) to lower CO_2 emissions, increase the usage of renewable energy sources, improve power dependability, and lower prices is introduced. The system's economic resilience is demonstrated by a sensitivity analysis to the carbon tax. In terms of solution diversity and quality, the GSA performs better than conventional techniques. The ideal configuration decreased environmental impact by 14.2% and increased the share of renewable energy by 18.4%. Similarly, in the second study, MOO is used to minimize power supply losses and cut costs. To determine which algorithm best balances cost and performance, seven algorithms are examined (Giant Trevally Optimizer or GTO, Gazelle Optimization Algorithm or GOA, Honey Badger Algorithm or HBA, Manta Ray Foraging Optimization or MRFO, Pelican Optimization Algorithm or POA, Sea Horse Optimizer or SHO, and Synergistic Swarm Optimization Algorithm or SSOA). Three scenarios (balanced supply, energy scarcity, and energy surplus) are used to test them. The third study suggests a framework for the MOO to determine the ideal placement and scale for distributed renewable generating in power networks. Uncertainties like demand variations, equipment malfunctions, and resource availability are taken into consideration. An OPF model based on Monte Carlo (MCS-OPF) simulates network performance and assesses the total cost of the system. A novel optimization technique that takes into account social, technical, economic, and environmental aspects is presented in the fourth study. It optimizes CO_2 emissions, human development index or HDI, loss of power supply probability or LPSP, and levelized cost of energy or LCOE all at once. The Pareto front is generated and simulated using the NSGA-II and MOPSO algorithms. In the fifth study an MO problem centered on network loss minimization and voltage profile augmentation was developed. MATLAB-2015 has been used to write the Newton–Raphson approach for load flow and the black hole algorithm. Finally, the applicability of the New Improved Differential Evolution (NIDE) method to the MOO-based Reactive Power Planning (RPP) problem is discussed in the sixth study.

In [40], Pareto effective solutions to the multi-objective reconfiguration problem are found using a multi-objective Tabu Search technique. A test has been carried out on an IEEE system to show how the multi-objective method works and how effective its use is.

Thyristor-controlled series compensators (TCSCs) are used in the study conducted in [42] to enhance power system performance by lowering power losses, increasing transmission capacity, and stabilizing the voltage profile. The MOOPF problem is solved using the adaptive parallel seeker optimization algorithm (APSOA). By determining the ideal size and position, the technique also reduces the cost of TCSC installation.

The OPF problem in [44] is successfully resolved by a multi-objective particle swarm optimization (MOPSO) method, which produces high-quality Pareto solutions in a single run. Similarly to this, other multi-objective techniques such as variable constants particle swarm optimization (VCPSO), genetic algorithm (GA), and particle swarm optimization (PSO) are also used in [47] to optimize the size and placement of distributed generators (DGs) with the goal of lowering power losses and improving voltage profiles. VCPSO is the most effective of these techniques. Additionally, the successful integration of renewable energy sources (RESs) into distribution networks is simulated using heuristic techniques including Ant Lion Optimization (ALO), Gray Wolf Optimization (GWO), Whale Optimization Algorithm (WOA), and PSO [73]. These methods decrease computing times and improve efficiency and convergence.

A two-step MOOPF solution technique has been suggested in order to preserve the economy, ecology, and security elements while the power system is operating [45]. In step 1, the knee point-driven evolutionary algorithm (KnEA) for the MOOPF problem may be introduced in order to find the Pareto-optimal solutions. In step 2, decision makers are given option supports through an integrated decision analysis technique that combines the Fuzzy C-Means (FCM) clustering approach and grey relational projection (GRP).

For the MOOPF problem addressed in [46], a novel MO Modified Imperialist Competitive Algorithm (MOMICA) is employed, accounting for the effects of fuel cost, voltage deviation, active power losses, and pollution. The industry-standard IEEE 30-bus power systems are used to evaluate the performance of a novel MOMICA approach.

Because RESs are unpredictable and irregular, integrating them into OPF becomes much more complex. To tackle this issue, the study in [48] presents two multi-objective algorithms centered on non-dominated sorting: the Non-Dominated Sorting Genetic Algorithm (NSGA-II) and its updated variant, the Adaptive Crossover Non-Dominated Sorting Differential Evolution (ACNSDE). These algorithms utilize a state-of-the-art constraint management technique called Superiority of Feasible Solutions (SF). In scenarios involving stochastic wind and solar energy, the proposed methods may effectively achieve the objectives of multi-objective OPF optimization, according to the actual results from several test cases. They are also capable of creating balanced, competitive solutions.

The multi-objective optimal reactive power dispatch (MORPD) problem, which aims to minimize active power loss and voltage deviation, has been addressed with a two-step approach. Classification-Based Pre-Selection (CPS) and Pareto Domination-Based Multi-Objective Evolutionary Algorithm (CPS/MOEA) are two MOO algorithms used in the initial step of this method to obtain Pareto optimum solutions (POSs) with uniformly distributed attributes. To further enhance these answers and reflect the preferences of the decision-maker, the Fuzzy C-Means Algorithm (FCM) and the Grey Relation Projection

Method (GRP) are coupled in the second stage. This combination approach appropriately addresses and solves the MORPD model [115]. Similarly, MOOPF is investigated in [117–119] using the MOEA/D based on decomposition. This technique allows one execution approach to produce a set of non-dominated results, or Pareto solutions. An innovative hybrid MOEA is then used to solve the MOOPF problem, particularly when combining RESs like solar and wind energy. This hybrid MOEA guarantees a range of workable options and enhances the selection process by fusing decomposition with the sum of normalized objectives.

Using a weighted sum approach, the Multi-Objective Cuckoo Search Algorithm (MOCSA) is created and used to determine the optimal network reconfiguration while guaranteeing that the voltage profile aligns with the goal of reducing power loss [120]. The Whale Optimization Algorithm (WOA) is used in another study [121] to address MOO, which includes lowering bus voltage variation (VD) and real power loss in grid-connected micro electrical systems with non-firm tiny power plants. These techniques were evaluated and compared with PSO, GA, and Artificial Bee Colony (ABC) using IEEE 6 and 14 bus systems.

In [122], cost, Voltage Stability Index (VSI), and loss objectives are examined using an updated PSO and the MOOPF via Pareto optimum approach. The research investigation also explains the key concepts of Ant colony optimization (ACO), PSO, and hybrid swarm optimization. The results of this proposed method provide the best compromise outcome with the quickest execution time when compared to PSO. The stochastic search optimization technique and fuzzy multi-objective optimal power flow (FMOPF) are used to address the OPF problem [123]. The proposed method minimizes the fuzzy satisfaction function of the objective function, which comprises active power loss, the total system cost, and voltage magnitude deviation, using PSO. The simulated results showed that the PSO approach might theoretically and successfully identify the optimal solution for OPF when compared to existing approaches and the proposed FMOPF. GA is used to solve the OPF problem in [124–128]. The developed algorithm will be checked using Matpower, which uses the interior point method to solve OPF.

In order to solve optimization problems with one or more objectives, as well as objectives like loss, generation cost, and severity value, two novel optimization techniques are proposed in [129]: the Hybrid Fruit Fly-based ABC (HFABC) approach and the Non-dominated Sorting Hybrid Fruit Fly-based ABC (NSHFABC) approach.

The recently proposed Multi-Objective Search Group Algorithm (MOSGA) [130], which leverages the benefits of the first search group algorithm, provides a powerful solution to the MOOPF problem. The use of fast non-dominated sorting, crowding distance calculations, and retaining select algorithms enables the acquisition of a non-dominated set in a single computing run. Similarly, in [131], the standard IEEE 30 bus is modified to accommodate RESs, and the MOOPF problem is resolved by the multi-objective pathfinder algorithm (MOPFA), which uses an elect-dominated collection and congestion.

A Harris Hawks Optimization (HHO) strategy is used in [132] to address single and multi-objective OPF difficulties in order to reduce the production emissions producers. The results are compared to those of several AI techniques, such as the Salp Swarm Algorithm (SSA), the WOA, the Glow Worm Optimization (GWO), and the Moth Flame (MF).

In [133], a new approach to the OPF problem is introduced, which utilizes the data-driven stacked extreme learning machine (SELM) framework. Because of its rapid training capabilities, SELM eliminates the need for the laborious parameter tweaking process typically associated with deep learning algorithms. However, it becomes challenging to directly apply SELM to OPF due to the intricate relationship between OPF solutions and the system's operating status. A data-driven OPF regression architecture that separates

OPF model features into three stages is created in order to address the issue. This reduces the possibility of learning bias in addition to making learning simpler. Additionally, it is demonstrated that this approach can be readily adapted to handle different test systems with only slight adjustments to a few hyperparameters. A deep reinforcement learning (DRL) approach is proposed in [134] to dynamically search for the OPF of power systems with a large adoption of RESs. This method utilizes power systems' spatial–temporal (ST) graphical data. The OPF problem is formulated as a MOO problem that considers production cost, transmission loss, and voltage variation, and the optimal solution is found using deep deterministic policy gradient (DDPG). Furthermore, the underlying temporal interactions and linkages among nodes within power systems are taken into consideration in the development of a multi-grained attention-based spatial-temporal graph convolution network (MG-ASTGCN). The purpose of this network is to extract ST graphical correlations and characteristics in order to provide a comprehensive understanding of the graphical dynamics of power systems. This knowledge is finally incorporated into the DRL algorithm's sequential Deep Deterministic Policy Gradient (DDPG) structure. This combination increases the ability to effectively meet the OPF challenge.

In [135], the research proposes the Hybrid Flying Squirrel Search Algorithm (HFSSA). The OPF is solved using the Squirrel Search method, a method inspired by the flying squirrel's innate hunting style. To boost its effectiveness, a mathematical crossover process is added. Even though several optimization methods have been proposed to solve OPF problems, optimal efficiency is still necessary. The Slime Mould Algorithm (SMA), first presented in [136], was inspired by the way the slime mould oscillation mode behaves in nature. The proposed method is commended for its clarity, ease of use, and ability to move forward to the ideal solution while preventing local optima from stagnating.

In order to maximize reactive power in power systems while improving voltage security, a method known as Improved Multi-Objective Particle Swarm Optimization (IMOPSO) has been developed in [137,138]. By adding an Adapted Binary Crossover (ABX) to fine-tune the particles' new positions and a diversity maintenance method based on Crowding Distance (CD) computations, the standard MOPSO is enhanced. In [139–141], Artificial Bee Colony (ABC) has been employed to solve the mixed-integer nonlinear Optimal Reactive Power Dispatch (ORPD) problem, which entails adjusting both discrete and continuous control variables.

In [142], a Constrained Dynamic Multitasking Multi-Objective Optimization (CDMTMO) is designed to solve the MOOPF issue. It employs three concurrent populations to solve the main constrained problem, a constraint-relaxed variant, and an unconstrained-to-constrained transition. To facilitate knowledge transfer and boost the quality of the solutions, it integrates a pre-selection technique, an improved dual ranking, and an improved ε-constrained method. This paper [143], tackles the drawbacks of conventional centralized economic dispatch techniques, including their slow calculation and lack of privacy, in response to the complexity of large-scale multi-area interconnected power systems (LMIPSs). A Distributed Multi-Objective Grey Wolf Optimizer (DMOGWO) is suggested as a solution to these problems, enabling the autonomous optimization of each area's sub-problem with little boundary information sharing. DMOGWO is shown to perform better than centralized approaches by lowering goal values, protecting data privacy, and improving overall optimization performance in case studies on IEEE 39-bus and 118-bus systems. The study in [144] suggests a Modified Pigeon-Inspired Optimization (MPIO) algorithm to solve non-differentiable OPF problems with competing objectives. Even with valve-point loading effects, the method efficiently optimizes goals such as active power loss, emissions, and fuel cost by combining the Penalty Function Method (PFM) and then improving it with a Constraint-Objective Sorting Rule (COSR).

In [145,146], the significance of probabilistic assessment in systems with high wind turbine (WT) penetration to improve power system performance and manage increasing renewable integration is highlighted. Using a MOPSO algorithm, it suggests an optimal allocation strategy for Interline Power Flow Controllers (IPFCs) with the goals of reducing active power losses, raising the Power Flow Index (PFI), and taking IPFC installation costs into account. Strong performance on the IEEE 30-bus test system is demonstrated by the method, which takes into account uncertainties in loads and wind speeds and uses a k-means-based data clustering method (DCM) for probabilistic evaluation.

The research study conducted in [147] aims to maximize reliability and performance while minimizing costs in series-parallel energy systems, especially those that use gas and solar generators. It presents a hybrid meta-heuristic algorithm, known as Bat Algorithm with Generalized Flight (BAG) that is applied to multi-objective redundancy design in power systems, which integrates the Ushakov method using the Universal Moment Generating Function (UMGF) for reliability evaluation and combines the Bat Algorithm (BA) and Generalized Evolutionary Walk Algorithm (GEWA). The integration of distributed renewables, electric vehicles, and storage systems presents operational issues for active distribution networks (ADNs) during the green energy transition [148]. The study addresses this by presenting a multi-objective optimization technique based on Analytical Target Cascading (ATC) that coordinates demand response (DR) across station areas and manages voltage and power flow using a Dynamic Optimal Power Flow (DOPF) model with Second-Order Conic Relaxation (SOCR). In [149], a self-adaptive algorithm inspired by nature called HHO was used for MOOPF. It performed exceptionally well in terms of convergence and managing several competing goals.

In [150], Information Gap Decision Theory (IGDT) is used to manage uncertainties in a multi-objective framework that strikes a balance between system flexibility and economic efficiency. The Normalized Normal Constraint (NNC) approach is used and verified on the IEEE 33-bus system in various circumstances to reconcile competing goals and produce evenly distributed Pareto solutions. In [151,152], studies introduced an Improved Strength Pareto Evolutionary method 2 (ISPEA2) which is an effective multi-objective evolutionary method for balancing several stability objectives in power system operation. Similarly, in [153], to guarantee Pareto optimality, a MOO strategy utilizing Extended Lexicographic Goal Programming was created and adjusted with the goal of reducing operating expenses, emissions, and asset deterioration. In [154,155], MOPSO is used in microgrids to distribute energy resources optimally while minimizing costs and environmental effects. Similarly, in [156], a hybrid technique called Binary Particle Swarm Optimization—Shuffled Frog Leaping Algorithm (BPSO-SFLA) is used to locate and size DGs optimally in order to minimize losses and enhance voltage stability. The complicated combinatorial problem of network reconfiguration and DSTATCOM placement in distribution systems is solved in [157], by modified ACO. The results demonstrate the importance of this hybrid method for utility operators in resource-constrained contexts, as it combined DSTATCOM deployment with network reconfiguration to cut losses by 83.57% and increase DSTATCOM efficacy by 50.71%.

In [158], the best Time Series Aggregation (TSA) techniques for Multi-Energy System (MES) design were chosen using a two-step MOO framework that minimizes both the total annual cost and the probability of load loss. A potent hybrid meta-heuristic method known as Hybrid Wavelet Mutation-based Shuffled Frog Leaping method and Particle Swarm Optimization (HWM^{2}SFLA-PSO) was created in [159], to manage the MOOPF complexity, particularly with the addition of FACTS devices like TCSC and UPFC. Similarly, in [160–162], first a Weighted Teaching-Learning-Based Optimization (WTLBO) algorithm which is an enhanced version of TLBO that uses weighted aggregation was used to solve

OPF problems with higher accuracy and multi-objective handling. Secondly, the nature-inspired technique known as Biogeography-Based Optimization (BBO) was used to solve limited, non-linear, multi-objective OPF problems. Thirdly, an improved BBO variant called Quasi-Oppositional Biogeography-Based Optimization (QO-BBO) uses opposition-based learning to boost global search and convergence for OPF problems. In [163], for effective MOOPF optimization, a hybrid evolutionary algorithm called Multi-Objective Coyote Optimization Algorithm with Meta-Lamarckian Learning (MOCOA-ML) that combines adaptive local search, external archives, and elite sorting was used.

In order to improve voltage security through a combined preventive-corrective control strategy that includes load shedding, generation rescheduling, and optimal FACTS device deployment, the study in [164] suggested a Multi-Objective Differential Evolution (MODE) method. Similarly, in [165], a Fuzzy Adaptive Hybrid PSO-Differential Evolution (FAHSPSO-DE), which is a hybrid metaheuristic algorithm that effectively solves complicated, MOOPF problems by fusing fuzzy logic with self-adaptive PSO and DE was used. As developed in [166], the hybrid Data Envelopment Analysis and Electromagnetism-like Algorithm (DEA-EMA) is a reliable worldwide optimization technique for multi-objective hydropower scheduling. The research conducted in [167], employed an ISAO-BiTCN-BiGRU-SA-IPBLS and Two-Stage Robust Optimization approach which is a hybrid framework that combines robust optimization for MOO power system balancing, deep learning for interval prediction, and intelligent swarm algorithm optimization. In [168], tri-objective demand side management (DSM) scheduling issues in smart grids are resolved using the evolutionary technique known as Multi-Objective Wind Driven Optimization (MOWDO), which draws inspiration from wind movement.

In [169,170], a modular optimization framework called Multi-Objective Optimization with Decomposition Strategy makes it possible to analyze energy systems in-depth and scalable ways in order to reduce costs and emissions. Then, for steady and highly accurate electrical power system forecasting, the Multi-Objective Dragonfly Algorithm (MODA) is used to fine-tune the Elman Neural Network. In [171], a dimension learning approach has been added to the Improved Archimedes Optimization Algorithm (IAOA) to improve performance in OPF applications, particularly in scenarios including grid integration and emission reduction. With multi-objective ε-constraint handling, the Flow Direction Algorithm efficiently resolved OPF with renewable uncertainty and integrates FACTS in [172].

An Improved Analytic Hierarchy Process (AHP) with Fuzzy Chance-Constrained Programming for managing uncertainty and maximizing several goals in renewable-integrated power systems has been developed in [173]. By optimizing thermal limit settings in [174], the Multi-Objective Genetic Algorithm (MOGA) can increase power transfer capacity and decrease system oscillations. The problem of choosing affordable transmission investments for small-scale power systems, particularly in areas with a high frequency of load shedding, is examined in [175]. In expansion planning, a multi-objective optimization framework is used to balance the costs of investment, operations, and load shedding. Soft Open Points (SOPs) and energy storage systems (ESS) are becoming vital instruments for controlling power flow and voltage as distribution networks develop into interactive systems with transmission networks and customers. In order to enhance load balancing and economic performance, [176] suggested a MOO technique that configures SOP and ESS deployments utilizing grid structure features and voltage sensitivity analysis. For OPF in hybrid renewable-integrated power systems, the Equilibrium Optimizer (EO) metaheuristic algorithm is employed in research [177], in both single- and multi-objective versions. In order to solve MOOPF, the Multi-Objective Search Group Algorithm (MOSGA) which is a hybrid metaheuristic that improves the search group algorithm by including diversity-preserving techniques and Pareto-based sorting has been used in paper [130]. For multimodal multi-objective optimization problems (MMOPs), DRSC-MOAGDE is a mix of Dynamic Reference Spaces-based Clustering (DRSC) and Multi-Objective Adaptive Differential Evolution (MOAGDE) that maximizes Pareto front diversity and solution accuracy developed in [178]. To reduce power loss and voltage imbalance, a MOO model is used in [179] and solved using the weighted sum approach. This model produces better results in LED lighting systems across case studies of 15-bus and 33-bus.

A multi-objective optimal scheduling model for grid-connected microgrids (MGs) that uses probabilistic constraints to account for the uncertainty of renewable generation while integrating several dispersed energy sources was developed in [180]. Using Sample Average Approximation (SAA), the model is reconstructed as a multi-objective mixed-integer linear programming (MILP) problem with the goals of reducing operating expenses and increasing customer satisfaction. To guarantee optimal and adaptable ORPD across several test networks, inheritance-based NSGA-II (i-NSGA-II) in conjunction with roulette wheel selection has been used in [181], as part of a day-ahead and real-time adjustment method. In [182,183], because of the nonlinearity of the problem, the most effective solutions that balance emissions and cost were chosen using the MOPSO method, a fuzzy-based decision mechanism, and non-dominated sorting. In order to manage power flow in systems that include thermal, wind, solar, and small-hydro sources while taking renewable energy unpredictability into consideration, [184] proposes a hybrid OPF model. Multi-Objective Thermal Exchange Optimization (MOTEO), which draws inspiration from Newton's Law of Cooling, is used to solve the model. Non-dominated sorting and crowding distance methods are added for solution diversity.

A MOGA has been developed in [185–193], a parallel ε-variable multi-objective genetic algorithm (Pev-MOGA) effectively solves the probabilistic optimum power flow (POPF) problem, producing precise optimal solutions across IEEE 30, 57, and 118-bus systems under various renewable and electric vehicle (EV) integration scenarios. In order to integrate renewable energy sources and solve the OPF problem a Modified JAYA (MJAYA) algorithm was created [194]. In order to lower emissions and improve economic efficiency in power systems, the study developed in [195,196] presents a Hybrid Dynamic Economic Emission Dispatch (HDEED) model that combines thermal, solar, and wind energy sources. To efficiently address the non-convex and high-dimensional HDEED issue, a new upgraded Moth–Flame Optimization method with a position disturbance updating strategy (MFO_PDU) has been created. Framework for knowledge-driven optimization was conducted in [197]; it combines multi-objective optimization procedures with data mining approaches.

In order to reduce generating costs, pollution, power losses, and voltage variations, [198] addressed the MOOPF problem in power systems integrated with wind farms. An improved constraint-handling technique was added to a novel decomposition-based MO horse herd optimization algorithm (MOHHO) to preserve the viability of the solution. In order to balance economic and environmental considerations, a multi-objective optimization model (MOOM) was developed in [199] to optimize wind power accommodation and total purchasing cost at the same time. A hybrid particle swarm optimization and gravity search algorithm (HPSO-GSA) was used to solve the problem. The best solution from the Pareto front was then chosen using a fuzzy satisfaction function. In order to solve the stochastic MOOPF problem in transmission networks under uncertainty from wind, solar PV, and plug-in electric vehicles (PEVs), the research conducted in [200] introduced the Enhanced Wombat Optimization Algorithm (EWOA). Papers [201,202] have investigated how hybrid systems improve energy conversion in renewable energy installations, especially those that use graphene. In order to address the OPF problem while taking into account thermal generation combined with unreliable wind energy sources, the Grasshopper Optimization Algorithm (GOA) was used.

With the goal of lowering expenses and emissions while enhancing dependability of the use of renewable energy, the study conducted in [203] tackles the best multi-objective design of Hybrid Renewable Energy Systems (HRES) for both isolated-island and grid-connected modes. A unified MOO approach was presented in [204–208] to coordinate sub-grid activities in large-scale power systems with unequal distribution of renewable energy. Then, based on the physical topologies and operational characteristics of wind turbines and photovoltaic (PV) units, a comprehensive reactive power optimization model was created. A stochastic optimization model that accounts for operational and financial variable uncertainty was developed in order to evaluate the economic feasibility of a hybrid energy system that combines wind, photovoltaic (PV) generating, and battery storage.

Pareto Envelope-based Selection Algorithm (PESA), a MOO technique, was used in [209] to identify the best configurations that balance technical, environmental, and economic objectives. Similarly, in order to tackle the OPF problem, [210] introduced a Hybrid Multi-Objective Artificial Physical Optimization (HMOAPO) algorithm, which solves the uncertainties in wind energy generation. Animal Migration Optimization (AMO) and Artificial Physical Optimization (APO) are combined in the HMOAPO to improve convergence and do away with the requirement for external control parameters. The Multi-objective Snow Ablation Optimizer (MOSAO) is presented in [211] as a solution to complicated OPF problems in power systems that integrate FACTS devices with renewable energy.

5. Results, Challenges and Future Directions

Optimization problems in power systems can be approached in a number of techniques. There are 41 papers under assessment, which are grouped according to their applications, techniques, and formulation of the problem that necessitates the choice of objective functions. The aggregated findings are shown in Tables 3–5 correspondingly.

Table 3. Applications of multi-objective optimization in power systems.

Year	Electrical Network Reconfiguration	Economic Dispatch/Optimal Power Flow	Power Distribution Planning	Operational Planning with RESs Integration
2010		[161]		
2011		[44]		
2012		[162]		
2013				
2014		[46]		
2015				[48]
2016		[123]		[20]
2017				
2018		[45,122]		
2019	[33]	[35]		
2020		[115,117,127,144,145]	[125]	
2021	[120]	[124]	[147]	[22,84,134]
2022	[48]	[123,129–132,136,143]	[129]	
2023	[47]	[135,137,160]		[21]
2024		[163]		
2025				[18,19]

Table 4. Algorithms developed for multi-objective optimization in Power Systems.

Approach (Method)	References
GOA, GTO, HBA, MRFO, POA, SHO, SSOA	[19]
MCS-OPF	[20]
BHA, DE, NIDE	[22,31]
Tabu Search	[33]
APSOA	[35]
MOPSO, IMOPSO, PSO, VCPSO, GA, GWO, ALO, WOA, FMOPF, DMOGWO, BPSO-SFLA, MOCOA-ML	[44,47,84,122,123,137,143,156,163]
MO-CSA, ABC, ACO, MPIO-PFM	[120,121,144]
KnEA, FCM, GRP	[45]
MOMICA	[46]
NSGA, NSGA-II, ACNSDE, CPF, NSGSA	[18,21,48,125]
CPSMOEA, MOEA/D, BA-GEWA(BAG)-UMGF	[115,117,118,147]
GAOPF, NLP-OPF	[124]
HFABC, NSHFABC, BBO, QO-BBO	[129,161,162]
MOSGA	[130]
MOPFA	[131]
HHO	[132]
SELM, DRL, DDPG, MG-ASTGCN, WTLBO	[133,134,160]
HFSSA	[135]
SMA	[136]

Table 5. Formulation of the MOOPF problem: number of objective functions.

Number of Objective Functions	References
2	[19,20,31,33,44,47,84,115,120,121,124,137,143]
3	[22,122,123,125,129,130,132–135,147,156,161–163]
4	[18,21,35,45,46,48,117,118,131,144]
5	[136]
6	[160]

MOO is becoming more and more popular in power systems, as shown in Table 3. Applications were restricted to basic operations like reactive and economic power dispatch between 2011 and 2015. Interest quickly increased between 2016 and 2020, extending to topics like integrating renewable energy sources and reducing emissions. Since 2021, MOO has been used more frequently to address more general issues such as demand response, distributed generation, and system planning, which reflects a move towards more intricate and varied power system demands. Key research gaps are revealed by the examination of multi-objective optimization (MOO) applications in power systems. These gaps include a lack of attention to reliability, sustainability, and social or environmental impacts, as well as a lack of investigation beyond conventional goals like cost and loss minimization. The majority of research is still limited to benchmark test systems, lacking scalability to large, complicated grids and real-world validation. Furthermore, the promise of hybrid approaches that combine deterministic, stochastic, and AI-based optimization is still underutilized, and uncertainty resulting from the integration of renewable energy sources is frequently simplified or disregarded. More thorough, intelligent, and uncertainty-aware optimization approaches that are applicable to current dynamic power systems are obviously needed.

With a focus on nature-inspired metaheuristics like GA, PSO, and more recent bio-inspired techniques like GWO and HHO, Table 4 demonstrates the diverse array of optimization algorithms used to solve multi-objective problems in power systems. It also illustrates the variety of approaches that have been investigated, such as physics-based, evolutionary, swarm intelligence, approaches-based AI and hybrid approaches. The long list of references and algorithms demonstrates a consistent research effort to modify and enhance optimization methods for the intricate problems of contemporary power systems.

According to Table 5, the majority of MOOPF research focuses on issues that have three objectives, like losses, voltage and cost or emissions. However, a need for more thorough optimization is reflected in the growing interest in three-objective formulations. There is a shift towards addressing the complicated and contradictory objectives in power system planning and operation, as seen by the lower but significant amount of research that examine four or five objectives.

The increasing complexity of the grid presents a number of challenges for optimization in power systems. Intermittency, forecasting errors, and the need to instantly balance competing technological, financial, and environmental goals are all brought about by the extensive integration of variable RESs. The nonlinear, large-scale, and frequently stochastic character of these challenges results in significant computational demands, and operational data security, availability, and quality continue to be crucial issues. Furthermore, as digitalization increases, cybersecurity threats are introduced into optimization processes, making resilience and secure operation major objectives.

In order to satisfy the demands of intricate, renewable-rich grids, future trends in power system optimization will concentrate on creating faster, more resilient, and more adaptable methods. In addition to AI-driven solutions like reinforcement learning, deep learning, and transfer learning for real-time and predictive decision-making, promising approaches include hybrid frameworks that blend intelligent and classical methods for improved accuracy and convergence speed. Stochastic and resilient formulations will better manage renewable variability and uncertainty, while distributed and multi-agent optimization will allow scaled control of decentralized resources.

The complexity of an optimization problem increases as the number of objective functions increases. This increase in complexity is tied to the increase in the search space and computing time requirements. Additional objectives, such as voltage stability and losses, increase trade-offs and hinder convergence, whereas two-objective problems, such as cost–emission, are comparatively straightforward. While evolutionary and swarm-based algorithms like NSGA-II and MOPSO can handle larger dimensions with increased computational work, classical approaches struggle with more than two objectives. In general, additional objectives increase the diversity of solutions and the flexibility of decisions, but they also necessitate more sophisticated algorithms and lengthier optimization durations.

The uncertainty of renewable energy generation is modelled using a collection of probability density functions (PDFs), with a different function used for each renewable resource [4,91]. When dealing with renewable resources, the probability distribution is often chosen based on the resource's physical attributes and validated by fitting it to historical data. Wind speed is typically represented by the Weibull distribution, and solar irradiation by the Beta distribution [68–72]. Wind energy uncertainty: the Weibull distribution is the most widely used and mathematically supported distribution for modelling the PDF of wind speed (v) at a certain place. Solar Energy uncertainty: the Beta distribution is widely used to simulate the uncertainty in solar irradiance (G), because its values are essentially constrained (between zero and a maximum corresponding to clear sky circumstances) [73–76].

Data preprocessing ensures data quality and consistency in MOOPF based on machine learning and deep learning [4,105–108]. It entails normalizing or standardizing inputs (such as voltage, demand, and generation), completing missing values, and developing relevant features. The input (state space) for DRL is the power system's operating states, whereas the action space is made up of control actions (such as generator outputs and tap adjustments). Typically, the training scenarios are conducted using simulated or historical datasets that reflect different grid situations, like faults, load swings, and renewable uncertainty. An agent interacts with a virtual grid in DRL, which is modelled as a Markov Decision Process [108–111]. Through feedback and repeated trials, the agent learns the most effective control rules. Overfitting is a major problem since models that were trained on ideal or constrained data may not function well in real-world scenarios. Techniques including cross-validation, dropout, early halting, and data augmentation are used to decrease it. Model generalization and reliability in deep learning models are enhanced by methods like testing across unseen grid designs and exploration strategies [107–113].

6. Conclusions

The present paper provided an overview of the existing optimization techniques and their applications, with a focus on multi-objective optimization in power systems. Multi-objective optimization of power systems is an important and developing area of research. As the energy industry grows and gives efficiency and sustainability more and more consideration, the need for multi-objective optimization will only increase. Many opposing objectives from different stakeholders are necessarily included in the planning, construction, and operation of power systems. From network stability and environmental sustainability to economic effectiveness, governments, investors, and operators all have different priorities and objectives. The literature review highlighted the important research initiatives in the field and demonstrated a range of tactics and methods. Numerous optimization techniques have been developed and applied by researchers to address the multi-objective challenges in power systems. The development of algorithms that employ artificial intelligence to solve the multi-objective optimization problem in power systems is the focus of current research and emerging trends as technology advances.

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Abbreviations

The following abbreviations are used in this manuscript:

ABC	Artificial Bee Colony
ABX	Adapted Binary Crossover
ACNSDE	Adaptive Crossover Non-Dominated Sorting Differential Evolution
ACO	Ant Colony Optimization
ADNs	Active Distribution Networks
AHP	Analytic Hierarchy Process
AI	Artificial Intelligence
ALO	Ant Lion Optimization

ANNs	Artificial Neural Networks
APSOA	Adaptive Parallel Seeker Optimization Algorithm
ATC	Analytical Target Cascading
BAG	Bat Algorithm with Generalized Flight
BBO	Biogeography-Based Optimization
BPSO-SFLA	Binary Particle Swarm Optimization–Shuffled Frog Leaping Algorithm
CD	Crowding Distance
CDMTMO	Constrained Dynamic Multitasking Multi-Objective Optimization
CFD/CFI	Constraint Feasibility Degree/Index
COSR	Constraint-Objective Sorting Rule
CPS	Classification-Based Pre-Selection
DCM	Data Clustering Method
DDPG	Deep Deterministic Policy Gradient
DEA-EMA	Data Envelopment Analysis and Electromagnetism-like Algorithm
DGs	Distributed Generators
DMOGWO	Distributed Multi-Objective Grey Wolf Optimiser
DOPF	Dynamic Optimal Power Flow
DR	Demand Response
DRL	Deep Reinforcement Learning
EAs	Evolutionary Algorithms
EO	Equilibrium Optimiser
ESSs	energy storage systems
EWOA	Enhanced Wombat optimization Algorithm
FAHSPSO-DE	Fuzzy Adaptive Hybrid Particle Swarm Optimization-Differential Evolution
FCM	Fuzzy C-Means
FMOPF	Fuzzy Multi-Objective Optimal Power Flow
GA	Genetic Algorithms
GEWA	Generalized Evolutionary Walk Algorithm
GOA	Gazelle Optimization Algorithm
GOA	Grasshopper optimization Algorithm
GRP	Grey Relational Projection
GSA	Gravitational Search Algorithm
GTO	Giant Trevally Optimizer
GW	Gigawatt
GWO	Glow Warm Optimization
GWO	Gray Wolf Optimization
HBA	Honey Badger Algorithm
HDEED	Hybrid Dynamic Economic Emission Dispatch
HDI	Human Development Index
HFABC	Hybrid Fruit fly-based Artificial Bee Colony
HFSSA	Hybrid Flying Squirrel Search Algorithm
HHO	Harris Hawks Optimization
HRES	Hybrid Renewable Energy Systems
HWMSFLA-PSO	Hybrid Wavelet Mutation-based Shuffled Frog Leaping method and Particle Swarm Optimization
IAOA	Improved Archimedes optimization Algorithm
IEEE	Institute of Electrical and Electronics Engineers
IGDT	Information Gap Decision Theory
IMOPSO	Improved Multi-Objective Particle Swarm Optimization
IP	Integer Programming
IPFCs	Interline Power Flow Controllers
IRENA	International Renewable Energy Agency
ISPEA2	Improved Strength Pareto Evolutionary method 2
KnEA	Knee Point-Driven Evolutionary Algorithm

LCOE	Levelized Cost of Energy
LMIPSs	large-scale multi-area interconnected power systems
LP	Linear Programming
LPSP	Loss of Power Supply Probability
MCS-OPF	Monte Carlo simulation–Optimal Power Flow
MES	Multi-Energy System
MF	Moth Flame
MFO_PDU	Moth-Flame Optimization Method with a Position Disturbance Updating
MG-ASTGCN	Multi-Grained Attention-Based Spatial-Temporal Graph Convolution Network
MGs	microgrids
MIP	Mixed-Integer Programming
MJAYA	Modified JAYA
MOADE	Multi-Objective Adaptive Differential Evolution
MOCOA-ML	Multi-Objective Coyote optimization Algorithm with Meta-Lamarckian Learning
MOCSA	Multi-Objective Cuckoo Search Algorithm
MODA	Multi-Objective Dragonfly Algorithm
MODE	Multi-Objective Differential Evolution
MOEA	Multi-Objective Evolutionary Algorithm
MOEA/D	Multi-Objective Evolutionary Algorithm based on Decomposition
MOHHO	Multi-Objective Horse Herd Optimization Algorithm
MOMICA	Multi-Objective Modified Imperialist Competitive Algorithm
MOO	Multi-Objective Optimization
MOOPF	Muti-Objective Optimal Power Flow
MOPFA	Multi-Objective Pathfinder Algorithm
MOPSO	Multi-Objective Particle Swarm Optimization
MORPD	Multi-Objective Optimal Reactive Power Dispatch
MOSAO	Multi-objective Snow Ablation Optimiser
MOSGA	Multi-Objective Search Group Algorithm
MOTEO	Multi-Objective Thermal Exchange optimization
MOWDO	Multi-Objective Wind Driven optimization
MPIO	Modified Pigeon-Inspired Optimization
MRFO	Manta Ray Foraging Optimization
NIDE	New Improved Differential Evolution
NLP	Nonlinear Programming
NNC	Normalized Normal Constraint
NSGA-II	Non-Dominated Sorting Genetic Algorithm
NSHFABC	Non-Dominated Sorting Hybrid Fruit Fly-Based Artificial Bee Colony
OPF	Optimal Power Flow
PESA	Pareto Envelope-based Selection Algorithm
PFI	Power Flow Index
PFM	Penalty Function Method
POA	Pelican Optimization Algorithm
POPF	Probabilistic Optimum Power Flow
POSs	Pareto optimum solutions
PSO	Particle Swarm Optimization
PV	Photovoltaic
QO-BBO	Quasi-Oppositional Biogeography-Based Optimization
QP	Quadratic programming
RESs	Renewable Energy Sources
SAA	Sample Average Approximation
SELM	Stacked Extreme Learning Machine
SHO	Sea Horse Optimizer
SMA	Slime Mould Algorithm
SOCR	Second-Order Conic Relaxation

SOPs	Soft Open Points
SSA	Salp Swarm Algorithm
SSOA	Synergistic Swarm Optimization Algorithm
ST	Spatial-Temporal
TCSCs	Thyristor-Controlled Series Compensators
TSA	Time Series Aggregation
TW	Terawatt
UMGF	Universal Moment Generating Function
VCPSO	variable constants particle swarm optimization
VD	Voltage Deviation
VSI	Voltage Stability Index
WOA	Whale Optimization Algorithm
WT	Wind Turbine
WTLBO	Weighted Teaching-Learning-Based Optimization

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