Neural Computing and Applications (2024) 36:17881–17929
https://doi.org/10.1007/s00521-024-10312-0

REVIEW

An in-depth examination of artificial intelligence-based methods for optimal power flow solutions

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Received: 16 December 2023 / Accepted: 29 July 2024 / Published online: 10 August 2024

Abstract
The fundamental objective of a modern power system lies in ensuring reliable and effective energy access for its customers. The assessment and determination of optimal operating conditions for power systems involve the utilization of the optimal power flow (OPF) tool. By considering critical factors such as generator power, bus voltages, and line power flow limits while satisfying the power balance equations, the OPF tool enables the identification of the most favorable configuration for efficient power system operation. Traditional optimization methods have limitations in addressing complex power system problems due to poor convergence and long computational times. As a result, computational intelligence tools have gained popularity in recent years. These tools are versatile and enable efficient solution of power system problems by effectively handling qualitative constraints. This paper presents a well-organized and comprehensive review of the algorithms used in power system optimization in the existing literature, encompassing the most recent developments in the field. Specifically, it examines the application of various population-based artificial intelligence techniques that have gained widespread adoption over the past decade (2012–2022). The aim of these techniques is to resolve an OPF problem. This paper organizes the reviewed papers into various types of population-based metaheuristic algorithms, each one implemented sequentially to deal with the OPF problem in the same chronological order in which they appeared in the literature.

Keywords Optimal power flow · Optimization algorithms · Artificial intelligence · IEEE power systems

1 Introduction

The first and most significant prerequisite for a modern power system network is that it functions reliably and securely to provide adequate, efficient, and cost-effective service to all customers. The restructuring of the electricity industry has further developed interest towards the optimal power flow (OPF) for the optimal deployment of resources. The OPF problem finds considerable importance in the operation, planning, economic scheduling, security monitoring as well as in the energy management systems (EMSs) of the modern power system networks. Furthermore, with the increasing size and complexity of the power system and the continuing trend toward integration of renewable energy sources (RES) leading to hybrid generation scenarios, the importance of OPF becomes even more apparent.

OPF solution aims to find the optimized schedule for each generator so that overall generation cost can be minimized while satisfying diverse constraints. The OPF study prioritizes the minimization of total generation fuel costs (FCM) as a primary objective due to its direct impact on the economy. Furthermore, several other objectives hold equal significance, such as active power loss minimization (PLM), reactive power loss minimization (RPLM), voltage stability enhancement (VSE), voltage deviation minimization (VDM), and emission minimization (EM) from the generating units, due to increasing environmental concerns. For practical systems, these objectives need to be

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considered simultaneously, which in turn requires conducting multi-objective OPF (MOOPF) studies. Consequently, the OPF problem can be perceived as a heavily constrained, highly nonlinear, mixed-integer, and typical nonconvex power system optimization problem (PSOP), while satisfying a combination of continuous and discrete control variables. The OPF problem formulation traces back to Carpentier's pioneering work in 1962 [1].

Previously, many classical optimization methods (deterministic methods) have been successfully employed for solving OPF efficaciously. Among these classical methods, the most popular were gradient-based techniques, Newton's techniques, interior point methods (IPMs), sequential linear programming (SLP), and sequential quadratic programming (SQP) [2]. These conventional techniques, which rely on derivatives and gradients, may be unable to find the global optimal function and are prone to converging to local solutions if the original prediction is close enough to a local solution. Unfortunately, the practical OPF conditions give rise to OPF that is strongly non-linear, non-smooth, and fundamentally multi-modal. Conventional techniques, therefore, lack accuracy in accurately modeling discrete control variables, essentially voltage regulating transformer tap positions and the switching of shunt compensators. Furthermore, the incorporation of multiple steam valves in the turbines of thermal generating units introduces additional modifications to the fuel cost characteristics of the generator, incorporating the absolute value of a sinusoidal function. As a result, optimization approaches that only locate local optima are found to be inappropriate for addressing real-world problems in modern power systems, as they fail miserably to cope with the nonlinearity inherent in the power system and perform unsatisfactorily due to the involvement of multiple-objective functions optimized simultaneously, the majority of which are conflicting in nature.

Recently, the fast evolution of various modern computational intelligence (CI) tools and techniques has encouraged researchers to apply them to find global optimal solutions. In contrast to conventional tools and techniques, which often get stuck in local optima, such tools demonstrate powerful global search capabilities. A large portion of the CI tools are population-based strategies that can significantly lessen the computation time of OPF. During the last two decades, researchers have shown a rapid shift in focus towards such population-based metaheuristics in solving the power system problems. Pandya et al. [3] presented a review of various classical optimization methods as well as a few AI methods for solving OPF problems. AlRashidi et al. [4] provided an extensive coverage of population-based CI tools applied until 2008 to resolve OPF problem. In [5], Frank et al. conducted a survey on both classical and stochastic optimization techniques widely applied to deal with OPF problems up until 2011. In the second of their two-part review, the authors looked at the development of non-deterministic methodologies and hybrid approaches for OPF. They provided an overview of the benefits, drawbacks, and computational attributes associated with each approach. Niu et al. [6] presented a detailed survey of OPF related research work carried out between the years 2000 and 2014, including frequently used heuristic optimization algorithms (HOAs) like evolutionary programming (EP), genetic algorithm (GA), differential evolution (DE), and particle swarm optimization (PSO). The authors also surveyed the literature on few hybrid methods on OPF. In 2017, Maskar et al. [7] made a brief survey on conventional and AI methodologies used to solve OPF and provided a literature coverage till 2016. In [8], the authors conducted a comprehensive review and comparison of OPF techniques for the most prevalent metaheuristics recorded in the literature until 2020.

In the context of the current study, OPF challenges are tackled through traditional metaheuristic and CI techniques. Nonetheless, it's crucial to acknowledge the increasing impact of machine learning (ML) in the OPF domain. ML offers promise for more efficient and reliable OPF in power systems through end-to-end learning and learning-to-optimize approaches. While the primary focus of this paper is on metaheuristic methods, the OPF domain has witnessed promising applications of ML approaches such as Deep Belief Networks (DBNs) for demand forecasting, Graphical Neural Networks (GNNs) for modeling complex relationships, Support Vector Machines for fault detection, and Random Forest for various power system optimization tasks.

This study endeavors to present a chronological and comprehensive review of population-based metaheuristic algorithms, with a specific focus on artificial intelligence (AI)-based algorithms, utilized for addressing OPF problems as documented in the literature until 2022. The study focuses on the salient features of diverse algorithms as they are applied to different power system networks. It takes into account a diverse range of objective functions, made up of both single-objective optimization (SOO) and multi-objective optimization (MOO) problems in the context of OPF. This provides a comprehensive understanding of the effectiveness of these algorithms in addressing OPF challenges. This study also examines the current trend towards implementation of hybrid algorithms which exploit the strength of each constituent algorithm to discover the best possible OPF solution. A broad and all-inclusive coverage of the significant research contributions, published in highly reputed peer-reviewed international journals (indexed in SCI and SCIE), has been presented in this article. It focuses on the application of modern CI tools for solving

OPF problems. However, it is worth noting that the "No Free Lunch" (NFL) theorem serves as a poignant reminder that no single method can be universally regarded as the best solution for all optimization problems [9]. It emphasizes the critical importance of carefully evaluating and selecting tailored strategies that are effective for the specific problem at hand.

The graph depicted in Fig. 1 illustrates the cumulative number of OPF articles published in SCI-indexed journals has steadily increased over the years from 2012 to 2022, indicating a growing interest and recognition of OPF in the scientific community. A steep rise in the years 2021 and 2022 indicates a significant acceleration in OPF research.

2 OPF problem: mathematical structure

The OPF mathematical formulation is presented in the following subsection, while the constraints are detailed in the subsequent subsection [10].

2.1 General structure of OPF

OPF problem typically comprise of objectives and constraints. The OPF solution optimizes a predefined objective function by finding optimal settings for *control variables*. The optimized configuration of the power system is governed by variables, namely *state variables*. The power system must operate under two sorts of constraints: *equality constraints* and *inequality constraints*. All conditions of constraint satisfaction have to be followed to formulate a realistic problem. The formulation of single-objective OPF (SOOPF) problems is as follows:

$$\text{Min}: f(x,\ u) \tag{1}$$

subject to:

$$g_i(x,\ u) = 0 \quad i = 1, 2, 3, \ldots\ldots, m \tag{2}$$

and

$$h_j(x,\ u) \leq 0 \quad j = 1, 2, 3, \ldots\ldots, n \tag{3}$$

The objective function is represented by Eq. 1, which is a function of the state variables x and the control variables u. Equation 2 represents the inequality constraints, while Eq. 3 represents the equality constraints. Here m denotes the count of equality constraints, while n denotes the count of inequality constraints.

In contrast, a MOOPF problem involves optimizing multiple objectives simultaneously, expressed as Eq. 4.

$$\text{Min}: f(x,\ u) = [f_1(x,\ u), f_2(x,\ u), \ldots\ldots\ldots, f_k(x,\ u)]^T \tag{4}$$

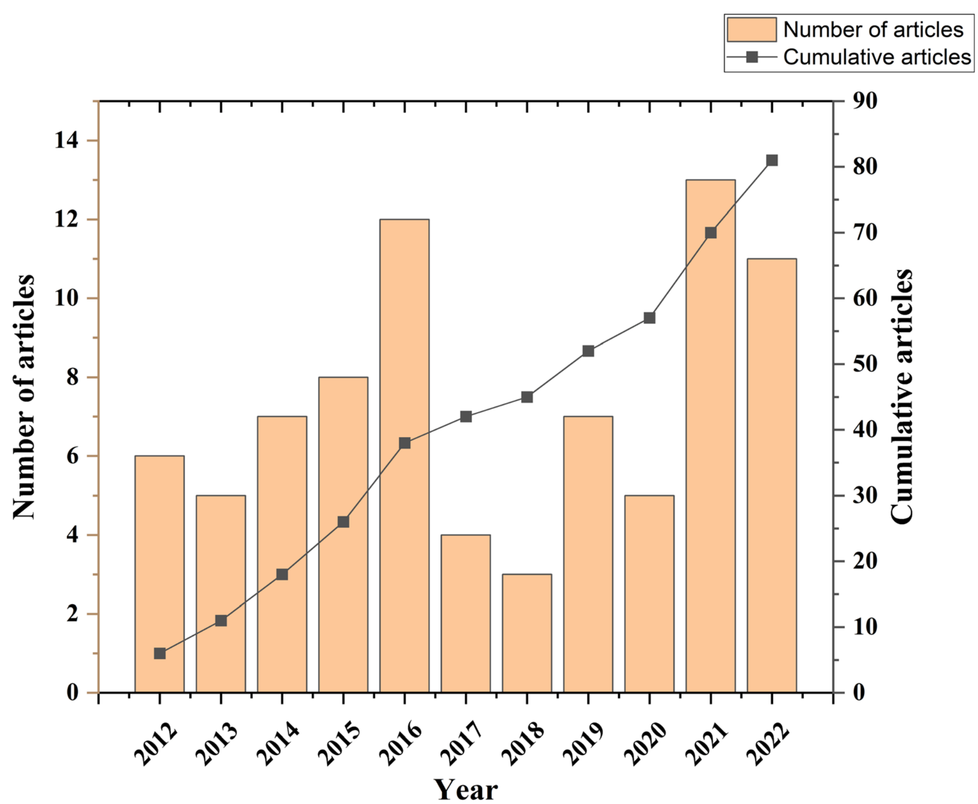

Fig. 1 Cumulative number of OPF articles published in SCI/SCIE-indexed journals from 2012 to 2022

here k represents the number of objective functions that are simultaneously optimized, while ensuring adherence to the constraints outlined in Eqs. 2 and 3.

The state vector i.e., the vector of dependent variables is given by Eq. 5 where P_G is the generator voltage,V_L is the load bus voltage, Q_G is the generated reactive power and S_{line} is the apparent power flow of the transmission line.

$$x^T = \left[P_{G_1},\ V_{L_1}\ldots, V_{L_{NPQ}}, Q_{G_1}\ldots\ldots, Q_{G_{NG}}, S_{line_1}\ldots\ldots, S_{line_{NL}}\right] \tag{5}$$

here P_{G_1} represents slack bus power. The notations NPQ, NG, and NL indicate the respective counts of load buses, generating units, and transmission lines. The status of the power system is represented by the vector of state variables (or dependent variables) which is given by Eq. 6.

$$u^T = [P_{G_2}\ldots, P_{G_{NG}}, V_{G_1}\ldots, V_{G_{NG}}, Q_{C_1}\ldots, Q_{C_{NC}}, T_1\ldots, T_{NT}] \tag{6}$$

here V_G symbolizes voltage at the generator bus, Q_C symbolizes shunt VAR compensation with NC representing the count of compensators, and T represents the tap changing transformer with NT representing the count of tap changing transformers.

2.2 Objective functions

The existing literature encompasses a range of objectives, including the ones detailed here. In the examined literature, these objective functions have been optimized both individually and simultaneously.

2.2.1 Fuel cost minimization (FCM)

The cost-related objective is fundamental in OPF and has been extensively analyzed in the literature. Equation 7 illustrates the approximate quadratic relationship between fuel cost (\$/hr) and P_G (MW).

$$FCM\ (P_G) = \left(\sum_{i=1}^{NG} a_i P_{G_i}^2 + b_i P_{G_i} + c_i\right) (\$/\mathrm{hr}) \tag{7}$$

For the i^{th} generator, with an active power output of P_{G_i}, the fuel cost coefficients are denoted by a_i, b_i and c_i.

a) FCM with valve-point loadings (FCM-VPL): In real-world power systems, multiple steam turbine valves can significantly impact the fuel cost characteristics of generators. This phenomenon is incorporated into mathematical models by adding a recurring rectifying sinusoidal term to the existing quadratic fuel cost (QFC) characteristics of selected generator units. Equation 8 depicts the modified cost function, with sine component, for i^{th} generator demonstrating valve-point loading (VPL) effect.

$$FCM_{VPL} = \left(\sum_{i=1}^{NG} a_i P_{G_i}^2 + b_i P_{G_i} + c_i\right) + \left|d_i \sin\left(e_i\left(P_{G_i}^{\min} - P_{G_i}\right)\right)\right| \tag{8}$$

where a_i, b_i, c_i, d_i and e_i are the fuel cost coefficients of ith generating unit exhibiting VPL effect, with d_i and e_i particularly representing VPL effect. $P_{G_i}^{\min}$ represents the ith generator's minimum allowable active-power-generation limit. The same basic fuel cost curves of Eq. 7 apply to all other units.

b) FCM considering prohibited operating zones (FCM-POZ): Thermal and hydro generators have prohibited operating zones (POZs) due to component limitations, like vibrations or resonance in generator components and associated equipment such as pumps or boilers, which could cause potential damage. Units with these zones exhibit discontinuous input–output characteristics, and operating within these zones is avoided for economic efficiency. The generation of units should remain within upper and lower limits of POZ. The fuel cost function taking POZ into account is either a quadratic function in Eq. 7 or function with VPL effect in Eq. 8. The operating constraints for i^{th} generator unit to ensure operation outside the POZ are defined in Eq. 9 as follows:

$$P_{G_i} \in \begin{cases} P_{G_i}^{\min} \le P_{G_i} \le P_{G_{i,1}}^{\mathrm{lower}} \\ P_{G_{i,k-1}}^{\mathrm{upper}} \le P_{G_i} \le P_{G_{i,k}}^{\mathrm{lower}} \ (k = 2, 3, \ldots., N_{poz}) \\ P_{G_{i,N_{poz}}}^{\mathrm{upper}} \le P_{G_i} \le P_{G_i}^{\max} \end{cases} \tag{9}$$

where N_{poz} is the number of prohibited zones for the ith unit, k represents the index of prohibited zones of i^{th} unit, $P_{G_{i,k}}^{\mathrm{lower}}$ and $P_{G_{i,k}}^{\mathrm{upper}}$ denote the lower and upper bounds (MW), respectively, of kth prohibited zone of i^{th} unit.

c) Fuel cost considering multiple fuel sources (FCM-MFS): In practice, thermal generators can operate using various fuel sources like oil and natural gas. With multiple fuel options, the cost function of generation units becomes a piecewise polynomial function, where each piece corresponds to a specific fuel type. This piecewise quadratic fuel cost (piecewise-QFC) for the i^{th} generator can be mathematically modelled by Eq. 10 as follows:

$$FCM_{MFS} = \left(\sum_{i=1}^{NG} a_{if} P_{G_i}^2 + b_{if} P_{G_i} + c_{if} \right) \quad (10)$$
for fuel type f

The bounds on P_{G_i} of i^{th} unit are defined as $P_{G_{if}}^{\min} \le P_{G_i} \le P_{G_{if}}^{\max}$; for each specific fuel type f.

2.2.2 Active power loss minimization (PLM)

This objective seeks to reduce the cumulative active power losses (P_{Loss}) in the system, which are computed as the discrepancy between overall generation and consumption. P_{Loss} in transmission lines is calculated using Eq. 11.

$$P_{\text{Loss}} = \sum_{L=1}^{NL} G_L [V_i^2 + V_j^2 - 2V_i V_j \cos\delta_{ij}] \quad (11)$$

where G_L is used to designate the conductance of line L between nodes i and j. V_i and V_j are the voltages at nodes i and j respectively, while δ_{ij} signifies the voltage angle difference between the two nodes.

2.2.3 Reactive power loss minimization (RPLM)

This objective aims to reduce the total reactive power losses (Q_{Loss}) within the system. These losses primarily result from the reactance of transmission lines and play a crucial role in assessing system stability and voltage regulation. Minimizing Q_{Loss} is crucial for efficient power system operation. The calculation of Q_{Loss} is performed according to the following Equation:

$$Q_{\text{Loss}} = \sum_{L=1}^{NL} B_L \left[V_i^2 + V_j^2 - 2V_i \, V_j \, \cos \delta_{ij} \right] \quad (12)$$

where B_L represents the susceptance of line L that contributes to reactive power flow between nodes i and j.

2.2.4 Voltage stability enhancement (VSE)

Ensuring acceptable voltage levels at all load buses under nominal operating conditions is vital for power system operation, highlighting the significance of voltage instability prediction. The voltage stability indicator (L-index) reflects the closeness to a voltage collapse condition at a bus. A reduction in the L-index can increase voltage stability. Typically, the L-index ranges from 0 (indicating no-load) to 1 (representing a voltage collapse state). L-index is defined based on local indicator L_i as presented in Eq. 13:

$$L - index = \max(L_i) \quad (13)$$

where L_i represents the individual L-index for i^{th} load bus. Further information can be found in [10].

a) *VSE during contingency* Maintaining voltage stability is critical for power systems, particularly during unexpected events such as line outages or generator failures. Enhancing voltage stability during transmission line contingencies involves simulating scenarios in which the outage of one (N-1 contingency) or more transmission lines is used to assess the system's response and identify critical lines. The objective of VSE in such contingency conditions is frequently explored and addressed in OPF literature.

2.2.5 Severity index minimization

The severity index (SI) measures the severity of line overloads in the power system. Contingencies are screened based on the severity index, where a higher index value indicates a greater degree of severity of the contingency. The SI is determined according to the formula provided in Eq. 14:

$$SI_{line} = \sum_{i=1}^{NL} {}_{line \in L_0} \left(\frac{S_{line_i}}{S_{line_i}^{\max}} \right)^{2m} \quad (14)$$

where S_{line_i} and $S_{line_i}^{\max}$ both in MVA represent the actual and maximum power flows in the i^{th} transmission line, respectively; L_0 denotes the collection of overloaded lines, and m is an integer coefficient. System operators can use the SI to prioritize actions to address critical issues, ensuring system stability and minimizing the risk of failures. The Equation in 14 is commonly used for SI minimization in OPF literature.

Unlike the Severity Index (SI), which focuses solely on line overloads, the *severity value minimization* (SVM) function offers a comprehensive formulation. SVM aims to reduce the overall severity of violations in the power system by considering factors such as line power flows (overloading) and bus voltage deviations. By minimizing this severity function, the power system can operate more securely within its operational limits, effectively handle contingencies, and maintain overall system stability.

2.2.6 Voltage deviation minimization (VDM)

Bus voltage stands out as a paramount indicator for maintaining safety and ensuring the effective operation of the power system. Improving the voltage profile involves minimizing voltage deviations at all load buses, i.e., PQ buses, from the reference value (V_D) of 1.0 p.u., achievable through the optimization of the objective function provided in Eq. 15:

$$VDM = \sum_{i=1}^{NPQ} |V_i - V_D| \tag{15}$$

where V_D is the desired voltage at all load buses.

2.2.7 Voltage security index (VSI)

VSI serves as a performance index to evaluate a power system's ability to maintain voltage levels within a predefined acceptable range, thereby indicating the system's stability and security. VSI is calculated using the formula provided in Eq. 16:

$$VSI = \sum_{i=1}^{n} \left(\frac{|V_i| - V_{avg}}{dV} \right)^{2n} \tag{16}$$

where V_{avg} is the average of the maximum and minimum voltages, dV is half the voltage range, and n is set to 1. Minimizing VSI indicates that the voltages across the system are closer to the average voltage, implying less fluctuation and greater stability.

2.2.8 Emission minimization (EM)

OPF aims to minimize emissions by optimizing the control variables of the system, which leads to a reduction of noxious gases in the atmosphere. The concentration of these gases in the atmosphere is directly linked to the active power generated in megawatts (MW), as depicted in Eq. 17:

$$EM = \sum_{i=1}^{NG} (\alpha_i P_{G_i}^2 + \beta_i P_{G_i} + \gamma_i + \omega_i \exp(\mu_i P_{G_i})(\text{ton/hr}) \tag{17}$$

where α_i, β_i, and γ_i represent emission coefficients, while ω_i and μ_i are associated with the exponential term, all pertaining to the same i^{th} generating unit.

2.3 Constraints

2.3.1 Equality constraints

In the OPF problem, the load flow equations are incorporated as equality constraints. The mathematical formulation is presented below:

$$\left.\begin{aligned} P_{G_i} - P_{D_i} &= V_i \sum_{j=1}^{NPQ} V_j \left(G_{ij} \cos\theta_{ij} + B_{ij} \sin\theta_{ij} \right) \\ Q_{G_i} - Q_{D_i} &= V_i \sum_{j=1}^{NPQ} V_j \left(G_{ij} \sin\theta_{ij} - B_{ij} \cos\theta_{ij} \right) \end{aligned}\right\} \tag{18}$$

In Eq. 18, $i = 1, 2, \ldots, n$, where n signifies the total count of buses in the network. Here, G_{ij} signifies the mutual conductance between any bus i and j^{th} load bus, while B_{ij} signifies the mutual susceptance between the same buses.

2.3.2 Inequality constraints

The operating bounds of the power system are determined through the following constraints:

a) Generation constraints For stable operation, the generators must operate within the following ranges of real power, reactive power, and voltages:

$$\left.\begin{aligned} P_{G_i}^{\min} \le P_{G_i} \le P_{G_i}^{\max} \quad i = 1, 2, \ldots, NG \\ Q_{G_i}^{\min} \le Q_{G_i} \le Q_{G_i}^{\max} \quad i = 1, 2, \ldots, NG \\ V_{G_i}^{\min} \le V_{G_i} \le V_{G_i}^{\max} \quad i = 1, 2, \ldots, NG \end{aligned}\right\} \tag{19}$$

here active power generation at i^{th} generator bus (P_{G_i}) is bounded by $P_{G_i}^{\min}$ and $P_{G_i}^{\max}$, while the reactive power generation (Q_{G_i}) is bounded by $Q_{G_i}^{\min}$ and $Q_{G_i}^{\max}$. Additionally, bus voltage (V_{G_i}) of i^{th} generator must stay within the limits of $V_{G_i}^{\min}$ and $V_{G_i}^{\max}$.

b) Shunt compensator constraints There must be specified limits on the lower and upper ranges of shunt compensation.

$$Q_{C_i}^{\min} \le Q_{C_i} \le Q_{C_i}^{\max} \quad i = 1, 2, \ldots, NC \tag{20}$$

c) Transformer constraints There is a range of tap settings for transformers that must be adhered to. The lower and upper limits are as follows:

$$T_i^{\min} \le T_i \le T_i^{\max} \quad i = 1, 2, \ldots, NT \tag{21}$$

d) Security constraints These constraints pertain to the maximum MVA limits on line flows and the permissible ranges of voltage magnitudes at load buses as expressed in Eq. 22:

$$\left.\begin{aligned} |S_{line_i}| \le S_{line_i}^{\max} \quad i = 1, 2, \ldots, NL \\ V_{L_i}^{\min} \le V_{L_i} \le V_{L_i}^{\max} \quad i = 1, 2, \ldots, NPQ \end{aligned}\right\} \tag{22}$$

3 Overview of artificial intelligence (AI)-based OPF solution methodologies

Several population-based metaheuristic techniques, which are a type of AI-based methodology, have been effectively employed to address power system optimization problems (PSOPs). These techniques have shown the capability to effectively explore the search area and identify optimal or near-optimal solutions. They are non-deterministic or stochastic search techniques capable of solving SOO problems and can be extended to handle MOO problems effectively. These techniques use population-based strategies for iterative solution finding and have shown promising results in discovering optimal or highly competitive solutions for PSOPs.

In this study, a temporal categorization approach is employed to organize and comprehend the development of various works over time. The reviewed works have been categorized into different groups based on population-based metaheuristics, which are optimization algorithms (OAs) that find their foundation in AI principles. Figure 2 presents an illustrative schematic diagram that provides an overview of the diverse OAs documented in the literature, with their year of inception, for solving OPF problems, including their classifications and subclassifications.

4 Evolutionary algorithms (EAs) for OPF solution

EAs are recognized as one of the earliest AI-based approaches applied to PSOPs. An evolutionary algorithm employs principles inspired by biological evolution to iteratively search for optimal solutions, such as mutation, crossover, and selection. Algorithms falling under this EA category strictly adhere to these principles.

4.1 Evolutionary programming (EP) based OPF

The EP is a stochastic optimization approach in evolutionary computing that employs evolutionary mechanics to produce optimal solutions to a given problem. Yuryevich et al. [11] first developed an algorithm based on EP methodology to address the OPF challenge. The authors utilized gradient information to enhance their suggested algorithm, resulting in increased convergence speed and improved handling of large-scale systems. Kahourzade et al. [12] compared three extensively employed OAs published in the literature, namely PSO, EP and GA, to evaluate their effectiveness in solving the OPF problem. They evaluated the algorithms on nine objective functions, which included both single-objective functions (SOFs) and multi-objective functions (MOFs), to capture the objectives of FCM, PLM, VSE, and EM. A fuzzy decision-making (FDM) mechanism was utilized to extract the optimal trade-off solution from each set of Pareto optimal solutions. The authors employed 30-bus IEEE test system to execute

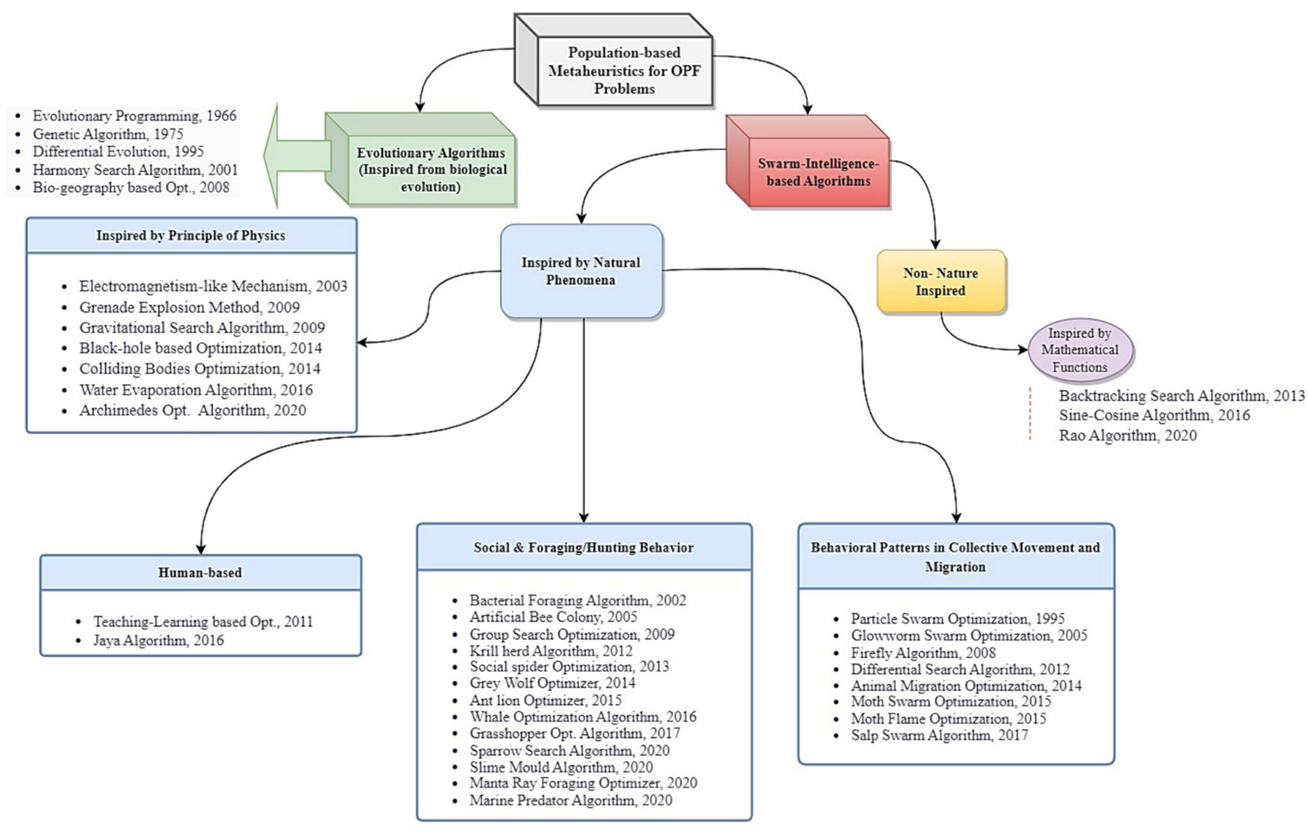

Fig. 2 Schematic overview depicting categorization of OPF algorithms and their inception over time

the three methods for conducting a comparative study. Depending on the overall cost of generation and the rate of convergence of the objective function, the best optimization scheme was selected for each case. The results proved the effectiveness of EP among other algorithms to offer best price in most of the cases. In short, the EP algorithm shows promise for addressing PSOPs. However, evaluating its performance on the specific problem at hand is crucial before making a final decision. Thorough comparisons with other relevant algorithms are necessary to ensure an informed choice.

4.2 Genetic algorithm (GA) based OPF

The GA is a metaheuristic population-based method developed by Holland [13] in the early 1970s. GA has been one of the most popular and widely used evolutionary tools to find optimal solutions to search problems. It relies on the principle of biological evolution, which happens through natural selection. In [14], Attia et al. utilized the Adapted Genetic Algorithm (AGA) with a variable population size (POP) based on different fitness functions to resolve OPF. Three distinct SOFs were selected: minimizing the fuel cost (FCM) function, FCM function considering multiple fuel sources for generating units (FCM-MFS), and minimizing voltage deviation (VDM). The validation of the proposed AGAPOP approach was conducted using the 30-bus IEEE test network, showcasing its feasibility and demonstrating a notable decrease in the required number of generations. For the FCM objective, total fuel cost was reduced to 799.8441 \$/hr (11.33% reduction from the base case), with population size varying from 400 to 312. The comparison with other OAs in the published works, such as improved GA (800.805 \$/hr), PSO (800.41 \$/hr), and DE (799.289 \$/hr), established the efficacy of the proposed AGAPOP approach. However, the waning popularity of GAs to solve OPF can be attributed to various factors, including the emergence of problem-specific algorithms with lesser algorithm-specific parameters, high computation costs, sensitivity to hyperparameters, scalability limitations, advancements in AI and optimization techniques, and the absence of well-established theoretical foundations. As a result, specialized algorithms are now preferred for more effective solutions.

4.3 Differential evolution algorithm (DEA) based OPF

Rainer Storn and Kenneth Price invented the DEA, a stochastic, population-based OA, in 1997 [15]. DEA stands out primarily due to its simplicity, robustness, and rapid convergence features, which are achieved by utilizing a minimal set of control variables. In [16], a DEA-based approach was applied, considering the objectives of FCM, PLM, RPLM, and VSI on a 30-bus IEEE test system. The study also focused on the FCM objective for the larger 118-bus IEEE test system. The research effectively resolved the MOOPF problem for the 30-bus system by considering various combinations of these objective functions. An optimal feasible solution was determined using the fuzzy-based Pareto front method for the MOOPF problem, considering trade-offs among multiple objectives. In addition to this, the given literature presented the inaugural application of a novel approach utilizing the grey wolf optimizer (GWO) algorithm to address the SOOPF challenge (described later in the article) in the 30- and 118-bus IEEE test networks. However, the DE algorithm was found to be exhibiting higher computational efficiency when tested on large 118-bus system as compared to the GWO algorithm for solving SOOPF problem. For a particular case of a single FCM objective in an IEEE 118-bus system, the proposed DE achieved a fuel cost of 129,582 \$/hr as compared to 129,720 \$/hr (the proposed grey wolf) with better convergence characteristics. In [17], a forced initialization multi-objective DEA (MODEA) was proposed, integrating a novel DE variant and the epsilon-constraint approach. The proposed approach for optimizing power flow, evaluated for both SOFs and MOFs considering objectives including FCM, VDM, VSE, and PLM, demonstrated robustness and exhibited excellent convergence characteristics. The authors in [18] introduced a multi-objective DE (MDE) algorithm, utilizing Pareto ranking approach in the selection operator to obtain a modified DE variant of mutation. The proposed DE variant, in conjunction with the epsilon-constraint approach, enhanced the best compromise solution through iterative fine-tuning in each generation using fuzzy logic. This refined solution was then utilized as input for the mutation operator. The efficacy of MDE algorithm was assessed on a 57-bus IEEE test network for mono-, bi-, tri-, and quad-objective OPF formulations. The authors also considered a 118-bus IEEE test network to evaluate the effectiveness of MDE in handling larger systems. S.S. Reddy in [19] implemented a new efficient MOO approach using DEA to optimize mixed control variables, encompassing continuous and discrete variables. The objectives for the MOOPF problem included FCM with a QFC function, QFC incorporating VPL & POZ, QFC considering a voltage-dependent load model, and PLM. The proposed approach outperformed Non-dominated Sorting GA-2 (NSGA-II) in terms of the spread and spacing of its solutions on the Pareto front, while achieving approximately ten times faster computation speed compared to NSGA-II. The feasibility of the suggested strategy for both the considered IEEE 30 and IEEE 300-bus networks in terms of execution time was confirmed through the simulation results. The proposed MOO approach on the 30-bus IEEE network achieved the FCM objective (basic QFC) in shorter computational time, i.e., in 17.0209 s, surpassing the performance of NSGA-II (183.2 s) and weighted summation (69.8 s). A notable outcome emerged for FCM objective with voltage dependent load on the same system, where the efficient MOO approach yielded a best compromise solution, characterized by a cost of electricity generation of 801.2480 \$/hr and power losses in the transmission network of 6.174 MW. In contrast, the NSGA-II algorithm had a generation cost of 812.6738 \$/hr and transmission losses of 5.9362 MW. Additionally, on the IEEE-300 bus system for voltage-dependent load FCM, the proposed approach achieved a better compromise solution with a generation cost of 809,027.9451 \$/hr and transmission losses of 628.3249 MW while being 10.83 times faster than NSGA-II (generation cost: 801,163.0894 \$/hr, transmission losses: 630.8413 MW). In short, DEA's prowess in handling multi-objective tasks, complex constraints, and mixed control variables makes it an excellent and reliable optimization tool for power systems.

4.4 Harmony search algorithm (HSA) based OPF

Geem et al. proposed harmony search (HS) in 2001 [20] based on the concept of musicians improving music in pursuit of a better harmony. Sinsuphan et al. [21] introduced an improved harmony search (IHS) method for solving augmented cost function with penalty terms as SOF and validated it by testing on different small and large-scale standard IEEE systems having 6, 14, 30, 57 and 118 buses for smooth cost functions (basic QFC) and 6, 14 and 30-bus systems for cost functions with VPL effect. In a performance comparison with 30 computational trials for each test case, IHS demonstrated superior robustness and effectiveness over SQP and GA. It outperformed them in terms of objective value and computational efficiency, particularly in large-scale systems with non-smooth fuel cost functions. SQP was found well-suited for small-scale systems (6, 14, and 30-bus) with non-smooth cost functions, offering faster computation times. But IHS was found to be the best algorithm in terms of both execution time and minimum objective function value. IHS outperformed GA by achieving a better objective value in significantly less CPU time, being approximately five times faster, especially for smooth fuel cost cases. For instance, in the FCM objective (basic QFC) on the 30-bus IEEE network, IHS achieved a lower average fuel cost of 463.5480 €/hr in just 92.6 s, outperforming GA which achieved 464.0290 €/hr in 457.5 s of CPU time. In [22], Pandiarajan et al. proposed the fuzzy-based HSA (FHSA) method that incorporates the fuzzy logic system (FLS) and HSA technique. In their work, the authors addressed the SOOPF problem with a focus on the FCM objective, while also aiming to minimize the severity index. They achieved this by determining the location for the strategic installation of a thyristor-controlled series capacitor (TCSC). The impact of using FLS to automatically adjust algorithm parameters, such as "pitch adjustment rate" and "bandwidth", was investigated. The proposed approach demonstrated superior performance compared to the traditional HSA method when applied to solving OPF in 30, 57 and 118-bus IEEE test networks. It exhibited improved optimal generation fuel cost and faster convergence to high-quality solutions. In [23], Abbasi et al. proposed an innovative differential-based HSA (DH/best algorithm) with three objectives of VDM, PLM, and active power generation reduction (MW/hr). The suggested approach was evaluated on the IEEE test networks consisting of 118 and 57 buses, formulating the objective functions as SOFs and MOFs. The HSA incorporates features like the DH/best algorithm, eliminating the need for a pitch adjustment parameter. The proposed DH/best algorithm offers advantages such as improved initialization compared to traditional random initialization methods and enhanced search capabilities due to an effective updating procedure. The proposed approach was simulated against NSGA-II, PSO, and the original HSA to validate its effectiveness.

4.5 Bio-geography based optimization (BBO) based OPF

Simon introduced BBO [24] in 2008, and the algorithm was implemented successfully in [25] to address a large complex economic dispatch problem. A novel adaptive real-coded BBO (ARCBBO) technique is presented in [26] to improve population diversity and exploration capabilities in the OPF problem by integrating an adaptive Gaussian mutation. ARCBBO was tested on IEEE test systems with 30 and 57 buses, evaluating objectives of FCM, VDM, VSE (normal and contingency), PLM, and EM. The 57-bus system was specifically examined for the FCM objective. Based on the achieved outcomes, it was confirmed that ARCBBO algorithm effectively and accurately mitigated premature convergence of solutions. When considering the FCM objective on the 30-bus system, ARCBBO demonstrated superior performance by achieving a fuel cost of 801.5159 \$/hr. This result surpassed the basic BBO, ABC, GSA, and MDE algorithms, although some algorithms like PSO, DE, enhanced GA (EGA) showed slightly better results. However, it's worth noting that these better results were deemed infeasible due to violations of the voltage magnitude limits of the load buses.

5 Swarm intelligence-based algorithms for OPF solution (non-hybrid)–inspired by natural phenomena

These algorithms have shown promise in solving OPF problems by mimicking the collective swarm intelligence and adaptive behavior of natural systems. As research in this area continues, researchers might be able to solve even more complex PSOPs through swarm intelligence algorithms.

5.1 Classification based on movement patterns & collective behavior in migration

5.1.1 Particle swarm optimization (PSO) based OPF

PSO, pioneered by Kennedy and Eberhart in 1995, is a population-based OA specifically designed for addressing global optimization problems. In [27], the PSO algorithm was first employed to deal with OPF issues with various SOFs, and its effectiveness was examined and evaluated on a 30-bus IEEE test network. Niknam et al. [28] introduced an improved PSO (IPSO) technique to address the OPF with single and multiple objectives, aligned with FCM, EM, PLM, and VSE objectives. To accelerate convergence, the authors employed chaos theory to fine-tune the inertia weight factor (ω) and utilized a self-adaptive approach to adjust the *cognitive* and *social coefficients* (c_1 and c_2, respectively) of the PSO algorithm. To prevent becoming stuck in local optima, the authors implemented a "mutation operator", thereby enhancing the algorithm's search capability. The fuzzy decision-making approach was employed to extract non-dominant solutions from the Pareto-optimal set, enabling the identification of the optimal feasible solution. The proposed IPSO achieved the best generation cost of 801.978 \$/hr compared to basic PSO (802.205 \$/hr), EP (802.62 \$/hr), improved EP (802.465 \$/hr), enhanced GA (802.06 \$/hr), fuzzy GA (802 \$/hr), modified DE (802.376 \$/hr), and other popular approaches for the SOOPF scenario. Furthermore, the bi- and tri-objective formulations for the considered objectives (MOOPF cases) also yielded superior results compared to the basic PSO and NSGA-II when tested on the 30-bus test system. However, in recent years, researchers have increasingly combined PSO with other algorithms to address its drawbacks, particularly the issue of being trapped in local optima.

5.1.2 Glowworm swarm optimization (GWSO) algorithm based OPF

In 2005, Krishnanand and Ghose presented the GWSO algorithm, an innovative OA based on swarm intelligence [29]. This algorithm emulates the flashing behavior of glow-worms, where the glow-worms can dynamically adjust the release intensity of luciferin molecules, resulting in their glow appearing at different intensities. Each randomly generated glow-worm in the exploration domain signifies a potential solution of the objective function and carries a specific amount of luciferin along with it. An individual's fitness value depends on the level of luciferin associated with their position, with brighter individuals representing better positions or better solutions. In [30], GWSO was applied to solve SOOPF and MOOPF problems. The MOOPF problem was formulated by considering the FCM and EM as objective functions. The proposed GWSO algorithm was assessed for its effectiveness in minimizing generation cost in a SOOPF problem on the 30-bus IEEE system and practical 75-bus Indian grid system. It was compared to PSO algorithm with dynamically tuned parameters. In addition, the proposed GWSO was designed for the MOOPF problem on 30-bus system to minimize cost (FCM) and emission (EM). The comparison of test results revealed that GWSO outperformed PSO in terms of providing better results with lesser number of iterations required to converge, as well as a reduced need for computational memory.

5.1.3 Firefly algorithm (FA) based OPF

Drawing inspiration from the blinking patterns and behavior of fireflies, the firefly algorithm was developed in [31] to enhance exploration at both local and global levels. In [32], the authors applied this algorithm for the first time to address OPF problems. They proposed the Gaussian-based Bare Bones Lévy Flight Firefly Algorithm (GBLFA) and its modified counterpart, the Modified GBLFA (MGBLFA), considering thermal units and RES such as wind and solar. To evaluate their approach, the authors conducted 10 case studies on the 30-bus IEEE network, focusing on objectives like FCM, EM, PLM, and VDM. The study showcased the potential influence of RES on optimizing the design of thermal generators, enabling cost-effective and low-emission solutions. The OPF cost function encompassed the fuel cost of thermal generators, carbon tax expenses linked to emissions from these thermal units, direct costs associated with RES, reserve costs, and penalty costs. GBLFA achieved an overall cost of 792.7272 \$/hr, while an even better overall cost of 792.6354 \$/hr was obtained from MGBLFA. The results demonstrated that MGBLFA outperformed previously reported methods in the literature by providing a superior carbon tax value for the 30-bus system.

5.1.4 Differential search algorithm (DSA) based OPF

The DSA, developed by Pinar Civicioglu [33], is a population-based metaheuristic inspired by nature. It draws inspiration from the random walk pattern observed in the migration of living organisms, specifically characterized by Brownian random-walk movement. However, DSA does not explicitly simulate the mechanisms of biological evolution. The algorithm emulates collective movement and migration of organisms in search of improved solutions. During migration, organisms form a superorganism comprising numerous individuals that gravitates towards areas rich in high-quality resources, such as the global optimum. In [34] DSA addressed the SOOPF problem with objectives of FCM (basic QFC, piecewise QFC, QFC with VPL effect), VDM, VSE (normal and contingency condition). The proposed DSA was validated on IEEE test networks consisting of 30 and 118 buses, with a single FCM objective implemented on the 118-bus network. DSA outperformed DE, GSA, and PSO on the 30-bus system, achieving a fuel cost of 799.094 \$/hr compared to 799.289 \$/hr, 798.675 \$/hr, and 800.41 \$/hr, respectively. Furthermore, DSA demonstrated superior scalability and outperformed GA and PSO when applied to the 118-bus system. In [35], an innovative DSA-based approach was suggested and applied to deal with SOOPF and MOOPF problems. The implemented approach utilized standard IEEE test systems with 9, 30, and 57 buses, incorporating objectives of FCM, VDM, PLM, VSE, and EM. For a specific FCM objective on the 57-bus system, the proposed approach successfully achieved a reduce fuel cost of 41,686.82 \$/hr. This result outperformed the outcomes obtained from alternative techniques such as ABC (41,693.95 \$/hr) and GSA (41,695.87 \$/hr), demonstrating the effectiveness and robustness of the suggested approach.

5.1.5 Animal migration optimization (AMO) based OPF

Li et al. introduced AMO in [36] taking inspiration from the animal migration behavior. As an approach to address the OPF, Dash et al. [37] introduced a new form of AMO called Boundary Assigned AMO (BAAMO). The proposed method underwent evaluation on IEEE test systems featuring 30, 57, and 118 buses, while considering the objectives of FCM, PLM, and VDM. The proposed approach demonstrated remarkable performance in terms of cost function compared to widely used approaches like PSO, GA, DE, ABC, and Gravitational Search Algorithm (GSA). The fuel costs for the 30, 57, and 118-bus systems were 798.012 \$/hr, 41,665.5 \$/hr, and 129,550.8 \$/hr, respectively. However, the computation time was somewhat high compared to other methods because the proposed approach updates the variables twice in one iteration.

5.1.6 Moth flame optimization (MFO) algorithm/moth swarm algorithm (MSA) based OPF

The MFO algorithm is a recently introduced population-based OA, presented by Mirjalili in 2015 [38], and imitates the special navigation mechanism, referred to as “transverse orientation”, a navigation strategy adopted by moths during nighttime. The MFO algorithm draws inspiration from this mechanism observed in moths. These insects are deceived by artificial human-made light sources, leading them to fly in spiral paths that ultimately converge towards the light. In [39], the MFO was validated on a standard IEEE test system having 30 buses with 5 different SOFs considering objectives of FCM having QFC curve, QFC with VPL effect and piecewise QFC (with multifuel options), objective of EM and objective of PLM. Contrasting with other popular algorithms like PSO, GWO, ABC, etc., the proposed MFO showcased its effectiveness in addressing the OPF issue through consistently discovering superior and legitimate solutions. To further evaluate the effectiveness of MFO and verify the significance of the obtained results, the authors conducted four distinct statistical tests that compared MFO with other OAs. These non-parametric tests validated the run-wise performance of MFO and confirmed its dominance over other similar algorithms. In [40], an improved MFO (IMFO) algorithm was introduced, featuring modified paths of moths spiraling around the flame. The proposed IMFO was validated on IEEE test networks consisting of 30, 57, and 118 buses. It was utilized to deal with SOOPF and MOOPF problems involving fifteen different objective functions. The simulation outcomes were compared to those obtained from other well-established OAs such as basic MFO, GA, PSO, and TLBO. The proposed IMFO was demonstrated to be effective in achieving precise, superior OPF solutions with rapid convergence. Buch et al. in [41] proposed an enhanced version of the basic MFO, namely Adaptive MFO (AMFO), to address large scale OPF issues. In the suggested approach, an adaptive mechanism for adjusting the direction of moths around the flame was contrasted with the basic MFO for optimizing fourteen well-known benchmark test functions. The authors utilized a large IEEE test system with 118 buses to illustrate the efficacy of suggested AMFO algorithm. They considered 13 different case studies for this purpose, reflecting SOFs like FCM (QFC function, QFC with VPL effect, piecewise QFC, and QFC with POZ), EM, VSE, VDM, PLM, and RPLM. For each objective function, the authors conducted three statistical checks to assess the performance of AMFO in comparison to other OAs in the literature, including basic MFO, grey wolf optimization algorithm, sine–cosine algorithm, and others. This study validated the effectiveness of the suggested approach in providing accurate OPF solutions with an improved convergence rate. The authors proposed that developing a multi-objective version of the algorithm could be pursued as future research work to address MOOPF problems.

Mohamed et al. in 2017 introduced the moth swarm algorithm (MSA) [42] using the conventional MFO algorithm as a foundation. The MSA, inspired from the orientation of moths towards moon light, features improved exploration and exploitation capabilities by utilizing new optimization operators to imitate a set of moth behavioral patterns observed in nature. The authors in this work proposed a novel MSA based approach where a variety of optimization techniques were combined to simulate moth swarm behavioral patterns. The proposed approach introduced new optimization operators, including adaptive crossover with Lévy-mutation for exploration and an immediate memory-based associative learning mechanism for exploitation. A comprehensive analysis consisting of 14 case studies was conducted, addressing various objectives such as FCM (QFC, piecewise QFC, QFC with VPL), EM, PLM, VSE (normal and contingency condition), and VDM. A comparative analysis between the suggested MSA and other existing OPF solution methods on 30, 57 and 118-bus IEEE networks established the superiority of MSA over previously proposed algorithms in the literature (modified PSO, modified DE, MFO, etc.). Bentouati et al. [43] proposed enhanced version of MSA (EMSA) incorporating "quasi-opposition-based learning" and validated on 30, 37 and 118-bus IEEE systems for a total of 12 cases having single and multi-objective formulations comprising technical, economical and emission objectives. EMSA showed better performance than basic MSA in terms of fast convergence ability and enhanced voltage profiles. Authors further suggested the scope of improving MSA to enhance the exploration performance with less computational time.

5.1.7 Salp swarm algorithm (SSA) based OPF

The Salp Swarm Algorithm (SSA) is a highly efficient and readily implementable OA that draws inspiration from the collective behavior of salp chains in the deep sea. Sattar et al. [44] introduced an improved SSA called ISSA, aiming to improve the search performance in original SSA by enhancing both exploration and exploitation for effectively addressing the challenges of the OPF problem. The OPF objective reflected the three types of QFC: basic QFC, piecewise QFC, and QFC with VPL effect and POZ. The proposed ISSA was evaluated on IEEE test networks consisting of 30, 57, and 118 buses and compared to SSA, MFO, GA, and other popular algorithms, revealing superior convergence characteristics. In a specific case on the 30-bus system, ISSA achieved the most economical solution regarding the FCM (QFC) objective, with a fuel cost of 800.4752 \$/hr, outperforming other algorithms such as basic SSA (801.1653 \$/hr), MFO (800.7134 \$/hr), and GA (800.5272 \$/hr) reported in the literature.

5.2 Classification based on social behavior & foraging/hunting behavior

5.2.1 Bacterial foraging optimization (BFO) algorithm based OPF

Passino introduced the BFO algorithm in 2002 [45], which is driven by the foraging patterns of *E. coli* bacteria found in the intestines of humans and animals. After going through number of generations, the genes of organisms showing poor foraging strategies get rejected and only those with superior strategies are naturally selected. Amjady et al. [46] put forward an improved version of bacterial foraging (IBF) to address problem of security constrained OPF (OPF-SC). The classical BFO algorithm was enriched with innovative search mechanisms and solution strategies to improve its search efficiency, exploration capacity, and convergence performance. Simulation results for the various test cases considering 26-bus test system with six generating units and standard IEEE test systems having 30 and 118 buses, for 20 trial runs for the IBF, were presented. The proposed IBF algorithm was evaluated by comparing its simulation results to those obtained from over 20 other OAs previously testified in the literature (including basic BFO, EP, PSO, and others) for solving OPF and OPF-SC problems. A comparative analysis of the proposed IBF algorithm, in comparison to alternative approaches, substantiated its robustness, simplicity, and improved computational efficiency.

5.2.2 Artificial bee colony (ABC) algorithm based OPF

The ABC algorithm, introduced by Adaryani et al. [47], is a heuristic OA that is inspired by the efficient foraging strategies employed by honey bee swarms. In the ABC algorithm, the position of a food source metaphorically represents a potential solution to an optimization problem, while the nectar content associated with that position determines the fitness of the solution. The proposed approach was utilized to tackle the MOOPF problem with diverse objectives involving FCM (basic QFC, piecewise QFC, QFC with VPL), PLM, EM, and VSE (normal and contingency states), and tested through a simulation study on IEEE test networks with 9, 30, and 57 buses. For the 57-bus system, only the objective of FCM was considered.

In the case of FCM objective on a 30-bus system, the ABC algorithm achieved the best fuel cost of 800.6600 $/hr, outperforming linearly decreasing inertia weight PSO (800.739 $/hr) and GSA (805.175 $/hr) in the same study. The results confirmed its effectiveness in generating accurate solutions, particularly for large power systems, while also exhibiting quick convergence features. While other published works achieved better fuel cost values, the authors justified them as unfeasible because of either reactive power limit violations or load bus voltage magnitude violations. Khorsandi et al. [48] presented a fuzzy-logic based modified ABC (MABC) algorithm for OPF, incorporating a mix of discrete and continuous variables for SOO of four competing objectives, viz. FCM with ripple effects of VPL, EM, PLM and VDM and simultaneous fuzzy-based optimization considering all four objectives. The suggested MABC approach was executed on IEEE test networks consisting of 30 and 118 buses, considering SOOPF and multi-objective mixed-integer OPF problems. Simulation outcomes demonstrated the efficacy of MABC in global search exploration and rapid convergence to higher quality solutions in a comparatively lesser number of iterations than several other OAs previously documented in the literature. Chen et al. [49] presented a multi-hive multi-objective bee algorithm (M2OBA) to deal with real world MOOPF problem. The suggested method expands the basic ABC algorithm to an interacting multi-hive model by including interaction exchange topologies. A multipopulational cooperative search mechanism was used in conjunction with multi-objective tactics to scale up the effectiveness of the bee foraging algorithm. The effectiveness of the proposed M2OBA was evaluated through implementing and testing it on a 30-bus IEEE test network. A comparative analysis was conducted with three well-known multi-objective optimizers, namely NSGA, MOPSO, and multi-objective ABC, in order to solve complex MOO problems. He et al. [50] suggested an improved ABC (IABC) algorithm to offer a solution for a fuzzy MOOPF model. The IABC algorithm incorporates the mutation and crossover operators from the DE algorithm for enhancing exploration capabilities and generating novel solutions. The SOOPF and MOOPF problems, which involve objectives such as FCM, EM, VDM, and PLM, were addressed using the proposed approach on 30, 57, and 300-bus IEEE test systems. The obtained results revealed that the optimizing scheme obtained by the suggested model was able to provide quick and stable convergence characteristics in comparison with ABC algorithm and other popular OAs like GA, PSO etc., resulting in more reliable and economic power system operations. Jadhav et al. [51] introduced a g-best guided ABC (GABC) for addressing both standard OPF problem and temperature dependent OPF (TDOPF). By incorporating the term representing the global best solution into the search equation, the authors succeeded in enhancing the exploitation characteristics of ABC. The robustness of the GABC in exploring the global optimum point was demonstrated through IEEE test networks consisting of 30 and 57 buses, considering single FCM objective (basic QFC function). The TDOPF was examined on the identical 30-bus IEEE test network to assess the influence of temperature (25 °C temperature rise) on both generation cost and power loss. The findings showcased promising prospects for addressing multi-objective TDOPF problems in the future. Bai et al. [52] implemented an improved ABC (IABC) based on orthogonal learning (OL) to tackle the complex OPF problem with objectives including FCM, FCM-VPL and PLM. The proposed IABC technique demonstrated increased exploitation capabilities and superior convergence characteristics when implemented on IEEE test networks consisting of 30 and 118 buses. The IABC approach showcased faster convergence and superior results in minimizing fuel costs for the 30-bus system. Compared to other methods like basic ABC, GSA, EGA, and MDE, the proposed IABC significantly lowered the total cost to 799.321 $/hr.

5.2.3 Group search optimization (GSO) algorithm based OPF

In 2009, He et al. introduced a novel nature-inspired swarm intelligence OA called Group Search Optimization (GSO) [53], drawing inspiration by the producer-scrounger behavior observed in group-living animals. The algorithm incorporates strategies used by animals to balance exploration and exploitation during foraging activities. In [54], GSO algorithm was evaluated on IEEE test networks with 30, 57, and 118 buses, considering objectives related to FCM, EM, VDM and VSE, resulting in the formulation of four SOOPF problems and two compound-objective problems. The simulation findings validated the efficacy of the examined approach in providing promising solutions with improved convergence characteristics within 100 iterations. In [55], an adaptive GSO (AGSO) algorithm was proposed to handle the issues of the MOOPF problem, which involved incorporating the objectives of EM and security index along with the primary objective of FCM. The authors utilized the fuzzy decision-making method to handle these multiple objectives of conflicting nature. The AGSO was created by making certain adjustments to the conventional GSO, wherein the ranging process was further organized by assigning the vision ability to other select members of the group. This adjustment enhances both the convergence behavior and accuracy of the algorithm, leading to more precise and efficient solutions. The AGSO algorithm was evaluated using 7 benchmark test cases and realized on IEEE networks with 30 and 57 buses, demonstrating its superiority over conventional GSO. Moreover, it ensured the secured operation of the networks in the event of a contingency.

5.2.4 Krill herd algorithm (KHA) based OPF

Gandomi and Alavi proposed KHA, a novel bio-inspired population-based algorithm in 2012 [56]. The algorithm is inspired by a very small sea animal krill and its style of living. Krill individuals navigate a multidimensional search area in their quest for the densest food sources. During this journey, they adjust their positions based on the movements of other krill individuals, as well as their own foraging behavior and random physical diffusion. In [57], the performance of basic KHA method was improved by incorporating the concept of chaos theory. It was found that the proposed chaotic KHA, which combines the basic KHA and chaos theory, was able to achieve enhanced computational speed and faster rate of convergence. The proposed approach was tested and validated on a standard 26-bus system and an IEEE test network of 57 buses. The results confirmed its superiority over recent CI-based techniques in terms of convergence rate and the identification of global optimal solutions for FCM, PLM, and VDM objectives. Roy et al. [58] presented a newly developed KH algorithm to address SOOPF and MOOPF problems. The foundation of the proposed approach rested upon the herding instinct of krill individuals and was successfully executed on IEEE test systems consisting of 30, 57, and 118 buses. The study encompassed the objectives of FCM, VDM, PLM, and VSE to formulate three distinct SOOPF problems and two distinct MOOPF problems. The authors incorporated genetic operators (crossover and mutation) in basic KH to augment the effectiveness of the suggested algorithm and to achieve an optimal equilibrium between its local and global search abilities. The suggested approach significantly improved the solution quality and provided faster convergence and superior computational efficiency in comparison to other OAs documented in the literature. In [59], a novel biologically inspired algorithm known as the stud krill herd (SKH) algorithm was first time used for the solution of SOOPF problems. Authors, herein, proposed a hybrid approach in which they hybridized KH algorithm with a stud genetic algorithm (SGA) to reach near-global optimum solution. They incorporated the concept of “stud selection and crossover operator” in the original KHA for extracting good OPF solutions and preventing local optima traps. The performance analysis on standard IEEE systems having 14, 30 and 57 buses demonstrated the feasibility of the proposed algorithm in obtaining superior optimum values when compared to other evolutionary algorithms examined in the same work.

5.2.5 Social spider optimization (SSO) algorithm based OPF

Erik Cuevas et al. developed the SSO algorithm in 2013 [60], which is swarm intelligence-inspired and mimics the cooperative behavior of social spiders while seeking food together. A novel improved SSO (NISSO) algorithm was introduced in [61] to deal with OPF issue considering independent SOFs. The proposed algorithm underwent three enhancements, involving modifications to the position change of female spiders (ISSO1), position change of male spiders (ISSO2), and adjustments to the quantity of females and males (ISSO3). These enhancements (together yielding NISSO) surpassed the conventional SSO approach, resulting in a faster convergence and higher quality solutions. The proposed methodology was verified on IEEE test networks with 30 and 57 buses, as well as a larger 118-bus system, considering the objectives of FCM (basic QFC, QFC with VPL effect, and piecewise QFC), PLM, EM, VDM, and VSE for SOOPF formulation. The proposed NISSO approach demonstrated its effectiveness in delivering superior optimum solutions and achieving faster convergence compared to the original SSO algorithm and other existing methods. This advantage was particularly evident for large-scale systems.

5.2.6 Grey wolf optimizer (GWO) based OPF

GWO was first implemented to address the SOOPF problem in [16] and verified on 30 and 118-bus IEEE test networks. However, its computational efficiency was found to be lower when dealing with large systems (118-bus). The objectives considered were FCM, PLM, RPLM, and VSI. In the FCM objective of a 30-bus system, the GWO algorithm achieved a fuel cost of 801.41 $/hr in 15.8 s with a maximum of 300 iterations. In [62], the authors published an updated version of GWO known as the Crisscross Search based GWO (CS-GWO). Proposed CS-GWO offers a distinct advantage in the form of its single controllable parameter, specifically the vertical crossover probability. It incorporated horizontal and vertical crossover operators to augment population diversity and mitigate local trapping. The validation of the CS-GWO involved the use of IEEE test networks with 30 and 118 buses, covering 7 objective cases in total. The objectives considered included FCM (with and without VPL effect), PLM, and VDM, encompassing both SOOPF (for 118-bus system only), as well as MOOPF scenarios. The results indicated that CS-GWO exhibited superior performance compared to other well-known OAs, including PSO, ABC, Backtracking Search Algorithm (BSA), and GSA, particularly for large-scale systems. In particular, CS-GWO excels in delivering better solutions while achieving faster convergence speeds.

5.2.7 Ant lion optimizer (ALO) based OPF

In 2015, Seyedali Mirjalili introduced ALO, which emulates the intellectual aspects of antlions as they capture ants in their environment. In [63], Trivedi et al. utilized the ALO algorithm to tackle the SOOPF problem on the IEEE test network with 30 buses, considering the objectives of FCM, VDM, VSE, PLM and RPLM. ALO demonstrated superior convergence and outperformed FA and PSO techniques, affirming its effectiveness. ALO yielded the lowest fuel cost of 799.155 \$/hr in the FCM objective, surpassing FA (799.766 \$/hr), PSO (799.704 \$/hr), DE (799.289 \$/hr), and the black-hole based optimization algorithm (799.921 \$/hr). Belkacem Mahdad in [64] proposed a partitioned ALO (PALO) technique to improve OPF solution accuracy using multi-SVC and TCSC-based FACTS devices. The robustness of PALO was validated on 30-bus IEEE test network and two large Polish power system networks (300-bus and 2736 ps-bus). The validation included three objective functions (FCM, PLM, VDM) and took into account load growth. The proposed PALO was evaluated against recently published metaheuristics in the literature, therefore demonstrating its unique effectiveness in solving large-scale security OPF problems with various FACTS devices.

5.2.8 Whale optimization algorithm (WOA) based OPF

In 2016, Mirjalili and Lewis developed WOA, utilizing the bubble net feeding behavior observed in humpback whales [65]. Authors in [66] proposed a non-dominated sorting WOA (NSWOA) for SOOPF and MOOPF formulations. The study investigated the objectives of FCM, PLM, VDM, and VSE (*L*-index minimization) on 30-bus IEEE test network. The best compromise solution was chosen by selecting the option with the least Euclidean distance from the non-dominated solution set. The suggested technique outperformed existing methods in the literature, such as PSO, SCA, SSA, and others, in terms of fuel cost and power loss in multi-objective scenarios.

5.2.9 Grasshopper optimization algorithm (GOA) based OPF

The GOA is the recently innovated optimization technique presented by Mirjalili et al. in 2017 [67]. The philosophy behind this approach was influenced by the behavior of grasshopper swarms, where large groups collectively forage for food sources. A modified GOA (MGOA) technique was proposed in [68] as a solution to optimize OPF problems. The modification specifically focused on enhancing the mutation process of the traditional GOA. This was done to overcome challenges including delayed convergence, becoming stuck in local optima, and improving the global exploration process. The proposed algorithm was deployed on IEEE test networks consisting of 30, 57, and 118 buses. It considered various objectives such as FCM, EM, PLM, VDM, and VSE, covering a total of 13 distinct case studies in SOOPF and MOOPF formulations. Specifically, there were 8 case studies conducted on the 30-bus system, 4 case studies on the 57-bus system, and 1 case study on the 118-bus system (SOOPF). Comparative performance analysis of MGOA against conventional GOA, GA, PSO, and TLBO revealed that the proposed technique is not only more efficient but also exhibits superior performance.

5.2.10 Sparrow search algorithm (SPSA) based OPF

In [69], Jebaraj and Sithankathan proposed SPSA to resolve OPF. The capabilities of the SPSA optimizer were evaluated on IEEE systems with 30, 57, and 118 buses, involving 33 different economic and technical objectives. These functions encompassed single, bi-, tri-, and quad-objective formulations. For instance, when considering fuel cost as a SOF, the SPSA algorithm achieved fuel costs of 798.9536 \$/hr, 41,609 \$/hr, and 129,561.0305 \$/hr for the IEEE test systems with 30, 57, and 118 buses, respectively. These values were found to be superior than those reported in the existing literature, indicating improved performance by the proposed method. In the tri-objective formulation, focusing on the objective of FCM and VSE (*L*-index minimization) during a single-line outage contingency, the proposed method achieved a fuel cost of 804.2563 \$/hr. Despite the low *L*-index value resulting from the outage, the method demonstrated its effectiveness. This fuel cost result outperformed popular algorithms such as MFO, MPSO, MSA, and ABC, highlighting the superiority of the suggested approach in optimizing multi-objective cases.

5.2.11 Slime mould algorithm (SMA) based OPF

The SMA was proposed in [70] and is inspired by the natural foraging behavior of slime moulds that seek out food, encircle it, and release enzymes for digestion. In [71], authors proposed SMA to handle SOOPF and MOOPF problems, utilizing Pareto optimality and crowding mechanism and testing it on IEEE test networks consisting of 30, 57, and 118 buses. The study included 14 case studies with objectives centered around FCM, PLM, and EM. The SMA exhibited comparable computational times to other OAs, being slightly slower than EP, DE, and GWSO, while slightly faster than MFO and WOA for SOOPF problems on 30-bus network. The SMA delivered better performance in terms of objective values for the IEEE 30-bus network, achieved significant superiority for the IEEE 57-bus network, and demonstrated significant enhancements in both high-quality solutions and computational time, particularly in the case of the IEEE 118-bus network. The proposed SMA outperformed the PSO algorithm in generating diverse and superior two- and three-dimensional Pareto fronts across all test systems. In [72], a multi-objective SMA (MOSMA) was introduced to resolve the MOOPF problem on two IEEE standard test systems (30-bus and 57-bus), as well as one practical Iraqi Super Grid system. A collection of 29 case studies was presented, comprising both SOFs and MOFs with two, three, four, and five objective formulations. These case studies considered various objectives such as FCM, PLM, EM, VDM, and VSE. By employing Pareto theory, the authors deduced optimal solutions for MOOPF problems, while simultaneously utilizing fuzzy set theory to retrieve the most favorable solution. The MOSMA algorithm showed excellent convergence, high efficacy, and evenly spread-out solutions on the Pareto front, thus establishing its superiority over other recent OAs reported in prior research.

5.2.12 Mantra ray foraging optimizer (MRFO) based OPF

The MRFO algorithm was introduced by Zhao et al. in 2020 [73] and takes inspiration from survival skills of manta rays. The MRFO algorithm employs three foraging techniques, namely “chain”, “cyclone”, and “somersault”, to generate fresh solutions from a population of random ones. Kahraman et al. [74] presented improved multi-objective MRFO (IMOMRFO) as a solution for addressing the MOOPF problem. To augment the exploratory and exploitation capabilities of IMOMRFO, the authors developed a crowding distance-based Pareto archival process. The proposed IMOMRFO was assessed on 30 and 57-bus IEEE test systems, focusing on four objective functions: FCM, VDM, PLM, and EM, with simultaneous optimization of two or more objectives. In one scenario involving the simultaneous optimization of all four objectives, IMOMRFO achieved a fuel cost of 816.4599 $/hr, showcasing a 1.6536% reduction compared to the best value reported in existing literature for the 30-bus system.

5.2.13 Marine predator algorithm (MPA) based OPF

In [75], the MPA was created to find the best global optimum solution by drawing inspiration from foraging methods, Brownian motions, and the biological predator–prey interaction. In [76], the authors applied MPA to address the SOOPF problem, with objectives including FCM, PLM, VDM, and VSE. The suggested technique was tested and compared to various OAs such as SCA, PSO, and GSA on the IEEE 30-bus network. The MPA approach achieved a fuel cost of 799.0725 $/hr on 30-bus network, which is comparable to the findings derived from SCA, GWO, PSO, and other algorithms. Furthermore, an analysis was conducted on a larger IEEE 118-bus test network to determine the optimal fuel cost, which was determined to be 129,422.56 $/hr.

5.3 Classification inspired by principle of physics

5.3.1 Electromagnetism-like mechanism (EM) method based OPF

The EM technique was put forth in 2003 by Birbil and Fang [77] as a powerful population-based metaheuristic optimization strategy utilizing the concept of electromagnetic force of attraction or repulsion between electrically charged particles distributed across the search space. The particle exhibiting the highest charge, denoted as the optimal particle, exerts a strong attraction on particles with higher fitness values while repelling those with lower fitness values. An improved version of the EM (IEM) approach was provided in [78] for obtaining the optimal configurations for the control variables, thereby offering the optimal OPF solution for seven distinct single-objective cases with varying constraints. The proposed method was applied to IEEE networks with 30 and 57 buses, considering objectives such as FCM (basic QFC and piecewise QFC), VDM, VSE, PLM, and RPLM. A scalability test was conducted on a 57-bus system with the objective of FCM (basic QFC). Simulation results demonstrated superiority of improved version over the initial version of EM method and other established OAs (e.g., BBO, DE, PSO) in solution accuracy, convergence rate, and computational efficiency, all simultaneously. For a specific scenario in which the VDM objective is combined with the FCM to formulate a Single Objective Function (SOF), the proposed IEM achieved a fuel cost of 804.1084 $/hr and a voltage deviation of 0.1063. In contrast, the corresponding values for EM were 804.26 $/hr and 0.127, for BBO were 804.998 $/hr and 0.102, for DE were 805.2619 $/hr and 0.1357, and for PSO were 806.38 $/hr and 0.0891.

5.3.2 Grenade explosion method (GEM) based OPF

The GEM is a population-based novel metaheuristic approach developed in 2009 by Ahrari and Atai [79] and draws inspiration from the grenade explosion mechanism wherein a large amount of shrapnel is propelled by the explosion, thus effectively targeting the objects situated within a neighborhood radius. As a result of a shrapnel impact, the damage is evaluated, and the overall damage is correlated with the effectiveness or quality of the solution at the location of the object. GEM is a swarm-intelligence algorithm, where new particles are created in a similar manner as the explosion of a grenade, reflecting the problem-solving interactions observed in social insects. In [10], GEM approach was used to handle SOOPF and MOOPF problems, considering six different objectives involving FCM, VDM, VSE, EM, PLM, and RPLM. The MOO problem was formulated using fuzzy decision-making technique, where the objective functions were substituted with fuzzy membership functions. The decision maker was responsible for formulating a fuzzy goal for each objective function, and the algorithm testing was carried out using a standard 30-bus IEEE test system. SOFs, out of multiple objectives, were formed using weighted sum, exponential weighted method, minimal operator, and epsilon-constraint approaches. The superiority of the suggested GEM-based method was demonstrated in both single- and multi-objective scenarios.

5.3.3 Gravitational search algorithm (GSA) based OPF

GSA, a nature-inspired algorithm proposed by Rashedi et al. in 2009 [80], is a recently developed method capable of effectively addressing various challenging global optimization issues. Newton's Law of Gravity serves as a fundamental basis for a key component of the algorithm, governing the interaction among masses within the system. In their study [81], Duman et al. proposed GSA as a viable approach to tackle the OPF problem, taking into account objectives such as FCM (basic QFC, piecewise QFC, QFC with VPL), VDM, VSE (normal and contingency states). The proposed GSA was tested on IEEE test networks with 30 and 57 buses, and the derived findings reaffirmed its superior capability in effectively addressing the SOOPF problems. The GSA algorithm achieved the best fuel cost of 798.675 \$/hr on the 30-bus system for the FCM objective (basic QFC), surpassing the results of BBO (799.1116 \$/hr), DE (799.2891 \$/hr), PSO (800.41 \$/hr), improved GA (800.805 \$/hr), and other previously published results. The scalability test involved evaluating the 57-bus test system specifically for the FCM objective. Bhattacharya et al. applied GSA algorithm to solve three SOOPF and three MOOPF cases [82]. The authors tested the algorithm for solving OPF objective functions on a standard 26-bus system as well as a large-scale 118-bus IEEE system. They considered identical single, bi, and tri-objective cases for both systems during the testing. The acquired findings were compared against previously published algorithms, confirming the usefulness of the GSA-based technique in determining optimal values for the objective function across different scales of systems. In [83], Bhowmik et al. proposed the non-dominated sorting multi-objective GSA (NSMOGSA), a modified form of the classic GSA. In this approach, the non-dominated sorting mechanism was employed to alter the gravitational force acting on the agents while adhering to the fundamental equation of the original GSA. "Opposition-based learning" concept was used to augment the quality of solutions and to make them converge faster. The proposed NSMOGSA approach was evaluated using different SOOPF and conflicting MOOPF scenarios on a 30-bus IEEE test network considering objectives of FCM (basic QFC, piecewise QFC and QFC with VPL effect), EM, PLM, VDM, and VSE. The case studies conclusively demonstrated the dominance of the proposed method over other algorithms, showcasing faster convergence to high-quality solutions. NSMOGSA, for instance, demonstrated its superiority compared to other popular OAs documented in prior studies, such as GA, PSO, and DE, for the specific objective of FCM (basic QFC) after performing 50 individual runs on the 30-bus system. It achieved the best fuel cost value of 796.124 \$/hr, which is 0.56%, 0.21%, 0.65%, and 0.11% lower than ABC, GSA, MDE, and DE, respectively.

5.3.4 Black-hole based optimization (BHBO) algorithm-based OPF

The BHBO algorithm emulates the behavior of black holes, with candidate solutions represented as stars. These stars are drawn towards the optimal solution, replicating the black hole phenomena. The algorithm possesses a straightforward structure and, being parameter-less, eliminates the need for tuning internal parameters. Bouchekara in [84] implemented BHBO algorithm to address a variety of OPF problems while meeting various types of constraints. The author applied the approach to identify the optimal settings of OPF control variables for the 30-bus IEEE test network and the Algerian 59-bus network, considering various SOFs. However, the efficacy of the suggested approach in dealing with MOOPF problems was not examined.

5.3.5 Colliding bodies optimization (CBO) algorithm-based OPF

CBO is a newly formed population-based metaheuristic algorithm that derives its foundation from the law of physics of one-dimensional collision between two massed objects of specified velocities [85]. The CBO algorithm, formulated by Kaveh and Mahdavi, utilizes the law of conservation of momentum to guide the movement of the bodies towards improved positions within the search domain. An Enhanced CBO (ECBO) was proposed by Kaveh and Ghazaan [86], which adopted a regeneration mechanism that avoided solutions from falling into local optima. Bouchekara et al. [87] developed improved CBO (ICBO) algorithm which utilized three colliding bodies instead of two. Through 16 case studies, the ICBO approach was successfully applied to three IEEE test systems consisting of 30, 57, and 118 buses to resolve realistic OPF problems based on objectives reflecting FCM, VDM, and VSE, both for normal operations and branch contingency conditions. The findings of the performance evaluation study revealed that the proposed algorithm was highly robust and satisfied all the constraints for all cases considered in the study. It exhibited a remarkable capability in effectively deal with a variety of OPF cases. However, a multi-objective CBO algorithm is still to be developed and its scope is to be explored to solve MOOPF problems.

5.3.6 Water evaporation optimization algorithm (WEA) based OPF

Saha et al. [88] employed the Water Evaporation Algorithm (WEA), introduced by A. Kaveh et al. [89], to address the OPF problem. WEA draws inspiration from the behavior of water evaporation, a fundamental physical process involving the interaction between liquid particles and solid surfaces. By integrating concepts from molecular dynamics simulations, the algorithm analyses the effects of surface wettability on the behavior of water particles. The authors evaluated the algorithm on IEEE test systems consisting of 30 and 118 buses, considering single and bi-objective functions. The considered objectives included FCM (basic QFC, QFC-POZ, QFC-VPL effects-POZ), PLM, VSE, and VDM, but only the 30-bus system was tested for multi-objective optimization (bi-objective). WEA outperformed HSA, NSGA-II, and TLBO in a scenario that minimized fuel cost and *L*-index simultaneously. WEA achieved a fuel cost of 799.0183 \$/hr and an *L*-index of 0.1066 p.u., demonstrating superior outcomes compared to these established algorithms commonly found in the literature.

5.3.7 Archimedes optimization algorithm (AOA) based OPF

In [90], authors proposed an improved AOA (IAOA) where a trade-off between local and global exploration was attained employing a "dimension-learning-based search strategy", along with the "motion strategy" derived from AOA, which leads to better convergence characteristics. The proposed IAOA underwent testing on the IEEE test networks with 30 and 57 buses, as well as the 16-bus South Marmara regional transmission systems. With objectives encompassing FCM, PLM, EM, and VDM (voltage profile improvement), both SOF and MOF formulations were examined extensively. The obtained results were compared with TLBO, SCA, DSA, and various other widely used methods in the literature. For instance, for FCM as a single objective, IAOA achieved a remarkable result of 799.068 \$/hr, outperforming several other reported methods.

5.4 Classification based on inspiration drawn from human behavior (human-based algorithms)

Human-based problem-solving approaches make use of human qualities such as adaptation, teamwork, and experience-based learning. The following subsection outlines two predominant algorithms commonly found in the literature for addressing OPF problems.

5.4.1 Teaching–learning based optimization (TLBO) algorithm based OPF

The TLBO algorithm, formulated by Rao et al. in 2011, is a highly effective, parameter-free optimization approach using a population-based strategy, drawing inspiration from the teaching–learning phenomenon observed in a classroom. It mimics the knowledge transfer process from a teacher to learners. Moreover, the results achieved by the learners are shaped by the collective exchange of knowledge and interactions within the group, fostering a collaborative learning process that enhances the quality of solutions. Bouchekara et al. in [91] applied TLBO for solving SOOPF problem for different objectives reflecting FCM (basic QFC, piecewise QFC and QFC with VPL effect), VDM, VSE (normal and contingency condition). The proposed approach was validated on IEEE networks consisting of 30 and 118 buses, with a single FCM objective implemented on the 118-bus network to demonstrate its scalability. The proposed technique achieved a fuel cost of 799.0715 \$/hr for the basic FCM objective on the 30-bus system, demonstrating better or comparable results to those attained from alternative approaches documented in prior studies. A modified TLBO algorithm was used in [92] for solving MOOPF problem involving the objectives of FCM and EM. A modified phase that employed a self-adapting wavelet mutation (SAWM) technique was added to the original TLBO to improve its performance and explore a larger search space for optimal solutions. The proposed algorithm underwent testing using standard IEEE test systems consisting of 30 and 57 buses. The final outcomes validated the improved performance of the algorithm in terms of faster convergence rate with improved accuracy within a fewer number of iterations as compared with original TLBO. A novel hybrid algorithm formed by merging a modified imperialist competitive algorithm (MICA) with teaching–learning algorithm

(TLA), called a MICA-TLA, was developed and presented in [93]. The proposed MICA-TLA profits from TLA to enhance local search capability near the global optimal. The proposed modified approach was tested on the 30-bus IEEE test network under SOFs of varying nature such as basic cost function, cost function with VPL effect and POZs, piecewise QFC function. Additionally, it was tested on the 57-bus IEEE test network, focusing on cost-based SOF and a two-fold function considering objectives of FCM and VDM. The obtained simulation outcomes validated the suggested algorithm's supremacy over other basic population-based algorithms such as ICA, TLA, MICA etc., due to faster convergence towards finding the better-quality solutions. In [94], Ghasemi et al. used the TLBO algorithm with the Lévy mutation strategy to determine optimal control variables. The Lévy mutation operator is capable of enhancing the exploration and improving the diversity of population. The authors applied the approach in the same situation considering identical test systems with similar objectives. As compared to other stochastic approaches previously reported in the literature, the proposed Lévy mutation TLBO algorithm-based approach offered better quality results. Akbari et al. [95] introduced a modified version named Teaching–Learning-Studying-Based Optimization (TLSBO), which includes a studying strategy. The proposed TLSBO algorithm was assessed for its performance in solving SOOPF and MOOPF problems on the 30-bus IEEE standard test network, incorporating the objectives of FCM, PLM, VDM, and EM. In comparison to the original TLBO algorithm, the proposed TLSBO algorithm achieved a cost of \$815.4377/hr, outperforming the original algorithm's cost of \$816.4994/hr. Additionally, the TLSBO algorithm yielded a power loss of 6.34 MW, a voltage deviation of 0.3305 p.u., and an emission of 0.2742 ton/hr, while demonstrating faster convergence characteristics.

5.4.2 Jaya algorithm based OPF

R. Venkata Rao introduced the Jaya algorithm in [96], a population-based OA capable of addressing both constrained and unconstrained optimization problems. The Jaya algorithm aims to avoid getting stuck in local optima by exhibiting a tendency towards the best solutions while simultaneously moving away from the worst ones. The advantage of Jaya lies in its parameter-free nature, eliminating the need for any adjustment or tuning of parameters to provide a globally optimal or near-globally optimal solution. In [97], various frameworks utilizing the Jaya optimizer were proposed to address SOOPF and MOOPF problems. These frameworks consider different objective function conditions, such as FCM, VDM, VSE, PLM, EM, and combinations thereof, to formulate MOFs. The proposed OPF frameworks were validated on IEEE test systems having 30 and 57 buses with a total of 23 case studies. To attain the best compromise OPF solution, the authors combined Pareto concept with the proposed algorithm to derive a non-dominated solution set. The comparison of the suggested approach with other existing algorithms documented in previous studies revealed a favorable and promising performance of developed frameworks, along with steady convergence characteristics. A modified version of Jaya (MJAYA) was introduced in [98] to overcome the problem of premature convergence of the original Jaya. The authors applied MJAYA algorithm to solve OPF problem including RES and examined their effects on objective functions considering four distinct objectives of FCM, EM, PLM and VDM. The pricing and weighting parameters were utilized to transform the MOF into a SOF problem. The efficacy of the suggested MJAYA was validated on IEEE test systems (30 and 118-bus). A comparison of the suggested MJAYA algorithm with other published techniques revealed its superiority. Rao et al. [99] proposed an innovative approach known as adaptive multiple teams perturbation-guiding Jaya (AMTPG-Jaya) for engineering optimization problems. This approach was introduced for the first time in [100] to address the challenges associated with SOOPF cases. AMTPG-Jaya utilizes a set of movement equations to efficiently guide the movement of multiple populations, referred to as teams, in exploring a given search space. The number of teams keeps changing as the algorithm approaches towards the best candidate solution. In order to explore the versatility of the AMTPG-Jaya algorithm, it was executed on IEEE test systems having 30 and 118 buses with three SOOPF cases, namely fuel rate reduction, PLM, and VSE (minimizing *L*-index). The competitiveness of the algorithm was confirmed through a comparison with the basic TLBO algorithm. Furthermore, AMTPG-Jaya was evaluated against various stochastic algorithms in the literature, with an emphasis on solution quality, feasibility, and execution time. The proposed AMTPG-Jaya demonstrated excellent performance, especially for large-scale power systems.

6 Non-nature inspired algorithms for OPF solution (non-hybrid)–inspired by mathematical functions

Non-nature-inspired algorithms neither directly simulate nor are influenced by natural phenomena such as biological evolution, swarm intelligence, or genetic operations. In terms of population-based nature and search space exploration, these algorithms are related to swarm intelligence algorithms. These algorithms, which are inspired by both social and mathematical concepts, are now widely used in PSOPs.

6.1 Backtracking search algorithm (BSA) based OPF

The BSA is a population-based search method that Civicioglu developed in 2013 [101]. To produce trial solutions, it employs three genetic operators: mutation, crossover, and selection. Although the BSA uses genetic operators similar to those of evolutionary algorithms, it does not explicitly attempt to mimic the process of biological evolution. However, BSA utilizes the memory of previously generated solutions to gain experience, enabling it to guide the search process in subsequent iterations and achieve improved search direction. The single control parameter, the mix-rate parameter, makes the algorithm less sensitive to initial parameter values compared to other heuristic algorithms. BSA was first applied to provide a solution to the SOOPF problem in [102], wherein the authors considered the basic cost functions in four different cases with the VPL effect and POZ of power systems. The proposed algorithm was executed using the IEEE 30-bus test network, and its outcomes were contrasted with those of other established OAs such as GA, EP, DE, MDE, ABC, and others, as documented in prior studies. The results confirmed the superiority of the proposed algorithm in terms of generation cost and convergence speed towards the global optimum. However, the performance of the suggested approach on large-scale systems was not assessed. Chaib et al. [103] implemented BSA to resolve OPF issue with complex objective functions with discontinuities. The proposed approach was validated on standard IEEE 30-bus and 57-bus test networks, as well as a large-scale 118-bus system, for 16 different case studies of the OPF problem. It demonstrated superior performance and robustness compared to other algorithms in the literature (DE, PSO, ABC, GA, BBO), especially for large-scale networks. The proposed approach, however, was recommended for further studies to address MOOPF problems based on Pareto-optimal solutions. Daqaq et al. in [104] presented multi-objective BSA (MOBSA) to address OPF problem in power systems, considering FCM, PLM and VDM as objective functions. MOBSA was assessed on IEEE networks with 30, 57, and 118 buses, demonstrating its efficient generation of well-distributed Pareto optimal solutions. The optimal Pareto solutions were analyzed using a fuzzy membership technique to determine the best trade-off solution. The superiority, efficacy, and robustness of MOBSA were proven through comparison with other approaches (multi-objective DE, multi-objective ALO, etc.).

6.2 Sine–Cosine algorithm (SCA) based OPF

Introduced in 2016 by Seyedali Mirjalili [105], SCA is a promising population-based OA. It utilizes mathematical rules for efficient searching of optimal solutions. Attia et al. in [106] presented a modified SCA (MSCA) for addressing the OPF problem by reinforcing the basic SCA with Lévy flights and with a mechanism of adaptive tuning in the population size. This enhanced the likelihood of discovering global optima at a quicker convergence rate and improved its ability to evade local optima. The proposed approach underwent successful testing on both the 30-bus IEEE test network and a larger 118-bus IEEE network. It was evaluated for single-objective formulations that included FCM (with single and multiple fuel types), VDM and PLM objectives. The authors checked and established the superiority of proposed algorithm over the original SCA to attain the best feasible solution with faster convergence for addressing large-scale OPF problems. Additionally, to validate the proposed algorithms, a performance comparison was performed with other published OAs documented in prior studies. The results confirmed that the SCA and MSCA algorithms outperformed the others by attaining optimized control variables for the power system with significantly reduced number of iterations. Karimulla and Ravi in [107] proposed enhanced SCA (ESCA) by adding Lévy flights to solve MOOPF problem considering objectives related to FCM, PLM, EM and VSE, and tested on 30-bus IEEE test network. The power loss achieved was 4.7893 MW, which was lower than the power losses obtained using GA (5.35 MW), PSO (5.21 MW), and the Flower Pollination algorithm (4.80 MW). Furthermore, contrasting with other widely used OAs, the proposed approach exhibited superior outcomes for fuel cost (796.34 MW), *L*-index (1.04), and emission (0.2048 ton/hr).

6.3 Rao algorithm based OPF

The Rao algorithms, proposed by Rao [108] in 2020, are recent and advanced parameter-less metaheuristic optimization tools that do not require parametric tuning. The evaluation of the Rao variants (Rao-1, Rao-2, and Rao-3) was carried out in [109] on IEEE test systems consisting of 30, 57, and 118 buses to tackle the OPF problem. The assessment included objectives of FCM, PLM, EM, VDM and VSE, considering both normal and contingency scenarios. Among the three variants, the Rao-3 algorithm consistently outperformed both Rao-1 and Rao-2 algorithms, achieving the best optimized values for objectives of FCM, PLM, VDM, and VSE, while also demonstrating a comparable value for the EM objective. However, for IEEE

57-bus system, Rao-2 excelled by achieving the lowest real power loss. Hassan et al. [110] introduced the MRao-2 algorithm, a modified version of the Rao-2 algorithm, designed to address the challenges posed by OPF problems that incorporate RES under both normal and contingency conditions. The performance of the MRao-2 algorithm was enhanced by incorporating the quasi-oppositional and Lévy flight methods. The efficacy of the suggested approach was verified through its validation on both IEEE 30 and 118-bus test networks, incorporating objectives of FCM, PLM, EM, and VDM. Simulation results were compared with variants of Rao and other popular algorithms, such as atom search optimization (ASO) and marine predator algorithm (MPA). The MRao-2 algorithm showed smooth and fast convergence, even for large systems, outperforming other approaches documented in the literature.

7 AI-based metaheuristics for OPF: categorization and comparative analysis

Building on the detailed discussions in Sects. 4, 5, and 6, this section offers a comprehensive tabular overview that provides a detailed categorization and comparative analysis of individual AI-based metaheuristics that have been used in existing literature to address the OPF problem. Table 1 summarizes the number of publications from 2012 to 2022 that used individual AI-based metaheuristic algorithms for OPF, along with their respective references cited in this study. Articles that employed multiple algorithms are discussed separately in a subsequent section within this article. Table 2 presents a tabular summary of the OPF algorithms (non-hybrid) discussed in this study, along with their comparison to established algorithms. Besides serving as a quick reference for readers, Table 2 also incorporates pertinent information about each algorithm. It includes information about objective functions, types of OPF problems, selected bus systems, methodologies used, key outcomes, and findings. This thorough comparison with other well-known algorithms enables readers to efficiently evaluate these approaches.

Table 3 offers readers a comprehensive comparison of basic fuel cost results using different non-hybrid OPF algorithms across various standard IEEE test systems, as well as other benchmark systems. It highlights the achieved fuel costs for the IEEE 30-bus, 57-bus, and 118-bus systems, among others, showcasing the economic efficiency of each algorithm analyzed.

8 Hybrid optimization methods-based approach to solve OPF problem

More recently, the well-established AI methods have been combined into one powerful algorithm by many researchers. This hybridization yields hybrid algorithms which possess better and faster convergence characteristics than any of their component methods. Hybrid methods have gained popularity due to their ability to combine the advantages of individual methods while mitigating the limitations of each.

Kumar and Chaturvedi in 2013 [111] proposed a hybrid approach that combined fuzzy systems with GA (GA-Fuzzy) and PSO algorithms (PSO-Fuzzy). This approach aimed to optimize control parameters for the SOOPF problem specifically targeting the FCM objective. The approach was successfully executed on the modified IEEE 30-bus network. Integrating fuzzy with PSO yielded the lowest fuel cost among other OPF methods documented in the literature, including the GA fuzzy approach, while integrating fuzzy with GA showed improved average fitness performance for the modified IEEE 30-bus system. The authors found integrated approaches to be more effective and robust than simple PSO and GA approaches in handling the OPF problem.

A hybrid algorithm incorporating modified PSO and the Shuffle Frog Leaping Algorithm (MPSO-SFLA) was proposed in [112] as a solution to the challenges posed by the MOOPF problem, incorporating the objectives of FCM and EM simultaneously. The suggested optimization problem included a number of generating restrictions, such as POZs and VPL effects, to emphasize the practical aspects of power generation. Furthermore, a new operator, referred to as the "Self-Adaptive Probabilistic Mutation Operator" (SAPMO), was proposed and applied to resolve the shortcomings of original PSO. SAPMO aims to enhance the diversity of the population by promoting a more varied generation process. The authors took the advantage of a Pareto-based methodology to acquire a well-distributed set of Pareto-optimal solutions. Afterward, a fuzzy decision-making model was employed to determine the best compromise solution. The suitability of MPSO-SFLA was validated through its testing on the 30-bus, 57-bus, and two variants of the 118-bus IEEE test network. The obtained results were compared with those of existing methods (basic SFLA and basic PSO), revealing the superior efficacy of the proposed algorithm regarding convergence trend, computational time, solution quality, robustness, and enhanced local & global search capabilities.

A hybrid PSO and GSA (PSO-GSA) algorithm was proposed in [113] as a solution for addressing the OPF problem by integrating the global exploration capability of

Table 1 Publications utilizing individual AI-based metaheuristic algorithms for OPF

AI-based metaheuristics for OPF		Algorithms	Number of articles	References
Evolutionary		Evolutionary programming	2	[11, 12]
		Genetic algorithm	2	[12, 14]
		Differential evolution	4	[16–19]
		Harmony search	3	[21–23]
		Biogeography-based optimization	1	[26]
Swarm-intelligence based metaheuristics	Natural	Particle swarm optimization	2	[12, 28]
		Glowworm swarm optimization	1	[30]
		Firefly algorithm	1	[32]
		Differential search algorithm	2	[34, 35]
		Animal migration optimization	1	[37]
		Moth flame optimization/Moth swarm algorithm	5	[39–43]
		Salp swarm optimization	1	[44]
		Bacterial foraging	1	[46]
		Artificial bee colony	6	[47–52]
		Group search optimizer	2	[54, 55]
		Krill herd algorithm	3	[57–59]
		Social spider optimization	1	[61]
		Grey wolf optimizer	2	[16, 62]
		Ant lion optimizer	2	[63, 64]
		Whale optimizer	1	[66]
		Grasshopper optimization	1	[68]
		Sparrow search algorithm	1	[69]
		Slime mould	2	[71, 72]
		Mantra ray foraging optimizer	1	[74]
		Marine predator algorithm	1	[76]
		Physics inspired (EM, GEM, GSA, BHBO, CBO, AOA)	8	[10, 78, 81–84, 87, 88]
		Human behavior inspired (TLBO, Jaya)	8	[89–93, 95, 97, 98]
	Non-natural	Backtracking search algorithm	3	[102–104]
		Sine–cosine algorithm	2	[106, 107]
		Rao algorithm	2	[109, 110]

PSO (g-best) with local search ability of GSA. The validity of this hybrid approach was verified through testing on IEEE test networks consisting of 30 and 118 buses. The testing involved various single and twofold objectives, including FCM, VDM, PLM, and VSE. In a specific case involving FCM on 30-bus system, where two different subcases of load bus voltage limits were considered, the proposed PSO-GSA algorithm exhibited faster convergence to its global best compared to both PSO and GSA algorithms. Despite some methods yielding improved results, the authors identified that these outcomes were infeasible solutions as they violated the load bus voltages. However, the authors suggested the need for improving the computational speed of the proposed hybrid approach, especially when dealing with large-scale systems.

In [114], Reddy proposed the Hybrid DE-HS algorithm, a novel approach that combined DE and HS to address the SOOPF and MOOPF problems. The combination of the two algorithms led to the development of a powerful hybrid algorithm that integrated the original DE algorithm with HSA to achieve faster global convergence. The suggested algorithm considered three objective functions, namely FCM (with VPL and POZs), PLM, and VSE, and was tested on IEEE test networks with 30, 118, and 300 buses. In a 30-bus system for the FCM objective, DE-HS achieved an optimum cost of 799.0514 \$/hr, better than that reported by BBO, DE, modified DE, PSO, GA, improved GA, and

Table 2 Summary of OPF algorithms (non-hybrid) and comparative analysis with established methods

References	Algorithm	Objective function (OF)	SOOPF/ MOOPF/ Both	Test System (-bus IEEE network)	Strategy/methodology	Outcome/ findings
[11]	EP	FCM, FCM-VPL, FCM-MFS, VDM	SOOPF	30	The EP-OPF algorithm employs gradient information to identify the global optimal solution, utilizing a key strategy that involves integrating solution acceleration concepts using steepest descent method	Proposed EP-based algorithm maintains a solution population, reproduces the best solutions, and creates new ones through mutation to optimize the OPF problem and enhance voltage profiles
[12]	EP, PSO, GA	FCM, PLM, VSE, EM	Both	30	This work compares PSO, EP, and GA for MOOPF, using the Pareto optimal method and fuzzy decision-making to select the best solutions	EP outperforms PSO and GA in cost and convergence, but the ideal algorithm varies based on the objectives and trade-offs
[14]	AGAPOP	FCM, VDM, FCM-MFS	SOOPF	30	AGAPOP combines GA and fine-tuning to optimize high-dimensional problems, simultaneously flooding the problem space with solutions (POP) and dynamically adjusting parameters	AGAPOP significantly reduces fuel cost to $799.8441/hr in few generations, surpassing IGA, PSO, and DE approaches
[16]	DEA	FCM, PLM, RPLM and VSI	Both	30, 118	DEA uses a differential mutation operator and uniform crossover to generate new solutions, and then selects the best solutions to move on to the next generation	DEA excels in large-scale optimization, offering competitive solutions when compared to PSO, GSA, and TLBO
[16]	GWO	FCM	SOOPF	30, 118	GWO emulates wolf hunting behavior, effectively transitioning between exploration and exploitation strategies for global optimum discovery	GWO presents a viable option for large-scale optimization. The Authors suggest exploring GWO's potential for MOO problems in power systems

Table 2 (continued)

References	Algorithm	Objective function (OF)	SOOPF/ MOOPF/ Both	Test System (-bus IEEE network)	Strategy/methodology	Outcome/ findings
[17]	MODEA	FCM, VDM, VSE, and PLM	Both	30, 57	DE variant that converges quickly and discovers Pareto-optimal solutions in one run with adaptive ε-constraints	Faster convergence and superior solutions compared to BBO, EP, ABC, TLBO, LTLBO and many others
[18]	MDE	FCM, PLM, VDM, VSE,	Both	57, 118	MDE utilizes a modified DE/best/1 multi-objective model that emphasizes rapid convergence, improved search capabilities, and Pareto ranking	Proposed algorithm outperforms original DE variant
[19]	DEA	FCM-VPL, FCM-POZ, FCM-PLM, FCM-VDL modeling	MOOPF	30, 300	DEA combines the concept of mutation, crossover, and selection to efficiently explore the solution space for global optima	Outperforms NSGA-II with 10 times faster computation while excelling in multi-objective tasks, particularly through weighted summation
[21]	IHS	FCM, FCM-VPL	SOOPF	6, 14, 30, 57, 118	IHS algorithm dynamically adjusts PAR to optimize various problems, all without requiring prior knowledge or space limitations	Superior over SQP and GA especially for large-scale systems in terms of less CPU time and better objective function value
[22]	FHSA	FCM, Severity-index minimization	SOOPF	30, 57, 118	FHSA algorithm optimizes decision variables by combining historical values, improvisation, iterative improvement, and parameter adaptation	FHSA outperforms traditional HSA by achieving faster convergence to high-quality solutions
[23]	Differential-based HSA	VDM, PLM, Active power generation reduction	Both	57, 118	Incorporated DH/best algorithm eliminating need for PAR parameter	Enhanced search capabilities compared with NSGA-II, PSO, and the original HSA

Table 2 (continued)

References	Algorithm	Objective function (OF)	SOOPF/ MOOPF/ Both	Test System (-bus IEEE network)	Strategy/methodology	Outcome/ findings
[26]	ARCBBO	FCM, VDM, VSE (normal and contingency), PLM, EM	SOOPF	30, 57	Adaptive Gaussian mutation improves population diversity and exploration capability	ARCBBO effectively combated premature convergence, surpassing basic BBO, ABC, GSA, and MDE, although some solutions violated load bus voltage constraints
[28]	IPSO	FCM, EM, PLM, and VSE	Both	30	IPSO offers enhanced search ability through Chaos, self-adaptation, and mutation techniques to find a well-distributed Pareto front	Better results than PSO, EP, EGA, fuzzy GA, modified DEA for SOOPF scenario. Better results than PSO and NSGA-II for MOOPF scenario
[30]	GWSO	FCM, EM	Both	30, 75-bus Indian grid	GWSO uses glowworms to optimize multi-objective functions by assessing luciferin values, favoring movement towards brighter neighbors, and applying Pareto-based methods	GWSO surpasses PSO, yielding better results in fewer iterations and reduced computational memory usage
[32]	GBLFA, MGBLFA	FCM, EM, PLM and VDM	Both	30	Strategic use of Lévy, bare-bone, and Gaussian sampling	MGBLFA excelled in smaller systems, surpassing BBDE, BBPSO, LFA, and GBLFA, especially in terms of carbon tax value and effectively reducing the cost target for the IEEE 30-bus system
[34]	DSA	FCM, FCM-VPL, FCM-MFS, VDM, VSE (normal & contingency)	SOOPF	30, 118	DSA utilizes artificial organisms to fill the problem's search space, using Brownian-like random walks for migration and position adjustment	DSA outperformed DE, GSA, GA, BBO and PSO

Table 2 (continued)

References	Algorithm	Objective function (OF)	SOOPF/ MOOPF/ Both	Test System (-bus IEEE network)	Strategy/methodology	Outcome/ findings
[35]	Novel DSA-based approach	FCM, VDM, PLM, VSE and EM	Both	9, 30, 57	Superorganisms migrate to find global optimal solutions by choosing the best solution in each iteration	Proposed algorithm achieved superior solution performance compared to ABC and GSA
[37]	BAAMO	FCM, PLM, VDM	SOOPF	30, 57, 118	AMO and its variant BAAMO are applied in a two-phase process: the first phase evaluates fitness, guiding control variable optimization in the second phase	Better results than PSO, GA, DE, ABC, and GSA. Computation time is relatively high due to dual variable updates per iteration
[39]	MFO	FCM, FCM-VPL, FCM-MFS, EM, PLM	SOOPF	30	MFO iteratively updates moth positions based on their attraction to the best solutions (flames) and repulsion from the worst solutions, optimizing their positions in the search space	MFO outperforms flower pollination algorithm (FPA), PSO, GWO, ABC and other OAs by more effectively exploring and exploiting the search space to deliver superior results
[40]	IMFO	FCM, PLM, VDM, VSE, EM (total 15 combinations)	Both	30, 57, 118	Modified MFO concept by changing moth paths to create new spirals around a flame	IMFO excels over MFO, GA, PSO, and TLBO with quicker convergence
[41]	AMFO	FCM, FCM-VPL, FCM-MFS, EM, VSE, VDM, PLM, RPLM (total 13 case studies)	SOOPF	118	Basic MFO improved by incorporating a step size derived from different moth positions, with the goal of enhancing convergence speed while preserving MFO's essential traits	AMFO demonstrates superior searchability compared to MFO, GWO, DA, SCA, ALO, and GOA

Table 2 (continued)

References	Algorithm	Objective function (OF)	SOOPF/MOOPF/Both	Test System (-bus IEEE network)	Strategy/methodology	Outcome/findings
[42]	MSA	FCM, FCM-VPL, FCM-MFS, EM, VDM, PLM, VSE (normal and contingency)	Both	30, 57, 118	The novel MSA paradigm incorporates new optimization operators, such as adaptive crossover based on population diversity and an associative learning mechanism with immediate memory	MSA delivers valid and precise solutions compared to MPSO, MDE, MFO, and FPA, leveraging the strengths of these OAs
[43]	EMSA	FCM, PLM, VDM, EM, VSE	Both	30, 57, 118	Quasi-opposition-based learning is implemented to enhance basic MSA. Oppositional-based population is created using $x_{oi} = lb_i + ub_i - x_i$,where x_{oi} is i^{th} opposite-point	EMSA outperformed MSA with faster convergence and improved voltage profiles
[44]	ISSA	FCM, FCM-VPL, FCM-POZ, FCM-MFS	SOOPF	30, 57, 118	ISSA technique prevents stagnation in SSA by adding random mutation to enhance exploration and diversify the search	ISSA-based approach consistently provides the most cost-effective solutions when compared to basic SSA, MFO, IHS, GA, and other established algorithms
[46]	IBF	FCM, FCM-VPL, FCM-MFS, EM	SOOPF	26-bus, 30, 118	Modified DE mutation operator is incorporated in basic IBF to enhance exploration and diversify the search in the complex solution space of nonlinear OPF-SC problems	IBF surpasses basic BF, EP, PSO, GA, and various other OAs in delivering robust solutions
[47]	ABC	FCM, FCM-VPL, FCM-MFS, EM, PLM, VSE (normal & contingency)	SOOPF	9, 30, 57	Proposed ABC iteratively explores optimal solutions using employed and onlooker bees, guided by fitness evaluation and probabilistic selection	ABC demonstrates ability to find feasible and optimal solutions, compared to LDI-PSO and GSA

Table 2 (continued)

References	Algorithm	Objective function (OF)	SOOPF/ MOOPF/ Both	Test System (-bus IEEE network)	Strategy/methodology	Outcome/ findings
[48]	MABC	FCM-VPL, EM, PLM, VDM	Both	30, 118	MABC incorporates fuzzy logic-based membership functions and fitness calculations to evaluate the quality of each food source using $\mu_D(x) = \min\,(\mu_{f_1}(x),\ \mu_{f_2}(x), \ldots., \mu_{c_1}(x),\ \mu_{c_2}(x), \ldots)$ here, μ_D is the membership function for the optimal decision function	MABC outperforms different variants of PSO, SFLA and ABC by excelling in global search exploration while maintaining its efficiency, even as the problem dimension scales up
[49]	M2OBA	FCM, EM, PLM	MOOPF	30	M2OBA models bee colony foraging behaviors and uses multi-population cooperation to efficiently solve complex high-dimensional MOO problems	M2OBA, utilizing Pareto concept, external archive, greedy selection, and fuzzy membership approaches, outperforms MOPSO, MOABC, and NSGA-II
[50]	IABC	FCM, EM, VDM, PLM	Both	30, 57, 300	IABC rectifies the exploration–exploitation imbalance in ABC by introducing DE algorithm-inspired mutation and crossover operations, along with tent chaos mapping, to enhance exploitation	IABC outperforms ABC, MSFLA, GA, PSO, DE, and BBO algorithms, delivering superior solutions while requiring less computation time
[51]	GABC	FCM	SOOPF	30, 57 and 2383 & 2736 bus Polish systems	GABC enhances the original ABC algorithm's convergence and exploitation capabilities by introducing a "best solution" term in the search equation	GABC effectively tackles both conventional OPF and TDOPF problems, evaluating its impact on factors like resistance, generation cost, and total system loss

Table 2 (continued)

References	Algorithm	Objective function (OF)	SOOPF/ MOOPF/ Both	Test System (-bus IEEE network)	Strategy/methodology	Outcome/ findings
[52]	OL-IABC	FCM, FCM-VPL, PLM	SOOPF	30, 118	Incorporating Orthogonal Learning (OL) selectively during iterations efficiently create candidate solutions in the ABC algorithm, enhancing its exploitation capabilities	The OL-based IABC algorithm consistently outperforms basic ABC, GSA, and MDE, achieving lower costs and smaller deviations
[54]	GSO	FCM, EM, VDM, VSE	SOOPF	30, 57, 118	GSO involves a combination of producer-scrounger roles, resource scanning, and random walk dispersal to efficiently explore and exploit the search space	Better results than IPSO, BBO
[55]	AGSO	FCM, EM, VSE	MOOPF	30, 57	AGSO combines random initialization, Pareto-based decision-making, adaptive searching, and a maximum iteration-based termination to optimize MOOPF problems	AGSO improves the convergence behavior compared to traditional GSO
[57]	CKHA	FCM, PLM, VDM	SOOPF	57, standard 26-bus	Chaos theory is fused with the fundamental KHA to boost computational speed and accelerate convergence	CKHA, utilizing the logistic map, outperforms basic KHA, BBO, and GSA in delivering superior results with better convergence
[58]	KHA	FCM, VDM, PLM, VSE	Both	30, 57, 118	Proposed KHA combines induction, foraging action, random diffusion, and crossover/mutation operations from DE to select high-quality solutions	KHA approach minimizes fuel cost and outperforms BBO, PSO variants and Real-coded GA techniques
[59]	SKH	FCM, FCM-VPL, PLM, VSE, EM	SOOPF	14, 30, 57	SKH algorithm merges KH's global exploration with an SSC operator, enhancing efficiency by accepting superior solutions and updating krill positions based on fitness evaluations	SKH outperforms basic KH, ABC, PSO, and other algorithms by providing better solutions in a shorter number of iterations

Table 2 (continued)

References	Algorithm	Objective function (OF)	SOOPF/ MOOPF/ Both	Test System (-bus IEEE network)	Strategy/methodology	Outcome/ findings
[61]	NISSO	FCM, FCM-VPL, FCM-MFS, PLM, EM, VDM, VSE	SOOPF	30, 57, 118	NISSO algorithm uses a combination of SSO and a new mating operation strategy to improve the performance of SSO	NISSO consistently outperforms other methods, including SSO, by achieving superior optimization results in terms of OF values, convergence speed, and cost savings
[62]	CS-GWO	FCM, FCM-VPL, PLM, VDM	Both	30, 118	CS-GWO algorithm incorporates a crisscross search mechanism to address the premature convergence issue of GWO	CS-GWO surpasses not only basic GWO but also other algorithms including PSO, ABC, MSA, BSA, GSA, as well as hybrid approaches like NISSO, IABC, ICBO, and various others
[63]	ALO	FCM, VDM, VSE, PLM, RPLM	SOOPF	30	ALO mimics antlions' hunting behavior through random walks, trapping, sliding, prey-catching, and enhanced elitism to optimize power flow	ALO outperforms FA and PSO in OPF problem-solving, with faster convergence and potential efficiency improvements through penalty handling and randomization techniques
[64]	PALO	FCM, VDM, PLM	Both	30, 300 and 2736 ps-bus Polish system	PALO enhances exploration–exploitation balance through partitioning, updates control variables dynamically, and explores parallelism for efficient large OPF problem	PALO surpasses ALO on the Polish test system with an execution time of 35.2 s and a reduced power loss of 261.436 MW (from 326.129 MW)

Table 2 (continued)

References	Algorithm	Objective function (OF)	SOOPF/MOOPF/Both	Test System (-bus IEEE network)	Strategy/methodology	Outcome/findings
[66]	NSWOA	FCM, PLM, VDM, VSE	Both	30	NSWOA utilizes Pareto dominance to classify solutions and selects the best compromise solution based on minimal Euclidean distances	NSWOA, in contrast to OAs like PSO, SSA, SCA, and MPA, consistently demonstrates superior performance, leading to improved techno-economic outcomes
[68]	MGOA	FCM, EM, PLM, VDM, VSE	Both	30, 57, 118	MGOA solves OPF by improving mutation process in conventional GOA to keep local optima from stagnating	Comparisons with algorithms such as PSO, GOA, GA, and TLBO validate the effectiveness of MGOA
[69]	SPSA	FCM, FCM-VPL, FCM-MFS, EM, PLM, VDM, VSE	Both	30, 57, 118	SPSA simulates a sparrow society with two roles: producers actively seek food and guide others (scroungers), who follow and depart based on food discoveries and hazard awareness	Proposed sparrow-search algorithm surpassed several other OAs, including MDE, MFO, ABC, MPSO, MSA, and TLBO, across diverse objective functions and network sizes
[71]	SMA	FCM, PLM, and EM	Both	30, 57, 118	The SMA handles MOOPF using Pareto dominance and a crowding mechanism for managing Pareto repositories	SMA excels in solving SOOPF and outperforms in generating Pareto fronts for multi-objective cases, particularly in large power systems

Table 2 (continued)

References	Algorithm	Objective function (OF)	SOOPF/ MOOPF/ Both	Test System (-bus IEEE network)	Strategy/methodology	Outcome/ findings
[72]	MOSMA	FCM, PLM, EM, VDM, VSE	MOOPF	30, 57, Iraqi super grid	MOSMA combines non-dominated solutions from multiple populations iteratively to achieve predefined objectives or meet stopping criteria, employing the Pareto concept and fuzzy set theory	MOSMA proved effective, delivering economic, environmental, and technical benefits while surpassing various other OAs like GWO, SSO, WOA, and numerous others
[74]	IMOMRFO	FCM, EM, PLM, VDM	MOOPF	30, 57	IMOMRFO enhances MOO by applying a crowding distance-based Pareto archiving method	IMOMRFO enhances exploration and exploitation in its search space, surpassing methods like MOPSO and NSGA-II
[76]	MPA	FCM, PLM, VDM, VSE	SOOPF	30, 118	MPA is applied by iteratively optimizing objective functions through elite-prey interactions, three-phase exploration, and incorporating FADs (Foraging and Attacking Dynamics)	Comparisons with OAs like DSA, SCA, MSCA, PSO, and ABC confirmed MPA's effectiveness in delivering global best results for SOOPF problems
[78]	IEM	FCM, FCM-MFS, VDM, VSE, PLM, RPLM	SOOPF	30, 57	IEM improves the basic EM method with bounds normalization and optimizes variables through standardized ranges, customizable local searches, and force-guided particle movement	Comparisons against OAs such as BBO, ABC, PSO, and GA confirmed IEM's superior solution quality, with an 80% reduction in simulation time
[81]	GSA	FCM, FCM-VPL, FCM-MFS, VDM, VSE (normal & contingency)	SOOPF	30, 57	With the GSA, solutions are represented as objects with masses, attracting each other towards higher fitness values, resulting in global movement towards optimal solutions	GSA consistently outperforms BBO, DE, PSO, and MDE in various OPF scenarios

Table 2 (continued)

References	Algorithm	Objective function (OF)	SOOPF/ MOOPF/ Both	Test System (-bus IEEE network)	Strategy/methodology	Outcome/ findings
[82]	GSA	FCM, FCM-VPL, VDM, PLM	Both	118, standard 26-bus	GSA uses gravitational attraction as a guide for finding optimal solutions. As heavier masses attract stronger, better solutions are identified, resulting in better search space exploitation	In both SOOPF and MOOPF problems, the GSA is faster and provides better solutions than MIPSO, EP, GA, and BBO
[83]	NSMOGSA	FCM, FCM-VPL, FCM-MFS, EM, PLM, VDM, VSE	Both	30	NSMOGSA addresses the limitations of GSA by adding non-dominated sorting and opposition-based learning	NSMOGSA algorithm is superior to NSGA-II and other OAs, delivering superior OPF results with faster convergence
[84]	BHBO	FCM, VDM, VSE, PLM, RPLM	SOOPF	30, Algerian 59-bus	BHBO draws inspiration from black-hole phenomenon where absorption of stars by blackhole is governed by the equation: $x^i = x^i + rand \times (x_{BH} - x^i)\ \forall\, i;\ i \neq best$ where x^i is i^{th} star location and x_{BH} is blackhole location in search space	BHBO stands out as a promising optimization method due to its robustness and superior solution quality when compared to methods like GA and PSO
[87]	ICBO	FCM, VDM, VSE (normal and contingency)	SOOPF	30, 57, 118	ICBO improves optimization by introducing three-body collisions in each iteration, with one stationary and two moving bodies, increasing search directions and population diversification	ICBO algorithm excels as an efficient, robust, and versatile solution for diverse SOOPF problems, surpassing standard CBO and other established OAs like DE, PSO, ABC, GA, and BBO
[88]	WEA	FCM, FCM-POZ, FCM-VPL-POZ, PLM, VSE, VDM	Both	30, 118	WEA utilizes water evaporation on surfaces with different wettability to optimize by employing a two-phase approach for global and local search	WEA outperforms GSO, TLBO, PSO, and NSGA-II, among other popular OAs, in solving diverse OPF objectives

Table 2 (continued)

References	Algorithm	Objective function (OF)	SOOPF/ MOOPF/ Both	Test System (-bus IEEE network)	Strategy/methodology	Outcome/ findings
[90]	IAOA	FCM, PLM, EM, VDM	Both	30, 57, 16-bus South Marmara	IAOA algorithm optimizes the position of objects within a fluid by combining dimension learning (DL) strategies with standard AOA search strategies	IAOA outperforms AOA, TLBO, SCA, IABC and other established OAs in solving the OPF
[91]	TLBO	FCM, VDM, VSE (normal and contingency), FCM-MFS, FCM-VPL	SOOPF	30, 118	TLBO uses a knowledge-sharing strategy based on teachers' guidance and collaborative learning among learners, without the need for algorithmic parameters	TLBO serves as an effective tool for handling the OPF problem in power systems, outperforming other OAs like DSA, GSA, BBO, and PSO
[92]	MTLBO	FCM, EM	Both	30, 57	MTLBO algorithm employs a SAWM strategy, fuzzy clustering, and a smart population approach to enhance convergence speed and accuracy	MTLBO outperforms TLBO with faster convergence and improved accuracy
[93]	MICA-TLA	FCM, FCM-VPL, FCM-POZ, FCM-MFS	Both	30, 57	The fusion of ICA and TLA, with imperialists guiding their colonies and colonies sharing knowledge, leads to expedited convergence	MICA–TLA approach is less likely to get trapped in local minima, and it finds the optimal solution more quickly than ICA, TLA, and MICA algorithms
[95]	TLSBO	FCM, FCM-MFS, PLM, VDM, EM	Both	30	TLSBO improves TLBO by introducing a "studying strategy" where individuals learn from peers, enhancing global optimization	TLSBO outperforms original TLBO and other OAs by converging faster, finding better solutions, and being more resistant to local optima

Table 2 (continued)

References	Algorithm	Objective function (OF)	SOOPF/ MOOPF/ Both	Test System (-bus IEEE network)	Strategy/methodology	Outcome/ findings
[97]	Jaya	FCM, VDM, VSE, PLM, EM	Both	30, 57	The proposed Jaya optimizer utilizes multi-objective frameworks, including fuzzy set theory, to maximize technical, economic, and environmental benefits	Jaya outperforms other techniques in stability and performance, as confirmed by comparisons with DE, MDE, ABC, PSO, and various other methods
[98]	MJAYA	FCM, EM, PLM, VDM	SOOPF	30, 118	The MJAYA algorithm enhances conventional JAYA by modifying the equation that is used to update the best and worst solutions using: $$X'_{j,d,k} = X_{j,d,k} + r_{1,j,k} \times \left(X_{j,worse,k} - \left\lvert X_{j,d,k}\right\rvert\right) - L \times r_{2,j,k} \times \left(\left\lvert X_{j,d,k}\right\rvert^{2} - X^{2}_{j,best,k}\right)$$ here, $X_{j,d,k}$ is j^{th} decision variable for d^{th} member in k^{th} iteration. Both $r_{1,\ j,k}$ and $r_{2,\ j,k}$ are randomly generated coefficients in the range [0, 1] for each member of the population for j^{th} decision variable in the k^{th} iteration. Coefficient L varies in each iteration	MJAYA excels in OPF problem resolution, maintaining efficient convergence, even with RES, in comparison to MSA, ABC, CSA, GWO, BSA, and few other methods
[102]	BSA	FCM, FCM-VPL, FCM-POZ, FCM-VPL-POZ	SOOPF	30	BSA algorithm utilizes a combination of random mutation and non-uniform crossover techniques to effectively explore the search space and find optimal solutions	BSA excels in cost, efficiency, and achieving the global optimum, surpassing other heuristics like GA, SA, PSO, DE, and more in solving diverse SOOPF cases
[103]	BSA	FCM, FCM-VPL, FCM-MFS, VDM, VSE, EM,	Both	30, 57, 118	BSA algorithm uses multiple steps for optimizing solutions, including initialization, historical guidance, mutation, unique crossover, and a greedy update mechanism	BSA excels at solving OPF problems, especially in large-scale power systems, outperforming other established OAs like DE, PSO, ABC, GA, and BBO

Table 2 (continued)

References	Algorithm	Objective function (OF)	SOOPF/ MOOPF/ Both	Test System (-bus IEEE network)	Strategy/methodology	Outcome/ findings
[104]	MOBSA	FCM, PLM, VDM	MOOPF	30, 57, 118	MOBSA algorithm utilizes dual populations to enhance diversification in search directions and efficiently balances exploration and exploitation	MOBSA algorithm for solving MOOPF problems outperforms other state-of-the-art methods, including MODE, SPEA, MALO, NSGA-II, and quasi-oppositional TLBO
[106]	MSCA	FCM, FCM-MFS, PLM, VDM	SOOPF	30, 118	MSCA utilizes Lévy flights to enhance exploration and a dynamic ‘POP’ strategy to adapt the number of search agents, thereby improving its performance and convergence speed	MSCA with its fast convergence and scalability, surpasses algorithms like basic SCA, EGA, ABC, Jaya and numerous other OAs
[107]	ESCA	FCM, PLM, VSE, EM	Both	30	ESCA combining the SCA with Lévy flights and a Population (POP) strategy to enhance efficiency and balance exploration and exploitation in OPF problems	ESCA outcompetes GA, EGA, PSO, IPSO, FPA and other methods in MOOPF optimization for the considered objective functions (OFs)
[109]	Rao-1, 2, 3	FCM, PLM, VDM, VSE (normal and contingency), EM	MOOPF	30, 57, 118	Rao algorithms utilize the best and worst solutions, obtained through random interactions among candidates, for parameter-less optimization	Rao-3 consistently outperforms Rao-1 and Rao-2, and it also surpasses other widely used OAs for the considered OFs

Table 2 (continued)

References	Algorithm	Objective function (OF)	SOOPF/ MOOPF/ Both	Test System (-bus IEEE network)	Strategy/methodology	Outcome/ findings
[110]	MRao-2	FCM, PLM, EM, VDM	SOOPF	30, 118	MRao-2, utilizing Opposition-Based Learning (OBL), effectively handles OPF problems with RES by employing quasi-oppositional and Lévy methods	MRao-2 consistently outperforms Rao variants, MPA, ASO, and other OAs, achieving a significant 23.4% reduction in fuel costs when integrating RES into the IEEE 118-bus system

the General Algebraic Modelling System (GAMS) software, demonstrating the efficiency and feasibility of the proposed approach.

The PSO-SSO algorithm, introduced by El Sehiemy et al. [115], was utilized to solve the SOOPF and MOOPF problems in IEEE test networks with 30, 57 and 118-bus networks. The algorithm was evaluated through 18 case studies considering objectives that included FCM, VDM, PLM, VSE, and EM, representing economic, technical, and environmental benefits. In a single-objective case of PLM on a 30-bus system, PSO-SSO achieved a power loss of 2.858 MW, which is lower than the power losses of 2.902 MW and 3.278 MW achieved by SSO and PSO, respectively. For a bi-objective case involving EM and FCM in a 57-bus system, PSO-SSO attained an emission level of 1.3647 p.u. and a fuel cost of 41,672.56 $/hr, outperforming PSO (1.4263 p.u., 42,013.9 $/hr) and SSO (1.60 p.u., 41,824.46 $/hr) with faster convergence.

In 2018, Aydilek, I.B. introduced the Hybrid Firefly Particle Swarm Optimization (HFPSO) method [116]. Khan et al. [117] were pioneers in utilizing the Jaya-PPS algorithm as an OPF solution. The authors applied HFPSO to solve five SOFs, namely FCM, VDM, VSE, PLM, and RPLM, and examined its efficacy on a 30-bus IEEE test system. In a specific case that prioritized FCM, the authors compared the performance of the hybrid HFPSO approach with the conventional PSO algorithm, as well as other established algorithms such as Jaya, DE, and BHBO. On 30-bus system, HFPSO achieved a fuel cost of 799.123 $/h, outperforming the PSO result of 799.543 $/h, the DE result of 799.289 $/h, and the BHBO result of 799.921 $/h. These results were achieved by HFPSO in fewer iterations, highlighting its efficiency and effectiveness in solving OPF problems.

Khan et al. in [118] further expanded the scope of the problem to address MOOPF problem and proposed multi-objective HFPSO (MOHFPSO). To calculate Pareto optimal fronts and optimal solutions using the algorithm, non-dominated sorting strategies were developed and utilized. Authors tested the MOHFPSO on 30 and 57-bus IEEE test networks to minimize fuel cost (FC), power loss (PL), *L*-index (voltage stability), and voltage deviation, forming a total of 5 objective function formulations (three bi-objectives and two tri-objectives), and compared results with the MOPSO and other popular techniques documented in prior studies. As compared to MOPSO, the proposed MOHFPSO approach exhibited superior effectiveness and efficiency. For a specific scenario where FC and PL were considered simultaneously, MOPSO achieved a fuel cost of 822.32 $/h and a power loss of 5.7015 MW. In contrast, MOHFPSO demonstrated its superiority by achieving a fuel cost of 819.5330 $/h and a power loss of 5.6827 MW in a shorter simulation time on the 30-bus system.

In reference [119], an algorithm called Jaya-PPS (Jaya-Powell's Pattern Search) was put forward as a hybrid method to resolve OPF. The PPS is a derivative-free optimization search technique that utilizes the principles of the conjugate-direction method. The proposed hybrid approach was evaluated using the standard IEEE test networks of 30, 57, and 118 buses, with and without DG sources. The authors performed tests on these specific systems to explore the effectiveness of the developed algorithms (Jaya-PPS1, 2 and 3), considering the objectives of FCM, EM, PLM and VDM and their simultaneous combinations. The findings revealed that Jaya-PPS1 consistently yielded the lowest values for the combined objective functions across all four cases, which involved the 30 and 57-bus systems. The Jaya-PPS1 algorithm

Table 3 Comparison of fuel costs using OPF algorithms (non-hybrid) on standard test systems: (FCM single-objective)

References	Algorithm	Attained fuel cost ($/hr)			
		IEEE 30-bus	IEEE 57-bus	IEEE 118-bus	Other benchmark test networks
[12]	EP	800.04	–	–	–
[12]	PSO	802.79	–	–	–
[12]	GA	799.23	–	–	–
[14]	AGAPOP	799.8441	–	–	–
[16]	DEA	801.23	–	1,29,582	–
[16]	GWO	801.41	–	1,29,720	–
[17]	MO-DEA	799.0827	41,683	–	–
[18]	MDE	–	41,682	1,30,518.50	–
[19]	DEA	801.2480 (FCM + PLM)	–	–	IEEE 300-bus: 8,57,442.6782 (FCM + PLM)
[21]	IHS	462.0950 €/hr	584.9872 €/hr	3816.3 €/hr	IEEE 6-bus: 412.523 €/hr, IEEE 14-bus: 372.6214 €/hr
[22]	FHSA	799.914	41,658.18	1,32,138.30	–
[26]	ARCBBO	801.5159	41,686	–	–
[28]	IPSO	801.978	–	–	–
[30]	GWSO	799.05	–	–	75-bus Indian Grid: 1,10,046 Rs/hr
[32]	GBLFA	800.8726	–	–	–
[32]	MGBLFA	800.4802	–	–	–
[34]	DSA	799.0943	–	1,29,691.62	–
[35]	Novel DSA-based approach	800.3887	41,686.82	–	IEEE 9-bus: 1,132.1760
[37]	BAAMO	798.012	41,665.50	1,29,550.80	–
[39]	MFO	799.2029	–	–	–
[40]	IMFO	800.3848	41,667.15	1,31,820	–
[42]	MSA	800.5099	41,673.7231	1,29,640.72	–
[43]	EMSA	799.3582 (FCM + VSE)	41,666.2449	1,35,262.57	–
[44]	ISSA	800.4752	41,675.0203	1,29,460.84	–
[46]	IBF	802.325	–	–	Standard 26-bus: 15,441.7
[47]	ABC	800.66	41,693.9589	–	IEEE 9-bus: 1,132.1765
[50]	IABC	800.4215	41,684	–	IEEE-300 bus: 7,83,951
[51]	GABC	800.4401	41,684.20	–	–
[52]	OL-based IABC	799.321	–	129,862	–
[55]	AGSO	801.75	40,936.07	–	–
[57]	CKHA	–	41,660.4657	–	Standard 26-bus: 15,455.19
[58]	KHA	799.0311	41,709.2647	1,29,608.46	–
[59]	SKH	800.5141	41,676.9152	–	IEEE 14-bus: 8,080.7045
[61]	NISSO	799.7624	41,665.5404	1,29,879.45	–
[62]	CS-GWO	799.9978	–	1,29,544.01	–
[63]	ALO	799.155	–	–	–
[64]	PALO	799.916	–	–	–
[66]	NSWOA	800.26	–	–	–

Table 3 (continued)

References	Algorithm	Attained fuel cost ($/hr)			
		IEEE 30-bus	IEEE 57-bus	IEEE 118-bus	Other benchmark test networks
[68]	MGOA	800.4744	41,671.10	1,21,072.93	–
[69]	SPSA	798.9536	41,609	1,29,561.03	–
[71]	SMA	802.5449	41,697.1189	1,27,896.55	–
[72]	MOSMA	799.2557	41,633.61	–	–
[74]	IMOMRFO	801.3908 (FCM + VDM)	41,680.383 (FCM + VDM)	–	–
[76]	MPA	799.0725	–	1,29,422.56	–
[78]	IEM	800.0781	–	–	–
[81]	GSA	798.6751	41,695.8717	–	–
[82]	GSA	–	–	129,565	Standard 26-bus: 15,467.45
[83]	NSMOGSA	796.124	–	–	–
[84]	BHBO	799.9217	–	–	Algerian 59-bus: 1,710.0859
[87]	ICBO	799.0353	41,697.3324	1,35,121.57	–
[88]	WEA	798.9969	–	–	–
[90]	IAOA	799.068	40,911	–	–
[91]	TLBO	799.0715	–	1,29,682.84	–
[92]	MTLBO	801.8925	41,638.3822	–	–
[93]	MICA-TLA	801.0488	41,675.0545	–	–
[95]	TLSBO	815.4377	–	–	–
[97]	Jaya	798.9386	39,555	–	–
[98]	MJAYA	858.2281*	–	1,40,575.3099*	–
[102]	BSA	801.63	–	–	–
[103]	BSA	799.076	–	1,35,333.47	–
[104]	MOBSA	799.046 (FCM-VPL + PLM)	41,623.292 (FCM-VPL + PLM)	1,35,620.99 (FCM-VPL + PLM)	–
[106]	MSCA	799.31	–	1,29,620.22	–
[107]	ESCA	796.345	–	–	–
[109]	Rao-1, 2, 3	799.9683 (Rao-3), 799.9918 (Rao-2), 800.4391 (Rao-1)	41,659.2621 (Rao-3), 41,872.0668 (Rao-2), 41,771.1088 (Rao-1)	1,29,220.6794 (Rao-3), 1,29,256.5242 (Rao-2), 1,29,241.1787 (Rao-1)	–
[110]	MRao-2	800.4412	–	1,31,457.80	–

*modified test system

showed notable superiority over other algorithm variants in the IEEE 118-bus system, achieving a significant 1.52% reduction in fuel cost.

Gupta et al. [120] proposed a "sine–cosine mutation operator" and a modified Jaya algorithm (SCM-MJ) for OPF. The sine–cosine mutation operator enhances population-based OAs by preserving diversity and enhancing solution quality throughout the search. The algorithm underwent testing on the practical 59-bus Algerian system as well as the large-scale 118-bus IEEE test network, considering objectives such as FCM, PLM, and VDM. The SCM-MJ algorithm exhibited smoother convergence characteristics than the M-Jaya algorithm through the transformation of the MOF into a single-objective one by means of a weighted sum approach. Irrespective of the problem dimension or system size, the SCM-MJ method invariably yielded the lowest objective function value across all cases. In particular, in the case of the 118-bus test system, the SCM-MJ algorithm significantly reduced fuel consumption costs by 1.56% when compared to the base scenario.

In [121], Naderi et al. proposed the FAHSPSO-DE algorithm, a fuzzy adaptive framework that hybridizes self-adaptive PSO and DE algorithms. The hybrid approach was

Table 4 Summary of hybrid approaches for OPF in the last decade from reputable peer-reviewed journals

Authors	Year, References	Hybrid approach	Objective function	SOOPF/ MOOPF/ Both	Test System (-bus IEEE network)	Strength of hybrid approach
Kumar and Chaturvedi	2013, [111]	GA + Fuzzy PSO + Fuzzy	FCM	SOOPF	30 (modified system)	Proposed hybrid algorithms achieve improved average fitness characteristics and a faster convergence rate
Narimani et al.	2013, [112]	Modified PSO + SFLA (HMPSO-SFLA)	FCM, EM	MOOPF	30, 57, 118	PSO explores for promising solutions, SAMPO boosts solution diversity in modified PSO, and SFLA offers strong local search
Radosavljevića et al.	2015, [113]	PSO + GSA (PSOGSA)	FCM, PLM, VDM, VSE	Both	30, 118	PSOGSA merges PSO's exploratory strengths with GSA's local search but is slow on large-scale systems
S. S. Reddy	2019, [114]	DE + HS	FCM, VSE, PLM	Both	30, 118, 300	DEA explores search spaces and HS exploits solutions, achieving a balanced exploration–exploitation trade-off
El Sehiemy et al.	2020, [115]	PSO + SSO	FCM, VDM, PLM, VSE, EM	Both	30, 57, 118	Like PSO, PSO-SSO addresses premature convergence. Using SSO, it avoids suboptimal locals and thoroughly explores the search space
Khan et al.	2020, [117]	FA + PSO (HFPSO)	FCM, VDM, VSE, PLM, RPLM	SOOPF	30	FA excels in local exploitation; PSO ensures rapid global convergence. HFPSO balances both for high convergence efficiency
Khan et al.	2020, [118]	FA + PSO (MOHFPSO)	FCM, VSE, VDM, PLM	MOOPF	30, 57	MOHFPSO combines FOA's exploitation with PSO's exploration, using non-dominated sorting to find superior Pareto optimal solutions
Gupta et al.	2021, [119]	Jaya + PPS	FCM, VDM, EM, PLM	MOOPF (combined SOF)	30, 57, 118	PPS enhances local searches and escapes local optima; Jaya improves global exploration. Jaya-PPS balances both effectively
Gupta et al.	2021, [120]	SCM + MJ	FCM, VDM, PLM	SOOPF (MOF turned into SOF)	118, Algerian 59-bus	SCM introduces new solutions to avoid local optima, and MJ explores the search space effectively. SCM-MJ balances exploration and exploitation
Naderi et al.	2021, [121]	PSO + DE (FAHSPSO-DE)	FCM, PLM, EM	Both	30, 57, 118	FAHSPSO-DE uses fuzzy logic for dynamic parameter adjustment to optimize and effectively manage exploration and exploitation
Avvari and Vinod Kumar	2022, [122]	(Pareto dominance & decomposition) + EA	FCM, EM, PLM, VDM	MOOPF	57, 118	The hybrid approach integrates decomposition and local dominance, enhancing MOEA's exploration and exploitation, achieving a more uniform Pareto front and improved convergence
Mallala et al.	2022, [123]	Fruit fly + ABC (NSHFABC)	FCM, PLM, SVM	Both	30, 118	NSHFABC combats ABC's premature convergence and enhances optimal value accuracy by utilizing both algorithms' exploratory potential
Mohamed et al.	2022, [124]	GBO + MFO	FCM, PLM (without/ with uncertain load demand)	Both	30	The GBO-MFO algorithm utilizes the MFO algorithm's spiral movement to avoid local optima and enhances convergence by incorporating the gradient search rule and a local escaping operator (LEO)

Table 5 Comparison of fuel costs using OPF algorithms (hybrid) on standard test systems: (FCM single-objective)

References	Algorithm	Attained fuel cost ($/hr)			
		IEEE 30-bus	IEEE 57-bus	IEEE 118-bus	Other benchmark test networks
[111]	GA + Fuzzy	801.21*	–	–	–
[111]	PSO + Fuzzy	800.72*	–	–	–
[112]	Modified PSO + SFLA (HMPSO-SFLA)	801.75	–	–	–
[113]	PSO + GSA	800.4985	–	1,29,733.58	–
[114]	DE + HS	799.0514	–	–	IEEE 300-bus: 8,33,892.0996
[115]	PSO + SSO	798.98	41,666.66	1,35,055.30	–
[117]	FA + PSO	799.123	–	–	–
[118]	FA + PSO (MOHFPSO)	800.138 (FCM + VSE)	41,601.043 (FCM + VSE)	–	–
[119]	Jaya + PPS	830.467* (Jaya-PPS1), 830.850* (Jaya-PPS2), 830.290* (Jaya-PPS3)	42,573.898* (Jaya-PPS1), 42,542.989* (Jaya-PPS2), 42,571.028* (Jaya-PPS3)	1,29,221.889 (Jaya-PPS1), 1,29,227.810 (Jaya-PPS2), 1,29,231.178 (Jaya-PPS3)	–
[120]	SCM + MJ	–	–	1,29,171.96	Algerian 59-bus: 1,688.5933
[121]	PSO + DE	799.8066	41,637.18	1,29,519.38	–
[122]	(Pareto dominance & decomposition) + EA	–	41,748.67 (FCM + PLM + VDM)	1,34,895.9 (FCM + PLM)	–
[123]	Fruit fly + ABC	800.212	–	1,31,400.63	–
[124]	GBO + MFO	807.12*	–	–	–

*modified test system

applied to single- and MOO problems on 30, 57, and 118-bus IEEE test networks, encompassing a total of 18 case studies with objectives related to cost, emission, and losses. In the IEEE 57-bus power grid, the algorithm significantly reduced total generation costs, resulting in a reduction of at least $150,000 annually. The medium-scale nature of the test system makes this accomplishment particularly remarkable.

In the literature [122], a proposition was put forth to enhance the performance of a multi-objective EA (MOEA) by combining decomposition and local dominance techniques. The authors proposed the use of these methods to achieve a Pareto front that is uniformly distributed and to improve convergence properties. To assess the effectiveness of this approach, the authors conducted tests on IEEE 57 and 118-bus systems, employing various case studies. These case studies represented multi-objective formulations with four objectives: FCM, EM, PLM, and VDM. The simulation results were contrasted with those obtained from MOPSO and NSGA-II methods, demonstrating competitive performance of the proposed approach.

The authors in [123] designed a non-dominated sorting hybrid fruit-fly-based ABC (NSHFABC) by combining the ABC and fruit fly algorithms to solve MOOPF problems. They validated the algorithm utilizing the IEEE 30-bus (MOOPF) and 118-bus test systems (SOOPF). A total of three objectives were examined: FCM, PLM, and SVM. In the 30-bus system, considering a single objective of minimizing fuel cost without ramp rate limits, the obtained value was 800.212 $/hr. With ramp rate limits, the fuel cost increased to 802.922 $/hr. Regarding severity values, without ramp rate limit constraints, it measured 1.304, while with ramp rate limits, it reached 1.534. In order to showcase the superiority of the suggested hybrid approach, a comprehensive evaluation was performed, contrasting it with established techniques including DE, enhanced PSO, and ant colony optimization (ACO), among others.

In [124], a hybrid of gradient-based optimizer (GBO) and MFO was utilized to optimize the OPF problem, taking into account the objectives of cost, losses, and their combination with constant load and uncertain load demand. The presented hybrid methodology was executed on a

30-bus IEEE test network with stochastic wind and FACT devices. Hybrid power systems were implemented at buses 5 and 11, in which wind generators replaced thermal generators. Three FACT devices were deployed at their optimal location and size, considering objectives of FCM and PLM in the grid. The proposed method achieved a generation cost of 807.12 $/hr when considering FACT devices. These costs are lower than those of other evaluated techniques, such as 807.2502 $/hr in GBO, 807.277 $/hr in SMA, and 807.4733 $/hr in MFO, as reported in the paper for the same modified test system.

Table 4 summarizes the hybrid approaches used to solve OPF in the past decade, along with their strengths. It also includes citations of the literature where these approaches were proposed, along with additional relevant information. Following this, Table 5 provides readers with a detailed comparison of basic fuel cost outcomes using various hybrid OPF algorithms across standard IEEE test systems and other benchmark systems.

Table 6 Ranking of OPF solutions: minimum fuel costs (IEEE 30-bus system)

S. No.	References	Algorithm	Attained fuel cost ($/hr)	S. No.	References	Algorithm	Fuel cost ($/hr)	S. No.	References	Algorithm	Attained fuel cost ($/hr)
1	[83]	NSMOGSA	796.124	27	[43]	EMSA	799.3582	53	[59]	SKH	800.5141
2	[107]	ESCA	796.345	28	[61]	NISSO	799.7624	54	[47]	ABC	800.66
3	[37]	BAAMO	798.012	29	[121]	FAHSPSO-DE	799.8066	55	[111]	PSO-Fuzzy	800.72*
4	[81]	GSA	798.6751	30	[14]	AGAPOP	799.8441	56	[32]	GBLFA	800.8726
5	[97]	Jaya	798.9386	31	[22]	FHSA	799.914	57	[93]	MICA-TLA	801.0488
6	[69]	SPSA	798.9536	32	[64]	PALO	799.916	58	[111]	GA-Fuzzy	801.21*
7	[115]	PSO-SSO	798.98	33	[84]	BHBO	799.9217	59	[16]	DEA	801.23
8	[88]	WEA	798.9969	34	[109]	Rao-1	799.9683	60	[19]	DEA	801.248
9	[58]	KHA	799.0311	35	[109]	Rao-2	799.9918	61	[74]	IMOMRFO	801.3908
10	[87]	ICBO	799.0353	36	[62]	CS-GWO	799.9978	62	[16]	GWO	801.41
11	[104]	MOBSA	799.046	37	[12]	EP	800.04	63	[26]	ARCBBO	801.5159*
12	[30]	GWSO	799.05	38	[78]	IEM	800.0781	64	[102]	BSA	801.63*
13	[114]	Hybrid DE-HS	799.0514	39	[118]	MOHFPSO	800.138	65	[55]	AGSO	801.75*
14	[90]	IAOA	799.068	40	[123]	NSHFABC	800.212	66	[112]	MPSO-SFLA	801.75
15	[91]	TLBO	799.0715	41	[66]	NSWOA	800.26	67	[92]	MTLBO	801.8925
16	[76]	MPA	799.0725	42	[40]	IMFO	800.3848	68	[28]	IPSO	801.978
17	[103]	BSA	799.076	43	[35]	Novel DSA-based approach	800.3887	69	[46]	IBF	802.325
18	[17]	MODEA	799.0827	44	[50]	IABC	800.4215	70	[71]	SMA	802.5449
19	[34]	DSA	799.0943	45	[109]	Rao-3	800.4391	71	[12]	PSO	802.79
20	[117]	HFPSO	799.123	46	[51]	GABC	800.44011	72	[124]	GBO-MFO	807.12*
21	[63]	ALO	799.155	47	[110]	MRao-2	800.4412	73	[95]	TLSBO	815.4377*
22	[39]	MFO	799.2029	48	[68]	MGOA	800.4744	74	[119]	Jaya-PPS3	830.290*
23	[12]	GA	799.23	49	[44]	ISSA	800.4752	75	[119]	Jaya-PPS1	830.467*
24	[72]	MOSMA	799.2557	50	[32]	MGBLFA	800.4802	76	[119]	Jaya-PPS2	830.850*
25	[106]	MSCA	799.31	51	[113]	PSO-GSA	800.4985	77	[98]	MJAYA	858.2281*
26	[52]	OL-based IABC	799.321	52	[42]	MSA	800.5099				

*modified 30-bus

Table 7 Ranking of OPF solutions: minimum fuel costs (IEEE 57-bus system)

S.No	References	Algorithm	Attained fuel cost ($/hr)	S.No	References	Algorithm	Attained fuel cost ($/hr)
1	[97]	Jaya	39,555	21	[93]	MICA-TLA	41,675.05
2	[90]	IAOA	40,911	22	[59]	SKH	41,676.92
3	[55]	AGSO	40,936.07	23	[74]	IMOMRFO	41,680.38
4	[118]	MOHFPSO	41,601.04	24	[18]	MDE	41,682
5	[69]	SPSA	41,609	25	[17]	MO-DEA	41,683
6	[104]	MOBSA	41,623.29	26	[50]	IABC	41,684
7	[72]	MOSMA	41,633.61	27	[51]	GABC	41,684.20
8	[121]	FAHSPSO-DE	41,637.18	28	[26]	ARCBBO	41,686
9	[92]	MTLBO	41,638.38	29	[35]	Novel DSA-based approach	41,686.82
10	[22]	FHSA	41,658.18	30	[47]	ABC	41,693.96
11	[109]	Rao-3	41,659	31	[81]	GSA	41,695.87
12	[57]	CKHA	41,660.47	32	[71]	SMA	41,697.12
13	[37]	BAAMO	41,665.50	33	[87]	ICBO	41,697.33
14	[61]	NISSO	41,665.54	34	[58]	KHA	41,709.26
15	[43]	EMSA	41,666.24	35	[122]	(Pareto dominance & decomposition) + EA	41,748.67
16	[115]	PSO-SSO	41,666.66	36	[109]	Rao-1	41,771
17	[40]	IMFO	41,667.15	37	[109]	Rao-2	41,872
18	[68]	MGOA	41,671.10	38	[119]	Jaya-PPS2	42,542.989*
19	[42]	MSA	41,673.72	39	[119]	Jaya-PPS3	42,571.028*
20	[44]	ISSA	41,675.02	40	[119]	Jaya-PPS1	42,573.898*

*modified 57-bus

9 Comparative analysis of OPF algorithm performance

This section presents three distinct tables (Tables 6, 7 and 8), each dedicated to ranking OPF solutions based on the minimum fuel costs achieved for the IEEE 30-bus, 57-bus, and 118-bus systems, respectively. These tables quickly offer the reader comparative insights into which algorithms yield the most economical outcomes in terms of minimum fuel cost (FCM objective) under specific system configurations. Figure 3 illustrates the dispersion of OAs in tackling OPF problems, providing valuable insights into their percentage adoption in highly reputable peer-reviewed journal exclusively within the past decade.

Tables 6, 7 and 8 clearly show that while one algorithm may excel in a specific test system for a given objective (FCM), it may not perform as well in other systems. We have focused on fuel cost values (basic QFC) for comparison, as FCM is a fundamental objective commonly addressed in the literature, allowing for a consistent basis of comparison. Space limitations and the inconsistent presence of all OPF objectives across the literature reviewed further restrict the inclusion of multiple objectives. The choice of an algorithm for OPF problems is influenced by the nature of the problem, including the type of variables, the objectives to be optimized, and the desired balance between global exploration and local exploitation. While multiple trials and careful parameter tuning are essential for many algorithms, some metaheuristics may require minimal (e.g., CS-GWO, BSA) or no parameter tuning (e.g., BHBO, Jaya, Rao, TLBO), which can simplify the optimization process and enhance robustness.

Our review examines both individual OAs and hybrid approaches that combine fundamental metaheuristics. While hybrids offer the potential for superior performance by creating a balance between exploration and exploitation, especially in complex MOOPF problems, they also introduce increased computational complexity and require careful configuration tailored to specific OPF challenges.

As evidenced by Fig. 3 and supported by our comprehensive literature review, swarm intelligence algorithms, a key subset of AI-based computational intelligence tools, have emerged as a dominant approach for solving OPF problems. These algorithms, whether in their original form or as components in hybrid algorithms, are particularly well-suited for addressing OPF challenges involving

Table 8 Ranking of OPF solutions: minimum fuel costs (IEEE 118-bus system)

S. No	References	Algorithm	Attained fuel cost ($/hr)	S. No	References	Algorithm	Attained fuel cost ($/hr)
1	[68]	MGOA	1,21,072.93	20	[42]	MSA	1,29,640.7191
2	[71]	SMA	1,27,896.55	21	[91]	TLBO	1,29,682.844
3	[120]	SCM-MJ	1,29,171.96	22	[34]	DSA	1,29,691.6152
4	[109]	Rao-3	1,29,220.6794	23	[16]	GWO	1,29,720
5	[119]	Jaya-PPS1	1,29,221.889	24	[52]	OL-based IABC	1,29,862
6	[119]	Jaya-PPS2	1,29,227.810	25	[61]	NISSO	1,29,879.4536
7	[119]	Jaya-PPS3	1,29,231.178	26	[18]	MDE	1,30,518.5
8	[109]	Rao-1	1,29,241.1787	27	[123]	NSHFABC	1,31,400.6342
9	[109]	Rao-2	1,29,256.5242	28	[110]	MRao-2	1,31,457.8
10	[76]	MPA	1,29,422.56	29	[40]	IMFO	1,31,820
11	[44]	ISSA	1,29,460.8351	30	[22]	FHSA	1,32,138.30
12	[121]	FAHSPSO-DE	1,29,519.38	31	[122]	(Pareto dominance & decomposition) + EA	1,34,895.90
13	[62]	CS-GWO	1,29,544.01	32	[115]	PSO-SSO	1,35,055.30
14	[37]	BAAMO	1,29,550.80	33	[87]	ICBO	1,35,121.5704
15	[69]	SPSA	1,29,561.0305	34	[43]	EMSA	1,35,262.57
16	[82]	GSA	1,29,565	35	[103]	BSA	1,35,333.4743
17	[16]	DEA	1,29,582	36	[104]	MOBSA	1,35,620.99
18	[58]	KHA	1,29,608.4554	37	[113]	PSO-GSA	1,29,733.58
19	[106]	MSCA	1,29,620.22	38	[98]	MJAYA	1,40,575.3099*

*modified 118-bus

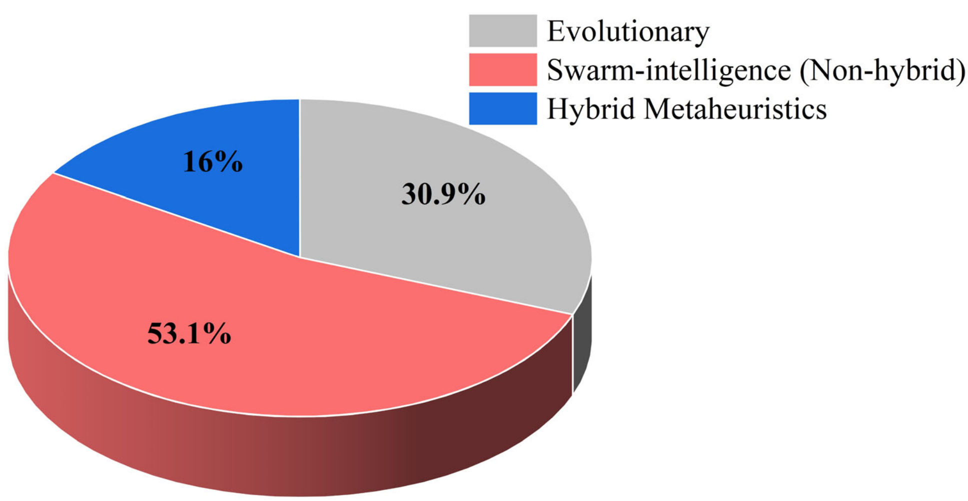

Fig. 3 OPF algorithm distribution: evolutionary (30.9%), swarm intelligence (53.1%), hybrid (16%)

multiple constraints and objectives, making them effective tools in this domain.

10 Future research directions

Integration of renewable energy technologies into conventional power systems has provided several benefits like reducing emission of greenhouse gases contributing to global warming and mitigating power transmission losses incurred while transmitting electricity from distant generating stations. The use of more than one resource when available is advantageous because the majority of RES are intermittent in nature. Implementation of hybrid algorithms to solve MOOPF problems and adapting RES for further cost reduction, alongside the environmental pollution reduction, opens up new opportunities for research and provides the future scope of work in this area.

Another area of potential research lies in studying the integration of various types of Flexible AC Transmission Systems (FACTS) devices for addressing OPF problems. Power system performance can be improved using these devices in steady-state operating conditions. Furthermore, the impact of FACTS devices needs to be considered in OPF when the system encounters contingencies, known as contingency-constrained OPF.

Overall, FACTS devices combined with a stochastic multi-objective model can assist in addressing the challenge of OPF problems created by the increasingly prevalent use of RES. This model can minimize the risk of blackouts and other disruptions by considering the uncertainty of renewable energy output and other potential factors. Although research in this area may pose challenges, it is essential to ensure the reliable operation of power systems amid the increasing penetration of renewables.

11 Conclusions

Power system optimization is a challenge that AI methods can solve well, especially in large, complex systems requiring multi-objective optimization (MOO). In this work, an exhaustive attempt has been made to review all the notable findings of eminent researchers in the area of power system optimization to address issues related to OPF, utilizing modern population-based computational intelligence tools, or AI tools. Significant emphasis has been placed on literature that was published in highly reputable peer-reviewed international journals, with particular attention given to the period from 2012 to 2022. The selection criteria for inclusion prioritized articles published in SCI/SCIE indexed journals.

All modern AI techniques have been reviewed categorically and chronologically for solution of different types of OPF problems. Several combined AI techniques (hybrid methods) have also been reviewed, claiming to effectively address OPF problems in large-scale electrical grids. However, it is essential to note that the choice of an algorithm is highly problem-specific, and according to NFL theorem, no single optimization algorithm can solve all optimization problems universally. The study presented in this paper is expected to be helpful for potential researchers in identifying the future research directions in the domain of power system optimization.

Author contributions Literature search, data analysis, and original draft preparation were conducted by Udit Mittal. The review, editing, and supervision were carried out by Uma Nangia and Narender Kumar Jain. All authors read and approved the final manuscript.

Funding The authors declare that no funds, grants, or other support were received during the preparation of this manuscript.

Data availability The datasets analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Conflict of interest The authors have no relevant financial or non-financial interests to disclose.

Ethical approval The research conducted is a literature review, relying solely on published works, and no interactions with human participants and/or animals took place.

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