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A REVIEW OF METAHEURISTIC OPTIMIZATION ALGORITHMS FOR POWER SYSTEM APPLICATIONS

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ABSTRACT
Modern electric power systems are becoming increasingly complex due to rising electricity demand, renewable-energy integration, distributed generation, energy storage, electric vehicles and smart-grid technologies. These developments create challenging optimization problems involving nonlinearities, nonconvexity, multiple objectives, uncertainty and operational constraints. This paper presents a review of metaheuristic optimization algorithms for power-system applications, focusing on their principles, classifications, applications, comparative characteristics, challenges and future directions. Major algorithms, including Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Differential Evolution (DE), Ant Colony Optimization (ACO), Simulated Annealing (SA), Cuckoo Search (CS), Grey Wolf Optimizer (GWO), Whale Optimization Algorithm (WOA) and Harris Hawks Optimization (HHO), are examined. Their applications in optimal power flow, economic dispatch, unit commitment, renewable-energy integration, distributed-generation allocation, transmission planning, microgrid management and power-quality improvement are discussed. The review highlights the growing importance of hybrid, multi-objective, uncertainty-aware, adaptive and machine-learning-assisted approaches for robust and efficient power-system optimization.

Keywords:
Metaheuristic Optimization; Power Systems; Optimal Power Flow; Renewable Energy; Economic Dispatch; Smart Grid.

1. INTRODUCTION

Modern electric power systems are undergoing significant transformation due to increasing electricity demand, integration of renewable energy sources, distributed generation, energy storage, electric vehicles, demand response and smart-grid technologies. These developments have created increasingly complex optimization problems characterized by nonlinear relationships, nonconvex search spaces, discrete and continuous decision variables, multiple objectives, uncertainty and numerous operational constraints. Effective optimization is therefore essential for achieving reliable, economical, efficient and sustainable power-system operation.

Traditional power-system optimization has commonly relied on mathematical programming techniques such as linear programming, nonlinear programming, quadratic programming, dynamic programming, mixed-integer programming and interior-point methods. Although these approaches remain valuable for problems with suitable mathematical properties, their effectiveness can become limited when optimization problems involve nonconvex objective functions, nonlinear power-flow equations, discontinuous operating regions, integer variables, valve-point loading effects, prohibited operating zones, stochastic renewable generation and large numbers of operational constraints.

Metaheuristic optimization algorithms have consequently attracted considerable attention because of their flexibility, derivative-free search capability and ability to obtain high-quality solutions without requiring strong assumptions about the mathematical structure of the problem. These algorithms provide alternative approaches for addressing complex engineering optimization problems and have been increasingly applied to various power-system problems. Frequently investigated methods include Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Differential Evolution (DE), Ant

Colony Optimization (ACO), Simulated Annealing (SA), Cuckoo Search (CS), Grey Wolf Optimizer (GWO), Whale Optimization Algorithm (WOA) and Harris Hawks Optimization (HHO). Their applications extend across optimal power flow, economic dispatch, unit commitment, renewable-energy integration, distributed-generation allocation, transmission expansion, capacitor placement, voltage optimization, microgrid energy management and power-quality improvement.
Despite their widespread application, no single metaheuristic algorithm can be considered universally superior. Performance depends on factors such as problem formulation, dimensionality, constraint-handling mechanisms, parameter settings, initialization, stopping criteria and computational environment. Recent developments have therefore shifted attention towards hybrid metaheuristics, multi-objective optimization, uncertainty-aware optimization, adaptive parameter control, machine-learning integration and physics-informed approaches. These developments highlight the need for a systematic understanding of the capabilities, limitations and appropriate application areas of different metaheuristic techniques.
Against this background, this paper reviews the principles, classifications, applications, comparative characteristics, challenges and future directions of metaheuristic optimization algorithms in power-system engineering. Section 2 presents the fundamentals and classification of metaheuristic optimization algorithms, covering evolutionary, swarm-intelligence and other nature-inspired approaches. Section 3 examines major applications of metaheuristic algorithms in power systems, including optimal power flow, economic dispatch, unit commitment, renewable-energy integration, distributed-generation placement, capacitor placement, transmission expansion, microgrid energy management and power-quality improvement. Section 4 provides a comparative evaluation of selected algorithms, with emphasis on solution quality, convergence, computational efficiency, robustness, scalability, hybridization, multi-objective optimization and uncertainty-aware optimization. Section 5 discusses the major challenges, research gaps and future directions, including premature convergence, parameter sensitivity, scalability, reproducibility, constraint handling, machine-learning integration, physics-informed optimization, real-time optimization, cybersecurity and renewable-dominated power systems. Section 6 concludes the review by summarizing the major findings and identifying promising directions for developing robust, efficient and practically deployable optimization approaches for modern power systems

2. FUNDAMENTALS AND CLASSIFICATION OF METAHEURISTIC OPTIMIZATION ALGORITHMS
Metaheuristics are high-level search strategies designed to guide optimization procedures toward promising regions of a solution space. They are generally stochastic and do not require gradient information. Their principal design challenge is to balance exploration and exploitation. Exploration searches diverse regions, while exploitation intensifies the search around promising solutions.

2.1 Power-System Optimization Problems
A general constrained power-system optimization problem can be expressed as:

$$\min_{\mathbf{x}} F(\mathbf{x}) \quad \text{............ (1)}$$

minimize F(x)
subject to:
$g_i(x) = 0, \; i = 1, 2, \ldots, m$ (2)
$h_j(x) \le 0, \; j = 1, 2, \ldots, n$ (3)

where F(x) is the objective function, x represents decision variables, $g_i(x)$ represents equality constraints, and $h_j(x)$ represents inequality constraints. Typical objectives include generation-cost minimization, transmission-loss minimization, voltage-profile improvement, emission reduction, renewable-energy utilization, reliability enhancement, congestion management, and improved power quality.

2.2 Evolutionary Algorithms
Evolutionary algorithms are inspired by biological evolution. Major examples include Genetic Algorithm, Differential Evolution, Evolution Strategies, Evolutionary Programming, and Genetic Programming. GA uses selection, crossover, and mutation to evolve candidate solutions, while DE relies on vector differences to generate trial solutions. These algorithms have been applied to economic dispatch, unit commitment, OPF, distributed-generation allocation, capacitor placement, transmission planning, and renewable-energy optimization.

2.3 Swarm-Intelligence Algorithms
Swarm-intelligence algorithms model collective behavior in biological systems. Examples include PSO, ACO, Artificial Bee Colony, Cuckoo Search, GWO, WOA, and HHO. Their population-based structure makes them suitable for nonlinear and multimodal optimization.

2.4 Particle Swarm Optimization
PSO was introduced by Kennedy and Eberhart (1995). Each particle represents a candidate solution with a position and velocity. The velocity and position updates are:

$$v_{i,d}^{t+1} = wv_{i,d}^{t} + c_1 r_1 (pbest_{i,d} - x_{i,d}^{t}) + c_2 r_2 (gbest_d - x_{i,d}^{t}) \tag{4}$$

and the position is updated according to:

$$x_{i,d}^{t+1} = x_{i,d}^{t} + v_{i,d}^{t+1} \tag{5}$$

where w is the inertia weight, c_1 and c_2 are cognitive and social coefficients, r_1 and r_2 are random numbers, pbest is the particle's best position, and gbest is the global best position. Modifications to inertia and particle behavior have been studied extensively to improve convergence and stability (Shi & Eberhart, 1998; Clerc & Kennedy, 2002; Bonyadi & Michalewicz, 2017).

2.5 Differential Evolution
DE is a population-based continuous optimizer that generates candidate vectors from differences between population members. A typical mutation operation is:

$$v_i = x_{r1} + F(x_{r2} - x_{r3}) \tag{6}$$

where F is the differential scaling factor and r_1, r_2, and r_3 denote distinct randomly selected individuals. DE has shown strong performance in continuous optimization and has been used in OPF and renewable-energy applications.

2.6 Ant Colony Optimization
ACO is inspired by pheromone-mediated path selection. Its search process is particularly relevant to combinatorial and network problems. A simplified transition probability is:

$$P_{ij}^{k} = \frac{\tau_{ij}^{\alpha}\eta_{ij}^{\beta}}{\sum_{l\in N_i^k}\tau_{il}^{\alpha}\eta_{il}^{\beta}} \tag{7}$$

where τ represents pheromone intensity, η represents heuristic information, and α and β control their relative influence.

2.7 Simulated Annealing
Simulated Annealing is inspired by metallurgical annealing and allows occasional acceptance of inferior solutions to escape local optima. The acceptance probability is:

$$P = \exp(-\Delta E/T) \tag{8}$$

where ΔE is the increase in objective value and T is the temperature parameter.

2.8 Recent Nature-Inspired Algorithms

GWO, WOA, CS, HHO, Salp Swarm Algorithm, Moth-Flame Optimization, and related methods have been increasingly investigated for power-system optimization. Mirjalili et al. (2014) introduced GWO, while Mirjalili and Lewis (2016) introduced WOA. Recent systematic evidence indicates that the popularity of algorithms should be evaluated according to actual search mechanisms and empirical performance rather than metaphorical novelty alone (Amaya-Contreras et al., 2024).

3. APPLICATIONS OF METAHEURISTIC ALGORITHMS IN POWER SYSTEMS

3.1 Optimal Power Flow

OPF determines the optimal operating state of a power network subject to physical and operational constraints. A simplified generation-cost objective is:

$$\min F = \sum_{i=1}^{N_G} \left(a_i P_{Gi}^2 + b_i P_{Gi} + c_i\right) \qquad (9)$$

subject to active- and reactive-power balance and operating limits. Modern OPF increasingly incorporates renewable generation, energy storage, smart-grid devices, and security constraints. Recent reviews emphasize the growing complexity of OPF and the continued development of metaheuristic, machine-learning, and mathematical approaches (Babiker et al., 2025).

3.2 Economic Dispatch

Economic Dispatch determines the generation levels required to satisfy demand at minimum operating cost:

$$\min F_T = \sum_{i=1}^{N_G} F_i(P_i) \qquad (10)$$

where the quadratic generator cost function is commonly represented by:

$$F_i(P_i) = a_i P_i^2 + b_i P_i + c_i. \qquad (11)$$

Subject to:

$$\sum_{i=1}^{N_G} P_i = P_D + P_L \qquad (12)$$

Metaheuristics are useful when economic dispatch includes valve-point effects, prohibited operating zones, ramp limits, spinning reserve, losses, emissions, and renewable uncertainty. Recent research continues to compare metaheuristics for multi-area economic dispatch (Wang & Xiong, 2025a, 2025b).

3.3 Unit Commitment

Unit Commitment determines the on/off schedule of generating units over a time horizon. Its mixed-integer, time-coupled structure makes it computationally challenging, especially when startup, shutdown, minimum up/down times, reserve requirements, and renewable generation are included.

3.4 Renewable-Energy Integration

Renewable-energy integration creates optimization problems involving PV and wind siting, capacity sizing, storage scheduling, renewable dispatch, hosting capacity, and microgrid management. A multi-objective formulation may be written as:

$$\min F(x) = [f_1(x), f_2(x), \dots, f_k(x)] \qquad (13)$$

Objectives can include cost, emissions, reliability, losses, voltage deviation, and renewable-energy utilization. Recent reviews emphasize advanced planning and optimization methods for integrating renewable resources into modern power systems.

3.5 Distributed-Generation Placement

DG allocation seeks optimal locations and capacities for distributed resources. A representative objective is:

$$\min F = w_1 P_{loss} + w_2 VD + w_3 C_{DG} \quad (14)$$

where P_{loss} is network loss, VD is voltage deviation, C_{DG} is the relevant cost, and w_1–w_3 are weighting factors.

3.6 Capacitor Placement and Voltage Optimization

Capacitor placement and voltage optimization seek to improve voltage profiles and reduce losses while accounting for discrete compensation levels. Metaheuristics can naturally handle the mixed nature of capacitor selection and continuous network operating variables.

3.7 Transmission Expansion Planning

Transmission Expansion Planning involves selecting new transmission investments while satisfying long-term operational requirements. The objective commonly combines investment, operation, congestion, and loss costs. GA, PSO, DE, ACO, and hybrid methods have been applied to this class of problem.

3.8 Microgrid Energy Management

Microgrid energy management coordinates renewable generation, conventional generators, storage, flexible loads, and grid exchanges. A generalized cost objective is:

$$\min F = C_{grid} + C_{DG} + C_{battery} + C_{emission} \quad (15)$$

Metaheuristics are useful because microgrid scheduling often combines discrete and continuous variables, nonlinear equipment constraints, uncertainty, and multiple objectives.

3.9 Power-Quality Improvement

Metaheuristics have also been used for harmonic reduction, filter design, reactive-power compensation, voltage regulation, FACTS-device placement, power-factor correction, and distribution-network reconfiguration. Such applications demonstrate the broad adaptability of population-based search methods.

4. COMPARATIVE EVALUATION OF METAHEURISTIC ALGORITHMS

Meaningful comparison should consider more than the best objective value obtained in a single run. Important criteria include solution quality, convergence speed, computational time, robustness, repeatability, scalability, constraint handling, parameter sensitivity, uncertainty tolerance, and real-time suitability.

Table 1. Comparative characteristics of selected metaheuristic algorithms.

Algorithm	Main Strength	Major Limitation	Typical Applications
GA	Flexible global search	May converge slowly	UC, ED, OPF, planning
PSO	Simple and fast convergence	Premature convergence	OPF, ED, DG, RES
DE	Strong continuous search	Parameter sensitivity	OPF, ED, RES
ACO	Effective combinatorial search	Computational overhead	Network planning
SA	Escapes local optima	Slow convergence	UC, planning
CS	Strong exploration	Parameter tuning	OPF, DG, RES
GWO	Simple search mechanism	Possible diversity loss	OPF, ED, DG
WOA	Exploration/exploitation balance	Premature convergence	OPF, RES
HHO	Strong exploratory behavior	Can be computationally demanding	OPF, ED, microgrids
Hybrid	Combines complementary operators	Higher complexity	Complex OPF and RES

4.1 PSO versus GA
PSO generally uses fewer search operators than GA and can converge quickly toward promising regions. GA can preserve diversity through crossover and mutation and is especially attractive for discrete or combinatorial representations. The relative advantage therefore depends on the structure of the power-system problem.

4.2 PSO versus DE
PSO uses personal and social experience, whereas DE uses vector differences. Both are strong continuous optimizers. Their complementary mechanisms have motivated hybrid PSO-DE approaches for difficult OPF and renewable-energy problems (Duman et al., 2020).

4.3 Hybrid Metaheuristics
Hybridization combines complementary search mechanisms, such as PSO-DE, GA-SA, or GWO-PSO. The objective is generally to combine rapid exploitation with stronger exploration. Hybrid methods can improve solution quality but may increase implementation complexity and computational cost.

4.4 Multi-Objective Optimization
Modern power-system planning frequently involves conflicting objectives. Multi-objective metaheuristics such as MOPSO and NSGA-II generate Pareto-optimal solutions, allowing decision makers to examine trade-offs among cost, emissions, reliability, losses, and renewable utilization.

4.5 Uncertainty-Aware Optimization
Uncertainty-Aware Optimization (UAO) is an optimization approach that considers uncertainty, variability, and incomplete information when searching for the best solution. Instead of assuming that system parameters are fixed and known exactly, it accounts for possible changes or errors in factors such as load demand, renewable-energy generation, fuel costs, voltage, weather conditions,

and power-system operating conditions. In power systems, uncertainty-aware optimization can help identify solutions that remain reliable, stable, and efficient even when actual operating conditions differ from predicted values. It is therefore particularly useful for modern power systems with high penetration of solar PV and wind energy, where generation can vary unpredictably. Renewable generation can be represented as:

$$P_{RES} = P_{forecast} + \varepsilon \qquad (16)$$

where ε represents forecasting error. Metaheuristics can be combined with Monte Carlo simulation, scenario generation, fuzzy logic, stochastic programming, chance constraints, and robust optimization to address uncertainty.

5. CHALLENGES, RESEARCH GAPS AND FUTURE DIRECTIONS

5.1 Premature Convergence

Population-based algorithms can lose diversity and converge around locally attractive solutions. Adaptive parameters, mutation operators, opposition-based learning, chaotic mechanisms, and multi-swarm strategies can help maintain diversity.

5.2 Parameter Sensitivity

Algorithmic parameters strongly affect convergence. For PSO, inertia weight and acceleration coefficients are important; for DE, scaling and crossover parameters are influential. Self-adaptive mechanisms are therefore important research directions.

5.3 Scalability and Realistic Validation

Many studies use IEEE benchmark systems, which are useful for reproducibility but may not represent the full complexity of actual power networks. Future research should evaluate large-scale networks, unbalanced distribution systems, realistic renewable profiles, dynamic loads, equipment constraints, contingencies, and communication limitations. A recent systematic review reported that most studies in its sample did not adequately represent important real-world scenarios (Amaya-Contreras et al., 2024).

5.4 Reproducibility and Statistical Validation

Because metaheuristics are stochastic, reporting only the best result is insufficient. Robust comparative studies should report mean, best, worst, standard deviation, confidence intervals, convergence behavior, computational time, and statistical significance across independent runs.

5.5 Constraint Handling

Power-system solutions must satisfy generator, voltage, line-flow, angle, storage, and network constraints. Future algorithms should incorporate feasibility directly into search and use repair, penalty, feasibility-preserving, or constraint-domination mechanisms.

5.6 Integration with Machine Learning

Machine learning can be used to predict promising search regions, approximate expensive power-flow evaluations, tune algorithm parameters, forecast renewable generation, and accelerate repeated optimization. Recent work on machine-learning-accelerated distributed OPF indicates strong potential for combining data-driven acceleration with optimization-based feasibility.

5.7 Physics-Informed Metaheuristics

Future optimization algorithms should exploit power-system physics, including Kirchhoff's laws, power-flow equations, generator characteristics, voltage stability relationships, network topology, and operational limits. Physics-informed search can reduce infeasible evaluations and improve computational efficiency.

5.8 Real-Time and Distributed Optimization

Future smart grids require rapid optimization. Promising approaches include GPU and parallel computing, distributed optimization, surrogate-assisted search, reduced-order models, warm starts, and machine-learning-assisted metaheuristics.

5.9 Cybersecurity and Resilient Optimization

Digitalized power systems are increasingly exposed to false-data injection, sensor compromise, denial-of-service, and malicious control actions. Future optimization frameworks should explicitly consider cyber uncertainty and resilient decision-making.

5.10 Renewable-Dominated Power Systems

High penetrations of solar PV, wind, battery storage, electric vehicles, distributed generation, and flexible loads create dynamic and stochastic optimization environments. Future research should move from static benchmark optimization toward dynamic, multi-period, stochastic, distributed, and real-time optimization.

6. CONCLUSION

Metaheuristic optimization algorithms have become important approaches for addressing complex optimization problems in modern power systems. Their flexibility, derivative-free search capability and ability to handle nonlinear, nonconvex, multimodal and constrained problems make them suitable for applications such as optimal power flow, economic dispatch, unit commitment, renewable-energy integration, distributed-generation allocation, transmission expansion, capacitor placement, microgrid energy management and power-quality improvement. This review examined major algorithms, including Genetic Algorithm, Particle Swarm Optimization, Differential Evolution, Ant Colony Optimization, Simulated Annealing, Cuckoo Search, Grey Wolf Optimizer, Whale Optimization Algorithm and Harris Hawks Optimization.

The review shows that no single metaheuristic algorithm is universally superior. Their performance depends on problem characteristics, dimensionality, constraint-handling mechanisms, parameter settings, initialization, stopping criteria and computational environment. Hybrid approaches can combine complementary search mechanisms, while multi-objective and uncertainty-aware methods provide greater suitability for modern power systems involving conflicting objectives and variable operating conditions.

Future research should focus on adaptive and self-adaptive algorithms, hybridization, uncertainty-aware optimization, physics-informed search, machine-learning integration, distributed and real-time optimization, cybersecurity and realistic large-scale validation. Greater emphasis should also be placed on reproducibility, statistical validation and practical deployment rather than isolated best-case results. Overall, integrating metaheuristic methods with power-system physical models and data-driven techniques offers significant potential for developing robust, efficient, scalable and reliable optimization solutions for increasingly renewable-rich and decentralized power systems.

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