

# Metaheuristic Algorithm for Smart Grids Problems: A Brief Review

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## ABSTRACT

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The modern Smart Grid fueled by extensive renewable energy, electric vehicles (EVs), and complex bidirectional power flows has rendered conventional optimization techniques obsolete. This pivotal study delivers an essential, systematic review establishing metaheuristic algorithms as the indispensable technology for mastering this operational complexity. The research methodically dissects the application of metaheuristics across eight critical domains, including Unit Commitment (UC), Distributed Energy Resource (DER) management, Optimal Power Flow (OPF), and EV/V2G coordination. By synthesizing prior investigations, the paper demonstrates that these advanced techniques consistently yield near-optimal, computationally viable solutions. The real-world impact is transformative: substantial cost savings, minimized power losses, effective peak load reduction, and dramatically improved voltage stability. Crucially, the work champions hybrid methodologies as the strategic tool to reconcile exploration and exploitation in solving the mixed-variable, multi-objective challenges inherent to power systems. Ultimately, this document validates metaheuristic optimization as the core enabling factor for a reliable, efficient, and sustainable Smart Grid. It serves as a vital strategy guide for researchers and practitioners, charting the roadmap for future directions, including real-time implementation and integration with Artificial Intelligence (AI).

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## 1. Introduction

Global electricity demand continues to rise sharply, driven by urbanization, population growth, industrial expansion, and the widespread adoption of digital technologies and electric vehicles (EVs) [1], [2]. This unprecedented pressure is straining conventional power systems designed for a steady, one-way flow of electricity from centralized fossil-fuel-based plants, making it difficult to adapt to today's dynamic, decentralized, and increasingly volatile energy landscape. Simultaneously, the global

imperative to combat climate change and reduce greenhouse gas emissions reinforces the urgent need for environmentally friendly energy solutions [3]–[5].

In response to these interconnected challenges, the Smart Grid has emerged as a transformative innovation in the electric power sector [6]. Through the integration of advanced communication networks, real-time data analytics, and automated control systems, the Smart Grid enables two-way data exchange between utilities and consumers. This facilitates dynamic load balancing, predictive maintenance, faster outage response, and optimal energy distribution [7], [8]. Most importantly, the Smart Grid provides a flexible and interactive infrastructure, enabling it to seamlessly integrate variable renewable energy sources (such as solar and wind) and distributed resources (such as rooftop solar panels and battery storage) [9], [10]. This adaptability not only improves the grid's reliability, efficiency, and resilience, but also supports the widespread adoption of clean energy, paving the way for an electricity system that is responsive to modern energy demand and aligned with long-term environmental sustainability goals [11], [12].

Although Smart Grid offers an evolution towards a smarter and more sustainable grid [13], its operational complexity—including the integration of intermittent renewable energy, dynamic demand management, ESS, EVs, and bidirectional distribution networks—poses significant optimization challenges [14], [15]. Crucial problems such as Optimal Power Flow (OPF) [16], Unit Commitment [17], economic dispatch [18], distributed energy resource scheduling [19], peak load management [20], and resource allocation are often nonlinear, non-convex, multi-objective, and have a very large solution space. In this context, metaheuristic algorithms emerge as highly effective computational approaches to solve complex optimization problems that cannot be solved efficiently by conventional purely mathematical methods (such as linear programming) [21], [22].

Metaheuristics are a class of high-level optimization algorithms inspired by natural phenomena, social behavior, or evolutionary processes [23] that combine the principles of exploration and exploitation to find near-optimal solutions in reasonable computational time, without requiring gradient information or convexity assumptions. Examples of commonly applied algorithms include Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO). For example, GA mimics natural selection and genetic evolution through selection, crossover, and mutation operations to produce increasingly better solutions; while PSO simulates the social behavior of flocks of birds or fish, where each "particle" moves based on individual and collective experience. Because of their ability to avoid local optima and handle nonlinearities, these algorithms are well-suited to address the uncertainty and complexity inherent in Smart Grid systems [24].

This article provides a systematic and structured analytical mapping of the application of various classes of metaheuristic algorithms from single-solution-based, population-based (evolutionary, swarm intelligence), physics-based, social-inspired, to hybrid metaheuristics in solving eight main categories of optimization problems in the Smart Grid. Specific contributions are structured as follows:

- **Detailed Classification:** A thorough classification of metaheuristic types, including their core working mechanisms, distinct advantages, and inherent disadvantages, presented in a comprehensive tabular format for straightforward understanding and comparative analysis.
- **Contextual Correlation Analysis:** An in-depth analysis correlating each critical Smart Grid technical challenge (such as Unit Commitment, OPF, DER management, DR, DG placement, ESS management, EV charging, and self-healing) with its most appropriate metaheuristic algorithm, substantiated by quantitative performance results extracted from recent scientific research.
- **Academic Reference:** Provision of a comprehensive academic and practical reference intended to assist researchers, academics, and industry practitioners in the systematic selection, development, and optimal implementation of metaheuristic optimization methods across various Smart Grid domains.

This article systematically explores metaheuristics in Smart Grid optimization. It begins with global power system challenges and introduces the Smart Grid as a digital, renewable-integrated solution. A comprehensive literature review covers metaheuristic types and Smart Grid fundamentals. The core discussion analyzes metaheuristic applications across eight key areas using a tabular synthesis of recent studies. The paper concludes that metaheuristics are essential for enabling a reliable, efficient, and sustainable Smart Grid.

## 2. Method

### 2.1. Metaheuristic Algorithm

A metaheuristic algorithm is a high-level computational approach designed to solve complex optimization problems, particularly when exact methods are impractical or inefficient [25], [26]. The term "metaheuristic" is derived from two words: "meta," meaning "above" or "beyond," and "heuristic," which refers to an experience-based search strategy or rule of thumb that does not guarantee an optimal solution but is capable of providing a reasonably good solution in a reasonable time [27], [28]. Generally speaking, a metaheuristic is not a specific algorithm but rather a general framework that can be adapted to various types of optimization problems, whether discrete or continuous, deterministic or stochastic, and constrained or unconstrained [29], [30]. The main characteristic of a metaheuristic is its ability to avoid getting stuck in local optima and to explore the solution space globally (global search), thus increasing the chance of finding a near-optimal solution. Metaheuristics are often inspired by natural phenomena, the social behavior of living organisms, physical processes, or the mechanisms of biological evolution [31], [32].

The balance between exploration and exploitation is a fundamental principle that determines the success of any metaheuristic algorithm [33]. Exploration, or diversification, refers to a broad, random search strategy across the solution space to discover new promising regions, with the primary goal of avoiding premature convergence to a local optimum. This mechanism ensures that the algorithm is able to "jump out" of the local optimum trap and discover areas that might contain the global solution [34]. Conversely, exploitation, or intensification, is a focused, in-depth search around the best solutions already found. The goal is to gradually improve the quality of solutions in the immediate neighborhood of a promising point. Effective metaheuristic algorithms must adaptively manage this trade-off, typically by emphasizing exploration in the early stages to find a diversity of solutions and then shifting to exploitation in the later stages to hone the best solution (refinement). Failure to balance these two mechanisms, either too random (over-exploration) or settling too quickly (over-exploitation), will reduce the algorithm's efficiency and probability of finding a near-optimal solution.

Refers to how quickly an algorithm finds a good (or near-optimal) solution and how quickly it stops improving on that solution. Metaheuristics often balance exploration (searching for new areas) and exploitation (improving solutions in areas already found) to achieve adequate convergence speed, although convergence to the global optimal solution is not guaranteed. Metaheuristics generally have good scalability because their computational complexity often grows polynomially (or slower) compared to exact methods, which may grow exponentially.

Metaheuristic algorithms can be classified into various types based on their source of inspiration, their search mechanism, or their algorithmic structure [35]. Generally, metaheuristics are divided into two broad categories: single-solution-based and population-based. However, more detailed classifications often refer to the algorithm's source of inspiration [36]. The following is a complete explanation of the types of metaheuristic algorithms:

#### 2.1.1. Single-Solution-Based Metaheuristics

Single-Solution-Based Metaheuristics is a class of optimization algorithms that work by iteratively improving a single candidate solution, as opposed to population-based approaches that use multiple solutions simultaneously. These algorithms rely on clever strategies such as temporarily accepting worse solutions, using prohibitive memory, or random perturbations to avoid getting stuck in local optima and expand the exploration of the solution space. This type works by iteratively

improving a single candidate solution by exploring its neighborhood [37]. The Single-Solution-Based Metaheuristics Performance can be seen in Table 1. Algorithms in this category are typically simpler and require less memory.

- Simulated Annealing (SA)

Inspired by the annealing process in metallurgy, where a material is heated and then slowly cooled to reduce crystal defects. SA uses the probability of accepting a poorer solution at the beginning of the process (at a high "temperature") to avoid local optima, then gradually becomes more selective as the temperature decreases [38].

- Tabu Search (TS)

Uses short-term memory (a tabu list) to prevent returning to recently visited solutions, thus encouraging exploration of new areas. This strategy helps avoid cycles and expand the search [39].

- Iterated Local Search (ILS)

Combines local search with a process of "perturbation" (disturbing the current solution) and acceptance of new solutions, allowing the algorithm to repeatedly escape from local optima [40].

- Variable Neighborhood Search (VNS)

Systematically changes the structure of the search environment to avoid getting stuck in a local optima VNS dynamically switches between neighbors with varying radii [41], [42].

**Table 1.** Single-solution-based metaheuristics performance [43]

Aspects	Advantages	Weaknesses
Memory Usage	Requires very little memory because it only stores one primary solution (plus a little additional information such as temperature or tabu lists).	—
Implementation Complexity	The algorithm structure is generally simple and easy to understand and implement.	—
Computation Time per Iteration	It is fast in each iteration because it does not need to evaluate or update multiple solutions simultaneously.	—
Scalability	It is suitable for high-dimensional problems or large solution spaces because it does not depend on the population.	—
Global Exploration	—	More prone to getting stuck in local optima because it only follows a single search path.
Solution Diversity	—	Lacks the natural diversity of population-based algorithms; less able to explore multiple regions simultaneously.
Dependence on Initial Solutions	—	The quality of the final solution is often heavily influenced by the search starting point.
Adaptability	Some variants (such as TS or SA) have adaptive mechanisms to avoid stagnation.	Without a good escape mechanism (e.g., a poor cooling schedule in SA), performance can degrade dramatically.
Result Consistency	—	

### 2.1.2. Population-Based Metaheuristics

Population-Based Metaheuristics is a class of optimization algorithms that work by simultaneously maintaining and updating a set of candidate solutions (called a population) during the search process. Unlike single-solution-based approaches that follow only a single search path, population-based algorithms leverage the diversity and interactions among solutions to explore the solution space more broadly and effectively. Each individual in the population represents a potential solution to the problem being optimized, and over iterations, this population evolves or adapts through

certain mechanisms such as selection, recombination, mutation, or information exchange to gradually improve the overall quality of the solutions. These approaches are generally more robust in global exploration, and therefore better able to avoid local optimum traps than single-solution-based methods. This algorithm works with a group of solutions (a population) that evolve or interact throughout the iterations. This approach is generally more robust in global exploration due to the higher solution diversity.

### a) Evolutionary Algorithms

Evolutionary Algorithms (EAs) are a group of population-based optimization methods inspired by the principles of natural biological evolution, particularly the mechanisms of natural selection, reproduction, genetic variation, and survival of the fittest. Solutions are considered as individuals that reproduce, mutate, and are selected based on their fitness. The Example of Evolutionary Algorithms can be seen in [Table 2](#).

**Table 2.** Example of Evolutionary Algorithms

Algorithm	Main Inspirations	Key Mechanisms
Genetic Algorithm (GA)	Darwin's theory of evolution and Mendelian genetics	Selection (roulette, tournament), crossover (recombination), random mutation [44]
Genetic Programming (GP)	Evolution of computer programs	Representation of solutions as expression trees; crossover and mutation in tree structures [45]
Evolution Strategies (ES)	Evolutionary adaptation in organisms	Focus on mutation of continuous parameters (often using a Gaussian distribution) [46]
Differential Evolution (DE)	Evolution through vectorial divergence	Create new solutions by adding the difference between two individuals to a third individual [47]
Evolutionary Programming (EP)	Evolution of behavior (not genetic structure)	Use only mutation (no crossover); competition-based selection [48]

### b) Swarm Intelligence Algorithms

Swarm Intelligence Algorithms are a type of population-based metaheuristics inspired by the collective behavior of social organisms, such as ants, bees, birds, fish, or other insects, in foraging, moving in groups, or completing tasks collaboratively. These algorithms work with a group of simple agents (called particles, individuals, or swarms) that interact locally with each other and with the environment, without centralized control. Through simple rules and limited information exchange, the overall system is able to generate intelligent behavior and find optimal or near-optimal solutions to optimization problems. Inspired by the collective behavior of living organisms such as ants, bees, birds, or fish. The Example of Swarm Intelligence Algorithms can be seen in [Table 3](#).

#### 2.1.3. Physics-Based Metaheuristics

Physics-Based Metaheuristics is a class of optimization algorithms inspired by the laws of physics, non-biological natural phenomena, or thermodynamic and mechanical processes. Unlike algorithms that mimic biological evolution or the behavior of living organisms, these approaches utilize principles such as gravity, electromagnetism, particle motion, metal cooling, or the dynamics of physical systems to guide the search for optimal solutions within a solution space. It can be seen in [Table 4](#).

#### 2.1.4. Human-Based or Social-Inspired Metaheuristics

Human-Based or Social-Inspired Metaheuristics is a class of optimization algorithms inspired by real-life human social, cultural, cognitive, or learning behavior. Unlike algorithms that mimic nature, evolution, or physics, this approach models the social interactions, strategies, or mechanisms used by humans, such as teaching, learning, competing, collaborating, or even playing sports, to solve optimization problems. Some algorithms are inspired by human social or cultural behavior. The Example of Human-Based or Social-Inspired Metaheuristics can be seen in [Table 5](#).

**Table 3.** Example of swarm intelligence algorithms

Algorithm	Inspiration from Nature	Key Working Principles
Particle Swarm Optimization (PSO)	The movement of flocks of birds or fish when searching for food	Particles move in solution space at a speed influenced by their personal best position and the swarm's global best position [49]
Ant Colony Optimization (ACO)	The behavior of ants in finding the shortest path	Artificial ants gradually build solutions and leave behind virtual "pheromones"; better solutions receive stronger pheromones [50]
Artificial Bee Colony (ABC)	The foraging behavior of honeybees	Consists of worker bees (exploiting food sources), observer bees (selecting sources based on information), and scout bees (searching for new sources) [51]
Firefly Algorithm (FA)	The flashing and mutual attraction behavior of fireflies	The brightness of a firefly's light is related to the quality of the solution; less bright fireflies move toward brighter ones [52]
Cuckoo Search (CS)	The parasitic egg-laying strategy of cuckoos	Using Lévy's random walk to explore the solution space; poor eggs (solutions) are replaced by new ones [53]
Bat Algorithm (BA)	Bat echolocation in hunting	Bats adjust frequency, speed, and loudness as they approach a target (optimal solution) [54]
Whale Optimization Algorithm (WOA)	The hunting strategy of killer whales (bubble-net feeding)	Simulate circular and constricting movements toward prey (the best solution) using spiral and shrinking mechanisms [55]
Grey Wolf Optimizer (GWO)	The social hierarchy and hunting of gray wolves	Simulate the roles of alpha, beta, delta, and omega; individuals follow the three best leaders in the population [56]

**Table 4.** Example of physics-based metaheuristics

Algorithm	Inspiration Categories	Description of the Working Principle
Gravitational Search Algorithm (GSA)	Physics (Newton's Law of Gravitation)	Solutions are viewed as masses in solution space. Masses with better quality (higher fitness) have a stronger gravitational force and attract other masses [57]
Black Hole Algorithm (BHA)	Physics (Astrophysics)	The best solution acts as a "black hole." Other solutions move around it. If a solution enters the event horizon radius, it is "removed" [58]
Water Cycle Algorithm (WCA)	Natural Phenomena (Hydrology)	Mimics the natural water cycle: rivers flow to the sea [59]
Harmony Search (HS)	Art/Music (Improvisation)	Inspired by the process of musical improvisation [60]

**Table 5.** Example of human-based or social-inspired metaheuristics

Algorithm	Social/Human Inspiration	Description of How It Works
Teaching-Learning-Based Optimization (TLBO)	Teaching and Learning Processes in the Classroom	Consists of two phases: (1) "Teaching" phase – the best solution acts as a "teacher" that improves the population average (the "class"); (2) "Learning" phase – "students" (other solutions) exchange knowledge to improve themselves through peer comparison [61].
Imperialist Competitive Algorithm (ICA)	Colonialism and Imperial Expansion	The best solution becomes "imperialism," while other solutions become "colonies." Imperialisms compete to attract the best colonies, and weaker imperialisms are eliminated over time, mimicking geopolitical competition until only one dominant power remains [62].
Soccer League Competition (SLC)	Football League Competitions	The population is divided into "soccer teams." Teams compete in simulated matches; the winning team strengthens its formation (improves its solution), while the losing team reshuffles (explores new solutions). This process mimics the dynamics of promotion, relegation, and player transfers in a real league [63].

### 2.1.5. Hybrid Metaheuristics

Hybrid Metaheuristics is an optimization approach that combines two or more metaheuristic techniques, or integrates metaheuristics with other methods (such as exact algorithms, specialized heuristics, or machine learning) to leverage the strengths of each component. The goal is to improve solution quality, accelerate convergence, and maintain a balance between exploration (exploring the solution space broadly) and exploitation (improving existing solutions). The Hybrid Metaheuristics can be seen in [Table 6](#).

**Table 6.** Example of hybrid metaheuristics

Algorithm	Combined Components	Hybridization Objectives
Memetic Algorithm (MA)	Genetic Algorithm (GA) and Local Search (e.g., Hill Climbing).	Combine global exploration of GA with intensive exploitation of local search to accelerate convergence to high-quality solutions [64].
PSO-GA Hybrid	Particle Swarm Optimization (PSO) and Genetic Algorithm (GA).	Combine the convergence speed of PSO with the genetic diversity of GA to avoid local optima [65].
ACO-TS	Ant Colony Optimization (ACO) and Tabu Search (TS).	Improve ACO path solutions with intelligent local search of TS to avoid cycles and improve route quality [66].
Hybrid Simulated Annealing–Genetic Algorithm (SA-GA)	Simulated Annealing (SA) and Genetic Algorithm (GA).	Use SA to maintain the diversity of the GA population and help escape local optima during evolution [67].
DE-PSO	Differential Evolution (DE) and Particle Swarm Optimization (PSO).	Utilize the DE mutation operator to enhance exploration and the PSO speed mechanism to accelerate exploitation [68].
Hybrid GWO with Local Search (GWO-LS)	Grey Wolf Optimizer (GWO) and Local Search.	Strengthen the relatively weak exploitation capabilities of GWO with local search around the best solution [69].

### 2.2. Smartgrids

Smart Grids represent a fundamental evolution of traditional electricity systems into intelligent, dynamic, and responsive digital energy ecosystems. Unlike conventional electricity grids, which operate one-way from large generators to passive consumers. Smart Grids are designed as two-way systems that allow energy and information to flow reciprocally between electricity providers, consumers, and distributed energy sources. This concept emerged in response to several global challenges: increasing energy demand, the urgency of decarbonization, the uncertainty of fossil fuel supplies, and the need for more reliable, efficient, and adaptive systems in the digital era and energy transition. Technically, Smart Grids integrate information and communication technology (ICT) into all layers of the electricity system [70], [71], small wind turbines, home battery storage systems, and electric vehicles that can act as sources or loads; automation and control systems such as SCADA (Supervisory Control and Data Acquisition) and EMS (Energy Management Systems) that enable remote network monitoring and control; and Demand Response (DR) mechanisms that enable utilities to encourage consumers to reduce load during peak hours through dynamic tariff incentives [72]–[74]. The illustration of smartgrid can be seen in [Fig. 1](#).

The Smart Grid's self-healing capability is one of its most transformative qualities. In the event of a disruption, such as a storm, a fallen tree, or equipment malfunction, the system autonomously identifies the disruption's position, isolates the affected segment, and redirects electricity via alternative pathways without necessitating operator intervention. This significantly diminishes the duration and scope of power outages. Moreover, the Smart Grid may assimilate renewable energy sources extensively [75], [76]. Renewable energy presents issues to frequency and voltage stability due to its intermittent nature, as solar and wind resources are not consistently available. Smart Grids achieve this by facilitating real-time coordination among generators, loads, and energy storage technologies (such as grid-scale batteries or pumped hydro), thereby dynamically balancing supply and demand [73], [77]. The main sections and development opportunities of smart grid systems in detail can be seen in [Table 7](#). The system consists of three main parts: Generation and Transmission, which focuses on the integration of renewable energy and large-scale energy storage; Distribution,

which is enhanced by smart devices and edge computing for automation and grid strengthening; and Users and Management, which encourages active consumer involvement through Demand Response programs and innovations in electric vehicles (EVs) and personal energy storage solutions. These three parts work synergistically to optimize electricity flow, enable operators to respond to changes in real time, and facilitate the transition to a smarter and more environmentally friendly energy system.



Fig. 1. Illustration of Smartgrids

Table 7. Main sections and development opportunities of smart grid systems

Main Sections	Brief Description	Development Opportunities
Generation and Transmission	Electricity generation from conventional and renewable sources, transmission to the main grid	Broader integration of renewable energy sources, energy storage technology, smart grid development (smart transmission)
Distribution	Electricity delivery to end consumers, equipped with smart devices	Fortification of the distribution network, installation of edge computing, load regulation, and automation of distribution processes
Users and Management	Active interaction between users and the grid management center	Demand response, advanced consumption management, electric vehicle innovation, and compact personal storage solutions

Smart Grids provide consumers unparalleled empowerment. Users can utilize a mobile application or web portal to track their energy consumption in real time, schedule household appliances (such as air conditioners, washing machines, or electric vehicle chargers) to function during periods of lower electricity rates, and sell surplus electricity generated from their solar panels back to the grid (net metering) [78], [79]. This establishes a novel model: prosumer (producer and consumer), wherein consumers transition from passive roles to active players in the energy market. The advantages of Smart Grids are multifaceted. These solutions minimize energy losses in the grid, prolong asset lifespan via predictive maintenance, enhance billing precision, and facilitate improved capacity planning for utilities. Consumers benefit from cost reductions, enhanced control, and contributions to environmental sustainability [80]. For communities and governments, Smart Grids support national energy security, create jobs in the green technology sector, and achieve climate

targets such as net-zero emissions [81]. Table 8 illustrates the benefits of Smart Grid and the challenges in its implementation.

**Table 8.** Advantages and challenges of smart grid implementation across key aspects

Aspects	Advantages	Disadvantages
Energy Efficiency	Enables more efficient energy management with real-time usage monitoring	Initial implementation requires significant investment in infrastructure and technology
Energy Integration	Supports broad and balanced renewable energy integration	Challenges in maintaining grid stability due to fluctuations in renewable energy sources
Reliability	Improves supply reliability with early disruption detection and automatic recovery systems	Higher complexity in system management and maintenance compared to conventional grids
Consumer Participation	Enables active consumer participation through demand response and distributed energy	Requires significant education and changes in consumer behavior
Monitoring and Control	Enables automatic control and monitoring with real-time data	Cybersecurity risks and vulnerability to digital attacks
Flexibility	Can dynamically and quickly adjust demand and supply	Dependence on stable and fast communications technology and network infrastructure

This change presents obstacles. The initial investment expenses are considerable, encompassing the replacement of physical infrastructure, the deployment of millions of smart meters, and the construction of data centers. Cybersecurity is crucial as enhanced connectivity creates avenues for assaults that may compromise the national electrical grid. Interoperability among devices from diverse manufacturers necessitates universal standards. Moreover, legislative structures in numerous countries are unprepared to support emerging business models, including peer-to-peer energy transactions and the proactive involvement of prosumers. Data privacy is an issue, as smart meters might disclose users' lifestyle habits through electricity use trends [82].

The forthcoming Smart Grid will progressively incorporate microgrids, artificial intelligence for demand forecasting and anomaly identification, blockchain for decentralized energy transactions, and digital twins as virtual replicas of the physical grid for simulation and optimization purposes. The Smart Grid is not merely a technological enhancement, but the cornerstone of a future energy system that is decentralized, digital, democratic, and sustainable, serving as essential infrastructure for achieving a low-carbon civilization and energy security in the 21st century [83]. Advanced control strategies such as Model Predictive Control (MPC) and Adaptive Control are crucial for dynamic Smart Grid management, where they require fast and adaptive optimization solutions provided by Metaheuristics and AI. MPC functions by relying on a system model and performing iterative optimization at each time step to, for example, control the charging/discharging of Energy Storage Systems (ESS) or Demand Response (DR) units; here, Metaheuristics (such as Genetic Algorithms) play a crucial role by being used to tune the optimal parameters (such as prediction windows or cost function weights) of the MPC offline to address changing environments (e.g., renewable energy availability). Meanwhile, Adaptive Control is specifically required to maintain grid frequency and voltage stability due to the intermittent nature of renewable energy; this technique uses AI-based or Machine Learning (including Reinforcement Learning) algorithms to continuously identify system changes in real-time and adjust the control parameters of generators or ESSs, thereby enabling the system to adapt adaptively and maintain grid reliability.

### 3. Discussion

This article takes data from 2024 to 2025 with the keywords metaheuristic algorithm and smartgrid. The utilization of metaheuristic methods in Smart Grid has emerged as an essential strategy for tackling the complexity, dynamics, and extensive nature of contemporary energy networks. The Smart Grid, incorporating renewable energy sources, energy storage, demand responsiveness, electric vehicles, and bidirectional networks, poses complex optimization challenges that are non-linear, non-convex, multi-objective, stochastic, and high-dimensional, frequently rendering exact methods (such as linear or dynamic programming) inefficient for their resolution. In this context, metaheuristics

provide flexible, robust, and adaptive solutions to diverse operational and planning difficulties inside the Smart Grid. Metaheuristics address intricate issues in the Smart Grid, encompassing scheduling and fault detection, via intelligent and adaptable optimization techniques. Fig. 2 presents an illustration.



**Fig. 2.** . Key smart grid optimization applications enabled by metaheuristic algorithms

Table 9 summarizes key optimization challenges across eight Smart Grid applications. These include Unit Commitment's large discrete search space, DER integration's scalability and uncertainty, Demand Response's user-centric multi-objective trade-offs, and optimal DG/ESS placement involving mixed variables and local optima. OPF faces non-linear, complex constraints, while EV/V2G coordination must handle scalability and bidirectional power flow. Self-healing requires ultra-fast decisions amid dynamic topology changes. Overall, these applications demand advanced optimization methods to manage non-linearity, uncertainty, mixed-variable spaces, real-time dynamics, and large-scale complexity inherent in modern Smart Grids.

Table 10 summarizes the application of metaheuristic algorithms in various critical aspects of smart grids, demonstrating their effectiveness in addressing the complexities of modern power systems. In generating unit scheduling (Unit Commitment), algorithms such as GA and PSO, as well as their hybrid variants, have proven to provide accurate and efficient solutions despite the non-linear nature and mixture of discrete and continuous variables. For Distributed Energy Resources (DER) integration, the ChPSO algorithm successfully reduced power losses by over 92% in an IEEE-33 bus system. In demand response management, a Black Widow Optimization-based approach with dynamic price elasticity optimized costs and coordination between suppliers and consumers. Optimal placement of DGs and capacitor banks using the Energy Valley Optimizer proved superior to other recent metaheuristic algorithms, while supporting long-term sustainability. In hybrid energy storage system (HESS) management, PI controller tuning using GWO improved transient response and extended battery life. For optimal power flow (OPF), GA and HPSO+GA demonstrated stable performance without iterations, avoiding solution divergence. In the V2G context, the integration of AI and metaheuristics improves grid stability and user satisfaction. Finally, in fault detection, the IPSO-LSTM-CNN framework provides the highest diagnostic accuracy for diesel generators in an AIoT environment. Overall, these findings confirm that metaheuristics, often combined with AI, form

the backbone of intelligent optimization in smart grids, addressing technical, economic, and operational challenges holistically.

**Table 9.** Key optimization challenges in smart grid applications

No.	Smart Grid Applications	Key Issues	Challenges
1	Generating Unit Scheduling Optimization (Unit Commitment – UC)	Identify the generating units to activate or deactivate and their hourly output power to satisfy demand at the lowest cost, while adhering to technical constraints such as ramp rate and minimum up/down time.	Large, discrete (on/off), non-linear solution space.
2	DER Integration & Management	Manage numerous distributed energy resources, including solar, wind, and batteries, to maintain voltage and frequency stability.	Scalability, uncertainty, real-time dynamics.
3	Demand Response (DR) & Load Management	Minimize peak loads through consumption shifting, ensuring minimal inconvenience to users.	User preferences, dynamic tariffs, multi-objective.
4	Optimal DG & Capacitor Bank Placement & Sizing	Identify the optimal placement and sizing of distributed generation (solar) or capacitor banks to reduce power losses, enhance voltage profiles, and defer infrastructure investments.	Mixed variables (discrete and continuous), multiple local optima.
5	Energy Storage System (ESS) Management	Identify strategies for battery charging and discharging to optimize profits through price arbitrage, enhance frequency stability, or offer backup support.	Uncertain price/demand prediction, real-time decisions.
6	Optimal Power Flow (OPF)	Administer generators, utilize tap transformers, and operate shunt capacitors to reduce power expenses and adhere to electrical limitations (voltage, current, etc.).	Non-linear & non-differentiable objective functions, complex constraints.
7	EV & Vehicle-to-Grid (V2G) Charging	Coordinate numerous electric vehicles (EVs) to prevent grid overload during peak hours and employ EVs as backup sources through vehicle-to-grid (V2G) technology.	Scalability, user preferences, bidirectional network integration.
8	Fault Detection & Self-Healing	Identify fault locations and evaluate alternative grid configurations to restore the power supply.	Critical response speed, dynamic network topology.

Although metaheuristic methods offer flexible and efficient solutions to complex (non-linear, multi-objective, and high-dimensional) optimization problems in Smart Grids, such as those seen in Unit Commitment, Demand Response, and Optimal Power Flow applications, their main drawback is that they do not guarantee finding a globally optimal solution; they generally sacrifice solution certainty for computational speed and the ability to handle large search spaces. Other drawbacks include sensitivity to algorithm parameters (e.g., mutation rate in GAs or inertia weights in PSO), where poor tuning can lead to poor performance or premature convergence to a local optimum. Furthermore, comparing and validating the performance of different metaheuristic algorithms can be difficult due to their stochastic nature and dependence on initial conditions, requiring iterative testing and rigorous statistical metrics to ensure the reliability of the solutions found in the dynamic and real-time context of Smart Grids.

#### 4. Conclusions

This study provides a comprehensive review validating that metaheuristic optimization is a crucial strategic driver for transforming complex power systems into reliable and efficient Smart Grids, successfully addressing non-linear and multi-objective challenges across eight key domains, from Unit Commitment to EV/V2G coordination. This success is based on the ability of algorithms (especially hybrid methodologies) to find near-optimal and computationally feasible solutions for peak load reduction, power loss minimization, and stability enhancement. However, future research should focus on integrating Metaheuristics with AI (specifically Reinforcement Learning) to enable real-time adaptive decision-making and neural network optimization; real-time validation on HIL

platforms to measure latency and practical feasibility; development of robust methods capable of managing risk uncertainty (such as renewable energy volatility) in dynamic multi-criteria optimization; and applications in emerging areas such as cybersecurity and transactive energy markets.

**Table 10.** Summary of metaheuristic applications in smart grid: Key issues and research findings

Issue	Finding
Generating Unit Scheduling Optimization (Unit Commitment - UC)	The crucial role of metaheuristic algorithms in solving Dynamic Unit Commitment (DUC) problems in power systems is emphasized. Through a PRISMA-based systematic literature review, 14 relevant studies were analyzed from 487 candidates. The results show that algorithms such as Genetic Algorithm, Particle Swarm Optimization, and their hybrid variants are capable of providing accurate, efficient, and computationally feasible solutions despite the high complexity, non-linearity, and mixed discrete-continuous nature of DUC [84].
DER Integration & Management	ChPSO, a hybrid Chimp-Particle Swarm Optimization algorithm for optimal Distributed Energy Resource (DER) placement in distribution networks, is proposed. Tested on the IEEE-33 bus system, it minimizes power losses and voltage deviations. With three and four DERs, real power losses dropped by 92.20% and 92.90%, respectively, demonstrating ChPSO's effectiveness in enhancing grid efficiency and reliability [85].
Demand Response (DR) & Load Management	A stochastic day-ahead EMS integrating price-driven demand response programs with flexible elasticity for a grid-connected microgrid is proposed. Using Black Widow Optimization and 15-min renewable forecasts, it optimizes scheduling of DERs and selects the best DRP via multi-criteria decision-making, reducing costs and enhancing coordination between providers and consumers [86].
Optimal DG & Capacitor Bank Placement & Sizing	The Energy Valley Optimizer effectively minimizes losses, enhances voltage stability, and reduces costs over 24 years in Algeria's 157-bus network by optimally placing DG and capacitors. Outperforming Liver Cancer, Walrus, and Zebra algorithms, it improves technical, economic, and environmental outcomes, advancing sustainable and resilient distribution systems [87].
Energy Storage System (ESS) Management	A metaheuristic-optimized EMS using GA, ACO, and GWO tunes a PI controller for HESS with solar PV. GWO achieves the best performance enhancing efficiency, reliability, and lifespan in renewable microgrids, outperforming conventional energy management strategies [88].
Optimal Power Flow (OPF)	Genetic Algorithm (GA) and a hybrid Particle Swarm Optimization-Genetic Algorithm (HPSO+GA) are proposed to solve the Optimal Power Flow (OPF) problem in the Iraqi 400 kV transmission network, comprising 58 buses. The objective is to minimize total active power losses and fuel consumption while satisfying system constraints. Simulations conducted in MATLAB demonstrate that both methods effectively reduce generation costs and transmission losses compared to existing approaches. A key advantage is their non-iterative nature, eliminating issues of solution divergence and sensitivity to initial conditions. The results validate the viability and robustness of these metaheuristic techniques for real-world OPF applications, offering efficient, reliable, and computationally stable solutions for modern power system operation and planning [89].
EV & Vehicle-to-Grid (V2G) Charging	AI-based methods enhance V2G systems by increasing network stability, lowering costs, and enhancing user satisfaction. While facing challenges in scalability and dynamic adaptability, these intelligent approaches demonstrate transformative potential for efficient, resilient, and user-centric V2G integration in next-generation smart grids [90].
Fault Detection & Self-Healing	An IPSO-LSTM-CNN framework enhances diesel generator fault diagnosis in AIoT systems by combining LSTM-CNN for feature extraction and IPSO for hyperparameter tuning. It surpasses RNN, CNN, GRU, LSTM, and CNN-LSTM in accuracy and robustness, offering a reliable AI-driven solution for intelligent industrial maintenance and improved operational reliability [91].

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