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Review

A review on microgrid optimization with meta-heuristic techniques: Scopes, trends and recommendation

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ABSTRACT

Microgrids (MGs) use renewable sources to meet the growing demand for energy with increasing consumer needs and technological advancement. They operate independently as small-scale energy networks using distributed energy resources. However, the intermittent nature of renewable energy sources and poor power quality are essential operational problems that must be mitigated to improve the MG's performance. To address these challenges, researchers have introduced heuristic optimization mechanisms for MGs. However, local minima and the inability to find a global minimum in heuristic methods create errors in non-linear and nonconvex optimization, posing challenges in dealing with several operational aspects of MG such as energy management optimization, cost-effective dispatch, dependability, storage sizing, cyber-attack minimization, and grid integration. These challenges affect MG's performance by adding complexity to the management of storage capacity, cost minimization, reliability assurance, and balance of renewable sources, which accelerates the need for meta-heuristic optimization algorithms (MHOAs). This paper presents a state-of-the-art review of MHOAs and their role in improving the operational performance of MGs. Firstly, the fundamentals of MG optimization are discussed to explore the scopes, requisites, and opportunities of MHOAs in MG networks. Secondly, several MHOAs in the MG domain are described, and their recent trends in MG's techno-economic analysis, load forecasting, resiliency improvement, control operation, fault diagnosis, and energy management are summarized. The summary reveals that nearly 25% of the research in these areas utilizes the particle swarm optimization method, while the genetic and grey wolf algorithms are utilized by nearly 10% and 5% of the works studied in this paper, respectively, for optimizing the MG's performance. This result summarizes that MHOA presents a system-agnostic optimization approach, offering a new avenue for enhancing the effectiveness of future MGs. Finally, we highlight some challenges that emerge during the integration of MHOAs into MGs, potentially motivating researchers to conduct further studies in this area.

1. Introduction

The growing demand for energy over a wide scale signifies the need for more electricity generation and transmission. The conventional fuel-based power system demands a high cost in large-scaling electricity generation and affects the environment by increasing CO_2 emission [1]. However, renewable energy sources (RESs) like bio-gas, wind, water, solar, etc. have drawn significant attention in recent years because of their capability for producing safe, reliable and low-cost power with maximum satisfaction. The use of RESs in generating energy requires a revision of the conventional framework by enabling the source-load controller, energy storage systems (ESSs), electronic converter, load, and coupling point through which the utility grid exchanges power [2]. The revised new framework containing the interconnections among these devices can be regarded as "microgrid" [3]. A microgrid (MG) has two operational modes: grid-connected mode and islanded mode when disconnected from the power grid. In both modes, the MG is capable of producing, distributing, and controlling its own power. Particularly in places with expensive or unreliable grid power, it can

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provide resilient and stable power supply [4]. MGs also provide flexibility, cost savings, and energy security for homes [5], businesses [6], and communities [7], making them an attractive option for achieving sustainable energy goals [4].

1.1. Background study

The sustainable operation of an MG may hamper in terms of efficiency, reliability, and cost-effectiveness if it is not optimized in design [8], control [9], and management [10]. The goals of optimization are to reduce energy waste, lower costs, and guarantee reliable and efficient operation of the MG under diverse conditions. In the MG aspect, the introduction of optimization techniques has made it possible for the system to efficiently control and manage energy generation, storage, and consumption, while ensuring that supply meets demand, minimizing costs, and maximizing efficiency. The prime requirement for optimization is the efficient management of energy in the MG aspect. Through the optimization, the MG can learn how to schedule energy consumption, manage energy flow between different MG components, and choose the best combination of RESs, ESSs and Distributed Energy Resources (DERs) [10].

The management of DERs leads the MG to offer affordable energy solutions for consumers by reducing energy expenses and accelerating higher reliability and efficiency. MGs can also ensure sustainability in terms of energy pricing, energy storage, and demand response through the effective use of DERs. However, the integration of multiple DERs with MGs may cause scalability issues due to the lack of sophisticated control technology and careful planning [11]. Through the optimal planning of DERs, MGs may avoid routine maintenance and management that might be required in remote areas and contribute to driving dependable future power generation systems with lower utility and consumer prices. A popular model named Reference Electrification Model (REM) can be used for the optimal planning of DERs [12]. This model utilizes information on DERs design, cost, and modes of electrification for the MG optimization of recommended areas. More additional factors, including energy demand, the possibility for green energy, and grid infrastructure, can be considered in order to determine the best combination of DERs, energy storage devices, or grid connectivity for the optimal MG design. The REM can simulate the behavior of various DERs, including ESSs, PV, and wind turbines, and assess how they operate under various operating regions. There are more available models found in the literature for the optimal design of MGs, including HOMER (Hybrid Optimization Model for Electric Renewables) [13], MAED (Model for Analysis of Energy Demand) [14], PLEXOS Microgrid [15], DER-CAM (Distributed Energy Resources Customer Adoption Model) [16], OSeMOSYS (Open-Source Energy Modeling System) [17]. By providing insightful information about the optimal positioning and implementation of DERs in MGs, these models can aid in the promotion of the transition to a more robust and environment-friendly MG.

The stability and dependability of an MG greatly depend on the appropriate control of its components, including generators, inverters, and ESSs. The MG stability can be confirmed under various operating situations, and its efficiency against disturbances can be improved by the optimal design of control mechanisms. For modern power systems, optimization is also necessary to manage the interaction between grids and MGs, minimize costs by optimizing resource allocation and storage design, estimate load, and take environmental issues into account [18].

Several challenges arise when optimizing the performance of MGs, such as uncertainty, scalability, a lack of technical skill, and system complexity. The integration of numerous RESs, ESSs, and loads creates a complex framework, which makes optimization difficult. The complexity can also increase with the development of new technologies like blockchain [19], quantum computing [20], and digital twins [21]. Additionally, uncertainty arises due to RESs unavailability and energy demand volatility. Cost reduction and scalability should also be considered when designing and optimizing MGs. Technical expertise in the fields of electrical engineering, control systems, and computational sciences is necessary. To address these challenges and improve MG performance, transdisciplinary optimization methods may be required [10].

1.2. Literature review

Several strategies have been proposed to address the optimization challenges of MG systems while ensuring scalability, flexibility, redundancy, and component placement and layout. These strategies aim to improve various MG features through optimization, such as energy management [22], cost [23], fault diagnosis [24], ESSs [18], load forecasting [18], and control [25] of MG components to maintain voltage, current, and power. ESSs can be utilized to store extra energy and reduce the unpredictability associated with RESs. Accurate forecasting models and effective integration of RESs can increase energy generation, enabling MGs to function more effectively, reliably, and sustainably. These techniques offer promising solutions for providing reliable and affordable energy through MGs [26].

Linear programming [41], quadratic programming [42], and mixed-integer linear programming (MILP) [43] are the conventional optimization methods used in MG optimization. Due to the precision and effectiveness of these techniques, MG optimization has made extensive use of them. For instance, in [44], the energy management system of an MG, which includes RESs, energy storage, and load management, was optimized by using the MILP model. The outcomes demonstrated that the suggested model might lower MG's operating expenses. However, optimizing the operation of MGs can be challenging due to factors such as market pricing, weather conditions, and non-linear and non-convex optimization issues [45]. Conventional optimization techniques (COTs) such as gradient descent [46], Quasi-Newton [47], and Powell's method [48] may not be effective in solving these problems since they can get stuck in a local optimum and fail to find the global optimum.

Model Predictive Control (MPC) has become a viable strategy for improving the performance of MGs in recent years. Using this method, the MG system's performance can be optimized by resolving an optimization problem at each time step while taking into account the system's dynamic behavior and a number of constraints, including energy storage and RESs. The MPC technique has received extensive study in the literature, and several studies among them have shown that it is efficient in lowering operational costs, enhancing system dependability, and lowering greenhouse gas emissions. As an illustration, an MPC-based strategy for the effective energy management of an MG with RESs, energy storage, and electric vehicles was presented in [36]. The outcomes demonstrated that the suggested strategy could greatly lower MG's operating costs while keeping the system's reliability. Overall, the MPC technique shows very promising results for improving the performance of MGs, but further study is required to fully assess its potential in practical constraint settings.

Meta-heuristic optimization approaches (MHOAs) have emerged as a potential solution to these practical complex optimization constraints and other optimization challenges in the MG domain. MHOAs are general-purpose optimization techniques that do not make assumptions about the nature of the problem or its mathematical characteristics. They are inspired by natural phenomena such as swarm activity, genetic evolution, and different animal behaviors. MHOAs use random search, local search, and global search tools to explore the optimal solution over MG optimization issues [49]. A popular MHOA named particle swarm optimization (PSO) has already shown its efficacy in improving the MG performance by solving the control optimization problems [50], mitigating the cyberattack possibility [21], ensuring the cost-effective MG modeling [51], and effectively detecting the operational anomaly [52]. It is durability, rapid convergence speed, and simplicity enable this wide range of applications in the MG domain. Another widely used MHOA, named ant colony optimization (ACO) [53], has already been considered for MG energy management.

Table 1
Different review works on microgrids network and their main focuses.

References	Main focus
Ref. [27]	Hybrid renewable energy based MG optimization using graphical construction, probabilistic approach, iterative technique, artificial intelligence (AI), dynamic programming, and linear programming.
Ref. [28]	Discussed the optimized framework of MG operation.
Ref. [29]	Discussed optimization tools and several methods for the hybrid energy storage used in MGs.
Ref. [30]	Explained the features and issues of AC MGs with their control strategy.
Ref. [31]	Introduced conventional strategies of controlling electrical parameters of an MG.
Ref. [32]	Described advanced and traditional optimization techniques utilized in MG control applications.
Ref. [33]	Optimization techniques of power and energy management system in shipboard MGs.
Ref. [34]	Discussed the issues and optimization strategies for controlling a hybrid MG.
Ref. [35]	Overview of individual and community MGs in terms of control and optimization techniques.
Ref. [36]	Stability parameter control of MGs based on prediction techniques.
Ref. [37]	MG management solution based on problems and constrains.
Ref. [38]	Energy management methods of isolated MGs based on regular requisites.
Ref. [39]	Overview of economic optimization using MHOA PSO.
Ref. [40]	In-depth review on MG structures, challenges and requisites.
Current study	Discussed MG optimization scopes, requisites, and opportunities of MHOAs, and summarized their recent trends in the MG's techno-economic analysis, load forecasting, resiliency improvement, control operation, fault diagnosis, and energy management.

Here, it initially creates an optimization problem related to energy management and uses the pheromone matrix to store data on the caliber of the solutions. By planning the energy output, storage, and consumption, it can help the MG lower operational costs, reduce carbon emissions, and maximize the use of RESs. Motivated by these diverse scopes of MHOAs in the MG system, a brief overview of various MHOAs is provided in this paper, including simulated annealing [54], genetic algorithms [55], water drops [56], grey wolfs [57], and others. Here, we also summarize the recent trends of MHOAs in MG applications as well as their implementation challenges. To elucidate the knowledge gap of previous review work, a summary of comparisons between this study and other review works in the MG domain is provided in Table 1.

1.3. Aim and contributions

Designing an appropriate optimization technique is crucial to effectively demonstrate the optimum performance of MGs in terms of energy management, load and energy pricing forecasting, condition monitoring, resiliency over the cyber and environmental threat, anomaly analysis and control performance. However, COTs pose hindrances in efficiently operating and managing MGs as they use static models that cannot work on dynamic nature of MGs. Additionally, limitations such as centralized control, simple cost function, lack of flexibility and scalability, local minimum, and high computational time to solve complex problems may limit the use of COTs. To overcome these difficulties, researchers have developed a global minima-based optimization framework, called meta-heuristic optimization framework, that offers scalability and multi-objective cost functions. Inspired by the mentioned advantages of MHOAs, this paper aim of this paper is to present a brief review of meta-heuristic techniques, and their scopes and trends in the MG domain. However, to emphasize the recent trends of MHOAs and capture the highly significant tasks of MHOAs in multi-objective optimization for MGs, we selected articles based on the following criteria.

- Choose around top 200 highly cited MG optimization articles from 2017 to 2023.
- Select the works associated with MHOAs.
- Choose top-tier journals and conferences works with high-reputation.
- Check the retrieved information on the selected articles .

The main findings of this paper are as follows:

- ***Studying the fundamentals of MG optimization:*** In this paper, we discussed the technical framework of MGs and explored the fundamental needs of implementing optimization frameworks in the MG domain.
- ***Investigating the scope of MG optimization:*** We discussed the scopes of optimization in the MG framework and inspected the reasons for applying meta-heuristic techniques. Furthermore, we explained the opportunities of MHOAs in the MG domain.
- ***Summarizing the trends of MHOAs in MG optimization:*** A brief discussion about the several recently used MHOAs in MGs is given in this paper, as well as summarizing their recent trends in the MG framework in terms of techno-economic analysis, load forecasting, control operation, energy management, resiliency, and anomaly analysis.
- ***Exploring the challenges and future research directions:*** Like with other optimization techniques, implementing MHOAs in MGs can pose some potential challenges. In this work, we discussed these challenges and presented potential research directions in this field. We also highlighted some future scopes for MHOAs in MGs where researchers can work to improve their operation and sustainability.

This paper is beneficial for both engineering and research communities as it offers an in-depth study on MHOAs and their significance in optimizing MG operations. This is important because with the emergence of the state-of-the-art energy technologies, novel optimization challenges for MGs are sure to be appeared. To deal with such unknown challenges, this study not only offers an inveitable platform for researchers and engineers to understand these challenges but also provides a systematic way out. Moreover, the challenges highlighted in this paper regarding the implementation of MHOAs in MGs inspire further research on the development of new and more effective optimization techniques.

1.4. Organization

The rest of this paper is organized as follows. Section 2 describes the fundamental framework of MGs. This section also studies the scope and need for optimization for MGs. In Section 3, the fundamental discussion of several MHOAs and their benefits in terms of MG applications are thoroughly explored. A study on the recent trends of MHOAs is investigated with their implementation challenges in Section 4. Sections 5 and 6 contain a discussion on the degree of MHOAs in terms of the number of works found in the recent literature and some future recommendations that may work for the further development of MHOAs in the field of MGs. This work concludes in Section 7.

2. Microgrid optimization: Framework, requisites, and scopes

2.1. Microgrid framework

MGs represent localized sources of electricity that can operate directly with the centralized power grid, or in an islanded mode, enabling

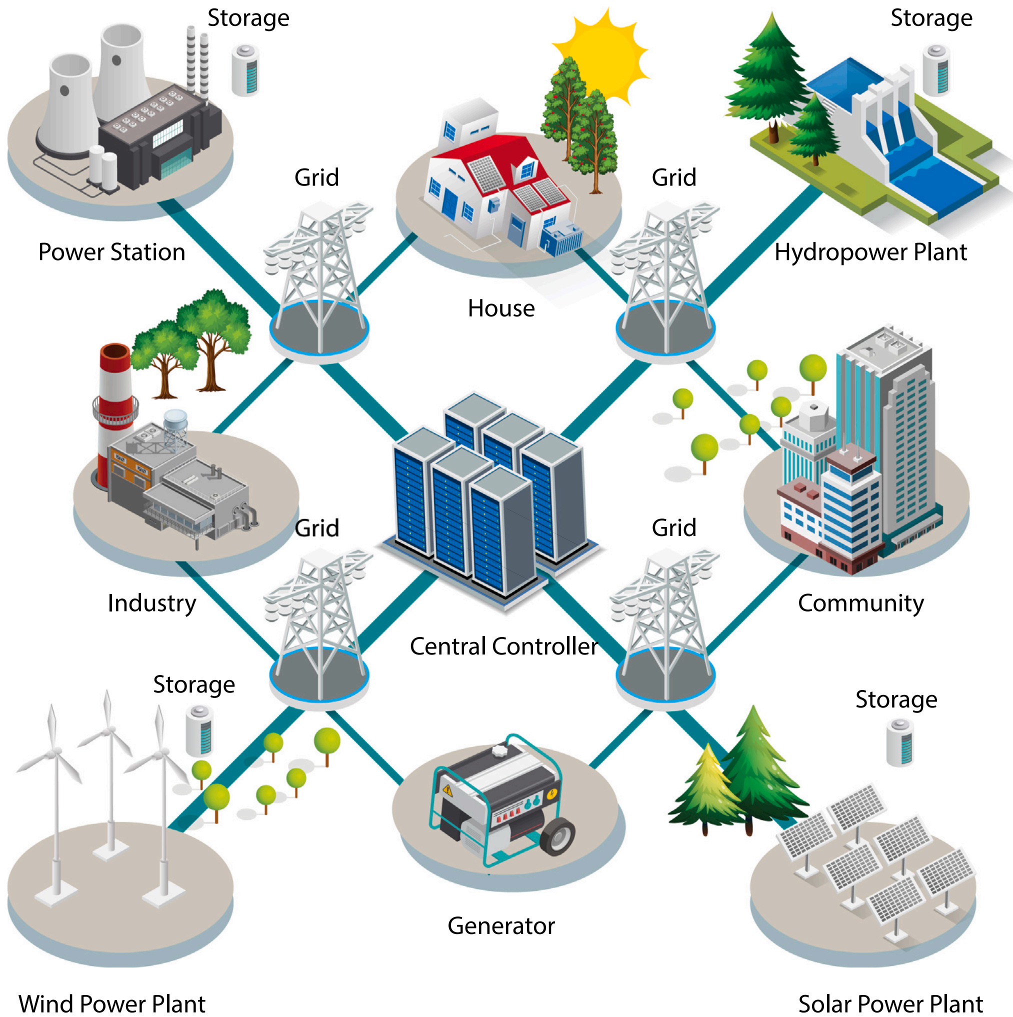

Fig. 1. A technical framework of microgrid system.

them to continue supplying power during unexpected events. With the current landscape of power generation changing, driven by the growing demand for affordable, green, and dependable electrical energy, the utilization of MGs has the potential to provide a creative, cost-effective, and environmentally responsible solution. MGs leverage the advantages to generate electricity and can address CO_2 challenges. To avoid significant investments in distribution and transmission lines to carry power to remote areas, the small-scale generation capability of MGs can be installed closer to consumers or in areas where there is no main grid accessibility. The essential components of MGs shown in Fig. 1, such as the MG central controller, source-load controller, RESs as the sources of input, and ESSs, perform their dedicated tasks for the effective operation of the grid system [1].

2.1.1. Power generation sources

This component of the MG system provides power for critical load operations, ensuring a continuous flow of power in the grid and contributing to a disturbance-free and efficient grid system. The source of input power for MGs comes from various RESs which are briefly described below.

(i) Wind turbine: The wind turbine harnesses the force of the air and requires less area to rotate compared to other types of turbines. It generates renewable electricity that can be supplied to the grid. The turbine is connected to a gearbox that amplifies the rotational speed generated by the turbine blades. This amplified rotational gear drives a generator which produces electricity. A step-up transformer is used to increase the voltage of the electricity, allowing it to be connected to the grid. In this system, the gearbox is used to amplify the rotational speed because the speed generated by the air on the blades is relatively low to drive a generator directly. Direct current generated by the turbine would also result in low-frequency electricity that is not useful [58].

(ii) Solar Cell: The solar cell is a widely used source of renewable energy that converts the sun's energy into electricity. It utilizes a p-type and an n-type semiconductor, with the p-type layer being thin and highly doped with phosphorous ions, while the n-type layer is thick and less doped with boron. When exposed to the sun, the p-type layer absorbs the energy and excites the electrons, which then move towards the n-type semiconductor, creating a direct current flow. Solar energy is considered a safe and cost-friendly alternative to other sources of energy, but it requires more space for generating electricity [58].

(iii) Hydro: Hydropower systems harness the potential and kinetic energy of water to produce renewable energy on a large scale. This is accomplished by using a turbine and generator to generate electricity. Water is stored in a reservoir or dam, where the potential energy of the water is used to rotate the turbines and generate electricity. Hydropower is not only a cost-effective and reliable source of energy but also contributes to flood control and preservation of natural environments nearby. It can be generated in the form of a dam or reservoir, by utilizing river water, or by harnessing the power of ocean waves [58].

2.1.2. Central controller

The central controller in an MG acts as a bridge between the medium-voltage (MV) and low-voltage (LV) sides of a grid. The LV side is primarily used by consumers, while the MV side is responsible for distributing electricity throughout the grid. The central controller connects all the components of the MG and issues commands to optimize the system's performance, making it both economically and technically efficient. In islanded mode, it is crucial for controlling secondary data and ensuring system effectiveness. Essentially functioning as a central processing unit, the MG central controller plays a vital role in controlling all aspects of the MG system [1].

2.1.3. Source-load controller

The source-load controller is a specialized controller designed to manage the load of storage devices based on an efficient cost function. Its primary purpose is to ensure that the electricity chain in the grid is maintained in accordance with the system's needs. The source-load controller can be classified into two types based on the load's condition: critical load and non-critical load controller. The critical load controller is used to maintain power to critical loads that require electricity in the absence of a primary source or when stored power is used to run the loads. On the other hand, the non-critical load controller is activated when the microgrid is functioning in its normal state and the power source is regulated by the controller [1].

2.1.4. Storage device

Storage devices are capable of collecting electrical energy for use as a backup power supply during times of low power production. They are particularly crucial as the primary power source for critical loads, providing an uninterrupted power supply to ensure smooth operation of system components. Various types of storage devices are available, which are discussed below:

(i) Battery: Batteries are a commonly used type of storage device that can store electrical energy in liquid and solid storage cells. Their charging and discharging modes enable them to store and supply electrical energy from and to the grid, respectively. Batteries come in various forms such as lithium polymer, alkaline, lead–acid, zinc-air, lithium-ion, carbon–zinc, and nickel-metal hydride. They stores energy in the form of ions and provide a steady current supply to the entire MG system in islanded or emergency mode [1].

(ii) Fly-wheel: A flywheel uses electrical actuators to rotate at a high speed, which allows it to store electrical energy from mechanical energy. The angular velocity of the rotating shaft is used to store energy in this system. A conventional flywheel typically consists of a bearing, a rotating shaft or wheel, and satisfies the equation of rotational energy of a rotating mass.

$$K = 1/2 * I * \omega^2$$

Here, K, I and ω represent the rotational energy, inertia and angular velocity, respectively. On the other hand, modern flywheels have magnetic bearings that reduce friction, allowing for more energy to be stored in the system.

(iii) Supercapacitor: A supercapacitor is a high-capacity capacitor that can store and release large amounts of energy quickly. It is designed to charge quickly and provide sustainable power to critical loads. The capacitor is composed of four parts: an aluminium-based current collector, an electrode made of carbon material, a potassium hydroxide sulphuric acid electrolyte solution, and a Kapton separator. The supercapacitor stores charge similarly to two parallel capacitors, also known as an electrical double-layer capacitor. The basic equation for the two parallel capacitors is represented by C_1 and C_2.

$$C_1 \propto \frac{A}{d}, C_2 \propto \frac{A}{d}$$

$$C = \frac{C_1 * C_2}{C_1 + C_2}$$

Here, C, A, and d represent the total capacitance, surface area of electrodes, and distance between the capacitor plates, respectively [1].

(iv) Fuel cell: Fuel cells have the potential to serve as a storage device in MGs by storing energy in the form of chemical energy. The atomic changes within the cell lead to the conversion of chemical energy to electrical energy, which powers the critical load. The fuel cell comprises of three components: negative anode, electrolyte, and positive cathode. Oxygen and hydrogen gases react within the system, generating heat and producing water and air as byproducts. As fuel cells produce zero carbon emissions and harmful byproducts, they are theoretically one of the best energy storage devices available [58].

These are the essential components used in all type of MGs. In Table 2, a detail classification of MGs in terms of source, scenario, and operation mode is described with their fundamental features.

2.2. Requisites for microgrid optimization

2.2.1. Energy security

To enhance energy security, it is important to optimize the operation of MGs in order to provide adequate backup power during outages or disruptions to the main grid. This optimization involves maximizing the use of available energy resources, backup generators, and batteries. By optimizing the operation of the MG, energy storage systems can be charged during periods of low demand and discharged during periods of high demand. During outages, it is essential to allocate energy resources effectively to ensure that energy is distributed efficiently and effectively. Demand response is another important aspect of energy security as it helps to manage energy demand during peak periods, reduce the strain on the MG and ensure that backup power is available to critical loads. Therefore, optimization is an essential tool for enhancing energy security by ensuring that backup power is available when needed, allocating energy resources effectively during outages or disruptions, managing energy demand, and allowing the MG to operate independently of the main grid [66].

2.2.2. Reliability enhancement

Optimization is crucial for enhancing the reliability of MG systems. This is because MGs are complex systems that operate under a variety of conditions, and failures can have significant consequences for energy supply and critical operations. Optimization can help to identify potential system failures before they occur, allowing for proactive maintenance and repairs. This can be achieved through advanced data analysis and modeling techniques, which enable optimization algorithms to identify weak points in the system and develop strategies to address them [67].

2.2.3. Cost reduction

By identifying and addressing inefficiencies in energy usage patterns and equipment operation, MGs can reduce their overall energy costs, increase their efficiency, and make better use of RESs. This can result in significant cost savings over time and ensure the long-term sustainability of MG systems. Optimization techniques include identifying and reducing energy waste, utilizing energy management systems to optimize energy usage patterns, and making better use of RESs. Additionally, optimization can help MGs make more informed decisions when it comes to equipment maintenance and replacement, which reduces the need for expensive emergency repairs, resulting in significant cost savings over time [68].

2.2.4. Customization

Optimization is critical in MG customization as it allows MGs to provide energy solutions that meet specific needs and requirements, while minimizing energy waste, reducing costs, and improving efficiency. By tailoring energy solutions to individual customers and industries, MGs can improve sustainability and comply with environmental and regulatory standards. By optimizing energy usage patterns and increasing the utilization of RESs, MGs reduce their environmental impact and contribute to global efforts to reduce carbon emissions. Finally, optimization in MG customization provides efficient, cost-effective, and sustainable energy solutions [69].

Table 2
Classification of microgrids in terms of source, scenario, and operating mode.

MG type	Features	Advantages
	Based on scenario	
Community MG [7]	1. Uses local renewable energy sources 2. Distribute power locally 3. Advanced control systems	1. Use energy more effectively 2. Increased community resilience 3. Less maintenance cost
Military MG [59]	1. DERs 2. Energy management software 3. Resiliency and redundancy 4. Cybersecurity 5. Remote monitoring and control	1. Cost reduction 2. Increase reliability and resilience
Commercial andIndustrial MG [60]	1. DERs 2. Energy management software 3. Cost savings 4. Resiliency and redundancy	1.Reduce production lost 2. Increase workforce capacity 3. Reduce cost
Residential MG [61]	1. DERs 2. Energy management software 3. Cost savings 4. Resiliency and redundancy 5. Sustainability	1. Reduce load-shading 2. Less transmission cost and losses
Virtual MG [62]	1. Aggregation of DERs 2. Energy management software 3. Cost savings 4. Resiliency and redundancy 5. Flexibility	1. No energy loss 2. Enhancing the stability and flexibility
Space MG [63]	1. Off-grid operation 2. Advanced energy storage systems 3. Miniaturization	1. Less weight 2. Minimize cost
	Based on source	
AC MG [64]	1. Produces AC power 2. Connects all sources and loads to an AC bus 3. Connects DC components to AC bus using converter	1. Generation in large quantities 2. Long-distance transmission
DC MG [64]	1. Produces DC power 2. Connects all components to DC bus	1. Single power conversion 2. Increased efficiency and stability 3. Decreased cost and size 4. Coupling of RESs with the utility grid is not synced
Hybrid MG [65]	1. Combination of AC and DC MG 2. Connects AC sources and loads to AC bus 3. Connects DC sources and loads to the DC bus 4. Includes configurations switching, parallel, and series	1. Ability to optimize generation units and loads 2. Absence of switching and interruptions 2. Improves power quality, local reliability 3. Lowers harmonics and voltage sag caused by feeder losses
	Based on operating mode	
On Grid/Gridconnected MG [4]	1. Main grid supplies electricity to load from the PCC 2. Excess power returns to the main grid through the PCC 3. Frequency control using phase-locked loop approach	1. Main grid regulates voltage and frequency 2. More power capacity
Off-grid/IslandedMG [4]	1. Main grid and microgrid are not connected 2. MG controls voltage and frequency	1. Increases transmission and distribution efficiency 2. Provides electricity to rural and other remote places

2.2.5. *Energy efficiency*

Optimization helps to improve energy efficiency by maximizing the use of RESs, minimizing energy waste, and reducing energy losses due to transmission and distribution. This includes optimizing the operation of distributed energy resources (DERs), managing the charging and discharging of ESSs, and balancing energy supply and demand. By improving energy efficiency, MG optimization helps to reduce energy consumption and lower costs [70].

2.2.6. *Sustainability promotion*

By implementing optimization techniques, MGs can reduce their reliance on fossil fuels and make maximum use of RESs. This can result in a significant reduction in greenhouse gas emissions and promote a more sustainable energy system. Additionally, optimization can help MGs increase their energy efficiency, which is essential for promoting energy conservation and reducing overall energy consumption. This is particularly important as the energy demands continue to grow, and we should find ways to meet these demands without compromising the environment [1].

2.2.7. *Grid stability*

Optimization is crucial for maintaining the stability of MGs by enabling efficient and effective management of their resources. By optimizing the use of DERs, MGs can maintain stable conditions even under variable load and generation changes. Optimization approaches improve grid stability by managing the flow of energy between the MG and the main grid. When an MG is connected to the main grid, it can provide or receive energy as needed, helping to stabilize the grid during periods of high demand or instability. The MG optimization also addresses some potential issues related to instability such as voltage fluctuations, frequency instability, and power quality problems. This is particularly important in areas with an unreliable or unstable grid, where optimized MGs can provide stable power and stabilize the energy system [4].

2.2.8. *Resilience enhancement*

Microgrid optimization promotes resilience by reducing the reliance on centralized power grids, which are vulnerable to outages, cyberattacks, and natural disasters. MGs can operate independently of the main grid, providing critical energy resources to communities during natural disasters such as hurricanes, earthquakes, or wildfires. By promoting resilience, MG optimization can help to ensure that energy is available even during times of the mentioned crisis [71].

2.2.9. Integration of energy technologies

Optimizing the operation of MGs provides a reliable way to integrate additional energy technologies, such as energy storage, electric vehicles, and demand response, into the energy system. By determining the optimum placement and use of these technologies, MGs can operate with the improved energy efficiency, reduced costs, and enhanced reliability. For example, ESSs can be optimized to store excess energy during periods of low demand and discharge energy during periods of high demand, thereby reducing the need for energy from the main grid [8].

2.3. Optimization scopes/problems in microgrid

The process of achieving optimal operations in terms of economic, environmental, and reliability is typically referred to as MG optimization. The areas of optimization include the integration of renewable energy, improvement of energy storage, islanding of MGs, resilience and security, control of voltage and frequency, improvement of energy efficiency, real-time control and monitoring, cost reduction, and interconnection with other MGs. To achieve these goals, various optimization approaches such as simulation, machine learning, and mathematical modeling can be applied. By optimizing MGs, it is possible to develop highly efficient and reliable energy systems to address the increasing need for clean and sustainable energy.

2.3.1. Energy management

Energy management optimization requires determining the most effective way to dispatch energy from multiple sources to meet the energy needs of the MG. To do this, it is necessary to forecast energy demand and the availability of different energy sources, and then optimize their dispatch to minimize the overall system cost [72]. Optimization methods such as mixed-integer programming, linear programming, and quadratic programming can be used to find the best solution.

2.3.2. Resource allocation

Optimizing resource allocation for MGs includes optimizing the allocation of energy sources, ESSs, loads, and resource sharing. This optimization process may take into account variables including accessibility, expense, effectiveness, energy demand and supply. The primary objective of energy source optimization is to choose the best site for sources to minimize implementation costs. On the other hand, energy storage optimization aims to achieve a balance between energy demand and supply, reduce dependence on expensive energy sources, and minimize the carbon footprint by selecting the optimal size, type, and location of the ESS. Additionally, the best distribution of resources can be determined by resource sharing optimization [73].

2.3.3. Load management

Load management optimization in MGs may be crucial for guaranteeing the system's effectiveness while avoiding energy waste and bringing down total energy expenditures. The goal of load management optimization is to allocate loads within the MG as efficiently as possible, taking into account variables like energy consumption, priority, and availability. By evenly distributing electricity inside the MG, it first ensures energy efficiency. This may happen due to maintaining a balance between energy supply and demand. Furthermore, optimizing load management can help MG operators save significant amounts of money by limiting energy use during peak hours. Finally, load management optimization ensures that the MG can handle abrupt changes in energy demand or supply without disruption by balancing energy demand and supply [4].

2.3.4. Voltage and frequency control

The system's safe, dependable, and effective functioning may depend on the optimization of the voltage and frequency regulation in MGs. This aspect of optimization in MGs can prevent equipment damage, power outages, and safety risks while also minimizing energy losses and achieving optimum efficiency by maintaining voltage and frequency within a defined range. The integration of RESs, which might be intermittent and produce voltage and frequency fluctuations, is made possible by optimizing voltage and frequency. The MG can withstand variations in intermittent energy generation without disturbances by stabilizing it through optimization. Furthermore, optimizing voltage and frequency control can assist MG operators in lowering their overall energy expenditures by reducing energy waste and increasing the use of RESs. This can be crucial in isolated locations with limited access to conventional energy sources and high energy prices [74].

2.3.5. MG resilience and security

By facilitating effective energy management and lowering sensitivity to power outages, optimization is essential to maintaining the resilience and security of MGs. Optimizing the allocation of resources can help the system continue to run during disturbances such as natural catastrophes or cyberattacks. Moreover, optimization can aid in identifying the system's weaknesses and potential threats so that preventative actions can be taken to address them. Therefore, optimization can be crucial to maintaining the security and resilience of MGs and enabling them to deliver dependable, high-quality energy to consumers [66].

2.3.6. Energy market participation

The MG operators may be able to effectively participate in the energy markets and reap financial rewards by optimizing MG operation. MG operators can optimize the allocation of resources such as energy storage, demand response, and renewable energy integration to participate in demand response programs, provide ancillary services to the grid, and trade energy in energy markets. They can also engage in energy storage markets and offer energy services like frequency management and peak shaving by managing energy storage installations. Moreover, optimization makes the MG capable of integrating RESs like solar and wind by guaranteeing that it can manage variations in energy supply and demand. Additionally, they can further increase revenue, lower energy expenses, and enhance the environment by engaging in energy markets through the optimization. Therefore, optimizing MG operation can offer financial rewards, preserve grid stability, and guarantee the system's dependable and effective functioning in the energy markets [70].

2.3.7. Fault detection and isolation

Fault detection and isolation optimization in MGs is crucial in ensuring uninterrupted power supply to linked loads and reducing downtime. This optimization seeks to locate and isolate faults within the MG, by detecting errors in the system and using methods like fault isolation and reconfiguration to ensure that the system continues to operate even when an error occurs [75].

2.3.8. Energy storage optimization

ESSs are often integrated into MGs to help balance the supply and demand for energy. To enhance the efficiency of ESSs within the MGs, optimization can be performed to determine their best size and placement. This entails considering factors such as the demand for and supply of energy, the cost of energy storage, and the effectiveness of the ESSs [8].

2.3.9. Microgrid islanding

When there is a grid outage, the MG can function independently of the main grid. This is known as MG islanding. When an islanding event occurs, the MG is capable of producing and distributing electricity to meet the energy needs of local loads without assistance from the main grid. Operators can prevent blackouts, brownouts, and other power quality concerns that could affect the MG's reliability by optimizing the MG's performance during islanding occurrences. If the MG is optimized during islanding events, it may also be possible to predict required energy sources to function in the islanded mode for a prolonged amount of time. To maximize the uptime of key loads, this entails choosing the best resource allocation and load-shedding tactics [76].

2.3.10. Cost optimization

Cost optimization aims to reduce the overall cost of running and maintaining the MG system by finding cost-effective energy sources and managing their dispatch, to meet local energy demands. To achieve maximum economic efficiency, cost optimization entails the management and allocation of resources, including energy storage, generation, and load management. The operators can reduce energy expenditures, increase system energy efficiency, and mitigate the impact of energy price variations on the MG by optimizing the distribution of resources. Cost optimization also helps MG operators to assess the viability of various energy sources, technologies, and business models and determine the most affordable solutions for the MG. This also enables MG operators to determine the most cost-effective solutions for the MG system by assessing the economic viability of various energy sources, technologies, and methods. Some common methods for cost optimization in MGs include economic dispatch and cost–benefit analysis [23].

2.3.11. Microgrids interconnection

By interconnecting multiple MGs, it is possible to create a larger energy system that allows the MG operators to interchange energy, share resources, and leverage the advantages of coordinated operation. This can open up new opportunities for optimization that involves maximizing energy transfer between several MGs for dependable and effective operation. To achieve this goal, strategies like virtual power plants and energy management systems can be applied [77].

2.4. Critical steps for MG optimization in real-time practices

The DERs can use a variety of RESs and technologies, including control mechanisms, inverters, and other elements, for integrating with the MGs, which creates a lot of optimization scopes. The following procedures outline what DER operators can consider when connecting MG scopes with MHOAs in practice [78].

2.4.1. Clarify the MG's scope

First, DERs need to establish a clear definition of the MG's scope by precisely locating it and determining its resource availability within the surrounding community and area. This information will serve as a basis for real-time optimization practices.

2.4.2. Determine the goals

The next step is to determine the goals of the MG, including reducing energy expenditures and ensuring a dependable power source that lowers carbon emissions. These goals will guide the optimization approach.

2.4.3. Collect information

The DER operators must gather information on the performance of the MG. It is necessary to include information on energy generation, storage, and consumption. This information will be incorporated into the optimization process. It should also guarantee that the MG should work at its most effective level.

2.4.4. Select optimization algorithms

Based on the objectives and information gathered, the DER operators can use MHOAs to develop optimization algorithms. The MG will operate as effectively as possible through these algorithms. Efficiency can be achieved by taking into account factors like resource availability, weather, and energy use.

2.4.5. Build testing and evaluating platform

The selected optimization technique can then be put to use in a simulation environment. DER operators can test different scenarios to confirm that the algorithms are operating as intended. Several models like HOMER, DERCAM, MAED, OSeMOSYS, and PLEXOS MG can be used for this purpose.

2.4.6. Track the operation and correction

After putting the optimization algorithms into practice in the real MG, DER operators need to monitor and modify the MG and MHOA as necessary. By doing this, the MG will be able to retain its optimum degree of efficiency and accomplish its objectives.

These actions can be taken by DER operators to successfully link MG scopes with MHOAs and improve the performance of MGs. This can lessen the economic cost and adverse environmental effects of the MG operation while simultaneously ensuring a reliable and durable power supply for communities.

3. Optimization methods: Meta-heuristic techniques and opportunities

Meta-heuristic algorithms are powerful search techniques designed to find the best answers for the difficult and complex optimization problems. Finding a near-optimal solution based on inadequate or incomplete information in the real world of limited resources, computational power, and time is vital. Meta-heuristics expertly direct search strategies and require highly effective exploration of search spaces to achieve solutions that are as close to ideal as possible. The methods used by meta-heuristic algorithms range from simple local search techniques to highly intricate learning procedures, all of which are non-deterministic and approximate in nature. Therefore, meta-heuristics are regarded as widely applicable and versatile approaches to problem-solving.

3.1. Opportunities for meta-heuristic techniques

Meta-heuristic optimization algorithms (MHOAs) are frequently better suited than other optimization techniques for addressing complex and dynamic optimization problems, as they can efficiently explore the solution space and avoid getting stuck in local optima. Unlike traditional optimization techniques, metaheuristic algorithms do not mandate a mathematical model of the problem, making them suitable for a broad spectrum of problems without requiring expert knowledge of the problem domain. There are several reasons why MHOAs have become popular, which we will explore in the following sections.

3.1.1. Hybridization

Hybridization aims to leverage the positive perspectives of every algorithm while minimizing any significant negative aspects. The results of hybridization can typically improve computational precision or efficiency. Meta-heuristic hybridization integrates a meta-heuristic with other optimization techniques, including mathematical programming, constrained programming, and machine learning, allowing for the concurrent operation of both components, which communicate with each other to aid in the search. The practical usefulness of numerous hybrid meta-heuristic algorithms in business and science has led to their creation to address a wide range of optimization problems [79].

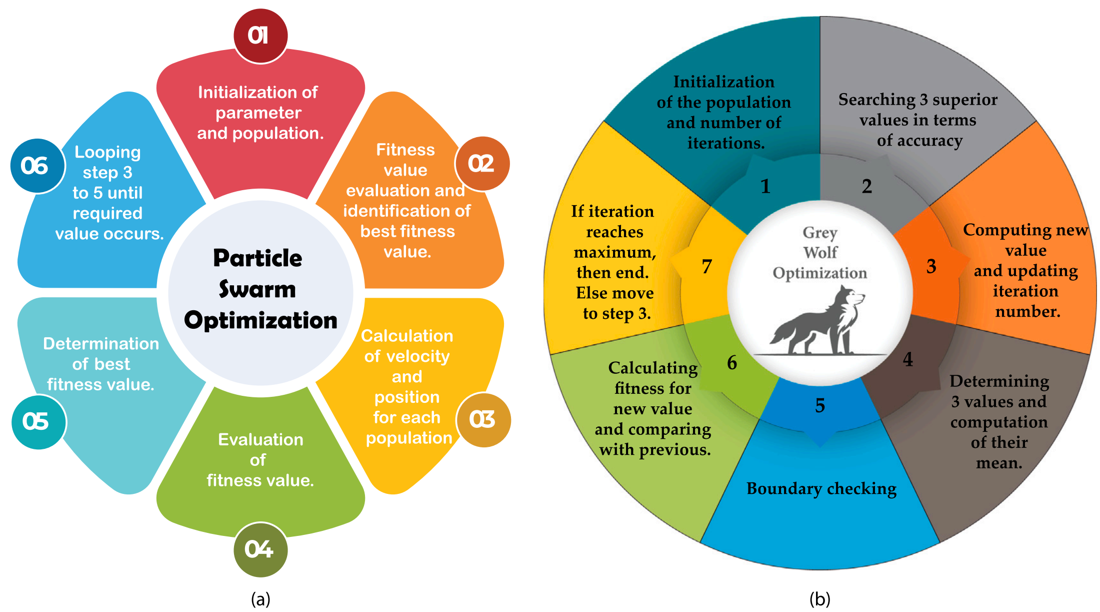

Fig. 2. (a) Particle Swarm optimization (b) Grey Wolf optimization.

3.1.2. Parallelizability

The parallelizability of meta-heuristic optimization methods is a fundamental benefit that enables the search process to be divided and solved simultaneously using multiple processors or computer nodes. This makes them scalable for large-scale optimization problems for real-world applications and significantly reduces the computation time required for optimization. The search process can be sped up using a variety of parallelization techniques, including multi-core processors, clusters, and GPUs. These parallelization techniques also make it possible to apply hybrid meta-heuristic algorithms, which combine the advantages of multiple optimization techniques [72].

3.1.3. Efficiency

The performance of a randomized MHOA can be evaluated based on its efficiency and effectiveness. Effectiveness is influenced by various factors such as stability, processing, and efficiency in generating precise solutions. It is a crucial measure for both continuous and discrete time-interval optimization issues, regardless of the number of objectives involved. Compared to their deterministic counterparts, meta-heuristic algorithms have been proven to be effective in solving a variety of problems. They possess a high level of robustness and can handle a variety of problems with ease. This resilience can be regarded as the key strengths of MHOA [80].

3.1.4. Multiple search techniques

Multiple search techniques can be used by MHOAs to quickly sift through the search space and identify the best answers. These techniques imitate the behavior of natural systems like swarm intelligence, evolutionary processes, and simulated annealing. The combination of these techniques enables meta-heuristic algorithms to efficiently search the solution space and avoid becoming stuck in local optima. Additionally, employing a variety of search techniques enhances the algorithm's robustness and permits a deeper study of the solution space. Therefore, the integration of several search strategies can be a key feature of meta-heuristic optimization algorithms, enabling them to successfully handle challenging optimization problems [54].

3.1.5. Adaptability

The adaptability of MHOAs is a critical characteristic that permits them to modify their search strategies and parameters to respond to changes in the problem environment or constraints. By adapting to the specific problem at hand, MHOAs can persistently search for optimal solutions even in the face of unexpected challenges or variations in the problem landscape. This adaptability is often achieved through the use of adaptive or self-adaptive strategies, which enable the algorithm to adjust its behavior based on feedback from the search process. Therefore, the adaptability of MHOA optimization is a vital capability, enabling them to handle complex and dynamic optimization problems effectively [81].

3.1.6. Constraints optimization

MHOAs excel in handling complex problems that involve multiple constraints. They are capable of optimizing problems with equality and inequality constraints, non-linear constraints, and non-convex constraints, which makes them highly versatile for real-world optimization problems. By efficiently exploring the search space, MHOAs can find optimal solutions even in the presence of intricate constraints. Thus, MHOAs are valuable tools for tackling challenging optimization problems that involve a variety of constraints [82].

3.1.7. Less computational complexity

The computational complexity of MHOAs is a critical factor that enables them to solve complex optimization problems within a reasonable timeframe. By ensuring less computational complexity in exploring the solution space, these algorithms can quickly identify high-quality solutions and avoid getting trapped in local optima. Moreover, their ability to handle multiple search strategies and adapt to changing problem landscapes enhances their less computational complexity and robustness. The benefits of less computational complexity extend beyond faster computation times, as it also enables the optimization of larger and more complex problems that would otherwise be impractical to solve with traditional optimization techniques [25].

3.1.8. Global optimization

Global optimization is a critical feature of MHOAs, enabling them to find the best solution in the entire search space, rather than just locally. Through the use of multiple search strategies and adaptive techniques, these algorithms can explore the solution space in a more comprehensive and efficient manner. Global optimization is especially relevant for complex optimization problems with large search spaces, where finding the optimal solution may be challenging. Meta-heuristic optimization algorithms have demonstrated their effectiveness in global optimization tasks like function optimization, parameter estimation, and feature selection [83].

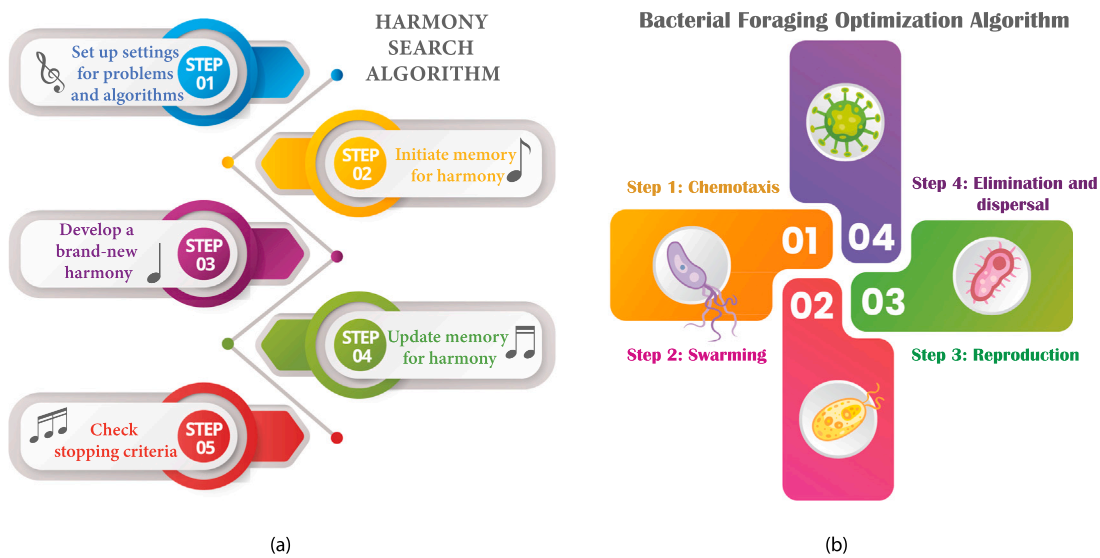

Fig. 3. (a) Harmony Search optimization (b) Bacterial Foraging optimization.

3.1.9. User-intelligibility

MHOAs are designed to be accessible to non-experts, with a range of software packages and libraries available that offer user-intelligible interfaces and documentation. These algorithms do not require a deep understanding of the problem domain or mathematical modeling, making them more accessible to a wider range of users. However, some knowledge of the algorithm and its parameters is still necessary to achieve optimal results. The user-intelligibility of MHOAs makes them a popular choice for solving complex optimization problems, even for users with limited expertise in optimization [72].

3.2. Meta-heuristic optimization methods

Algorithms known as meta-heuristic optimization methods employ heuristic search techniques to identify the best solution to a given problem. When the problem space is too big or intricate for conventional optimization techniques, meta-heuristics are frequently applied. Meta-heuristic algorithms built on the idea of swarm intelligence and evolutionary algorithms. The following part discusses the basic principle of some MHOAs.

3.2.1. Particle swarm optimization

One MHOA used to optimize MGs issues is Particle Swarm Optimization (PSO), which iteratively improves solutions. It is based on the flocking behavior of birds in search of food, which exhibits social behavior. Due to its distinctive searching mechanism, straightforward idea, computational efficiency, and simplicity of implementation, PSO has been widely applied in many engineering optimization areas. It can also be used to solve a variety of optimization issues in MGs, including energy storage, voltage profiles, line loads, power loss reductions, economic dispatch, and optimal power flows [52]. The steps of designing PSO techniques are reported in Fig. 2(a).

3.2.2. Grey-wolf optimizer

Grey Wolf Optimizer (GWO) is based on the social structure and hunting methods of grey wolves in the wild. The pack's hierarchy comprises four subtypes of wolves: alpha, beta, delta, and omega. The Alpha wolf leads and oversees the pack, with the Beta wolf assisting. The Delta wolf manages feeding the entire pack and takes on dangerous situations. The Omega wolf takes the frontline position in hunting and protects the pack, holding the lowest rank in the pack's hierarchy [84]. The following are the hunting steps:

1. Target searching.
2. Tracing, following and attacking the target.
3. Committing the attack.
4. Performing the action.

This method has been implemented in MG optimization problems, such as optimal power dispatch, optimal sizing and placement of DGs, and energy management. The steps of the algorithm can be illustrated in Fig. 2(b).

3.2.3. Harmony search optimization

Harmony Search optimization (HSO) is an evolutionary algorithm based on music. The harmonic perfection of music is served as the inspiration for this algorithm. Finding harmony in music entails choosing the right set of notes, just like looking for the optimal answer during the optimization process. The algorithm aims to achieve auditory aesthetic standards as the benchmark for the ideal harmony. Although it is a relatively new metaheuristic algorithm, its benefits and efficiency have been shown in various applications of MGs, including optimal DER sizing and location, energy source dispatch and scheduling, and DER coordination [85]. The five steps involved in this meta-heuristic method are shown in Fig. 3(a).

3.2.4. Bacterial foraging optimization

The Bacterial Foraging optimization (BFO) algorithm is a physiologically motivated MHOA that mimics bacteria's foraging activity to reduce energy consumption while searching for nutrients [86]. As a young conceptualization, it has gained a lot of interest from researchers. Chemotaxis, reproduction, and elimination-dispersal are the three main mechanisms used this numerical optimization to address the optimization problems. BFO has proven interesting applications in modeling the voltage control, MG optimization management, ESSs, and energy optimization in MGs. Additionally, it has shown to be a useful tool for non-convex optimization problems involving numerous variables. The steps for this bio-inspired algorithm are given in Fig. 3(b).

3.2.5. Differential evolution optimization

Differential Evolution (DE) is a potent population-based MHOA that iteratively enhances a specific solution to an optimization problem by using an evolutionary process. Population size, mutation scaling factor, and crossover rate are the prime control parameters for DE. It optimizes a problem through maintaining the population of potential solutions and creating new ones by merging existing ones using straightforward

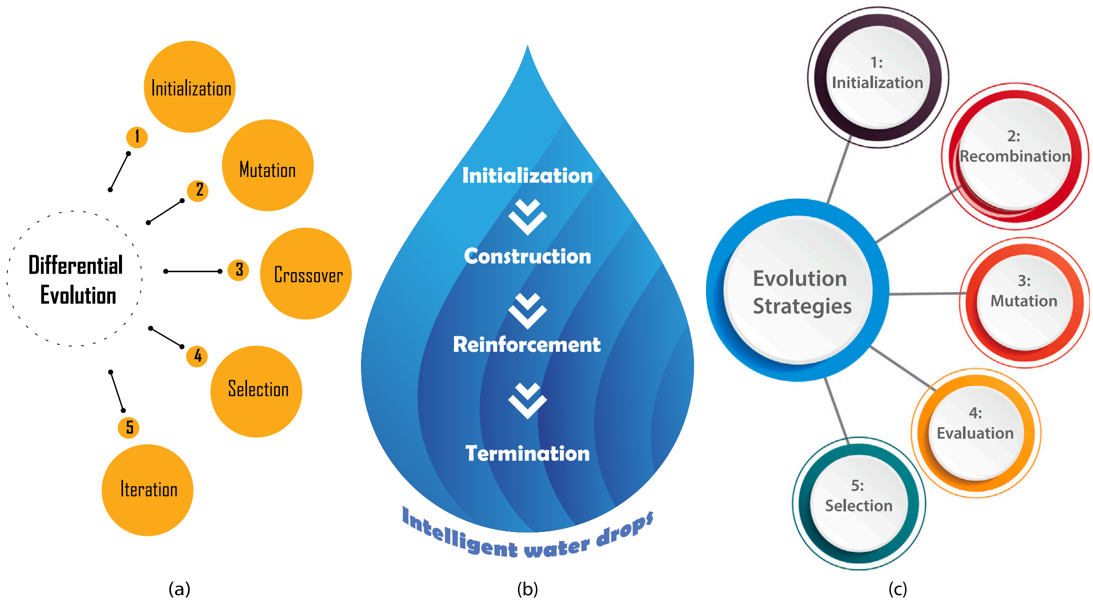

Fig. 4. (a) Differential evolution (b) Intelligent Water Drops optimization (c) Evolution strategies.

formulae. The best solution is kept for further optimization, and the selection technique is based on the fitness of that solution. DE can be used to optimize a variety of MG-related factors, including energy generation, load demand, energy storage, and grid connection [26]. The gradient is thus unnecessary because the objective functions are treated as black boxes that merely provides a measure of quality given an optimal solution according to the process of Fig. 4(a).

3.2.6. Intelligent water drops optimization

Shah-Hosseini recently developed a new MHOA named intelligent water drops (IWD) technique [87]. It is built on a river-like flowing system where the two primary elements are the present: velocity (IWD velocity) and the amount of dirt currently carried (IWD soil). This approach can be used to resolve maximizing or minimization issues in a variety of applications, including Internet of Things (IoT)-based MGs, optimal placement and sizing of RESs, smart MG optimization, and MG energy management. In Fig. 4(b), the designed steps for IWD technique is illustrated.

3.2.7. Evolution strategies

The ideas of adaptation and evolution by natural selection serve as the foundation for the family of Evolution Strategies (ES) optimization algorithms. It acts at the macro-level, concentrating on genomes, chromosomes, genes, and alleles. The use of self-adaptive mechanisms to regulate the application of mutation is one of the main characteristics of ES. These mechanisms seek to advance the search by not only evolving the solutions to the problem at hand but also some parameters for mutating these solutions. This can be used for a variety of MG optimization studies, such as maximizing DER utilization, improving power dispatch, and reducing overall MG energy costs [88]. The steps shown in Fig. 4(c) can be used to design this algorithm.

3.2.8. Genetic algorithm

The principles of heredity and population genetics are the foundations of bio-inspired metaheuristic Genetic algorithm (GA). The system depicts possible solutions as chromosomes and employs genetic operators like mutation and crossover to help the solutions change and get better over time. It is frequently used in machine learning for applications such as optimization, mapping, control, and others. The reduction of power loss in electrical grid networks is one such application of GA. In these scenarios, the number of appliances in the system is represented by the binary-coded chromosomal length [55]. It follows a certain set of steps for the design purpose illustrated in Fig. 5(a).

3.2.9. Fish swarm optimization

A population-based optimization algorithm that takes cues from fish's natural behavior is called the Fish Swarm Optimization (FSO). This metaheuristic algorithm simulates the three primary social behaviors of fish: foraging for food, swarming to defend against surprise attacks, and following others to increase the likelihood of a specific outcome. FSO has been successfully applied to various computational issues in engineering systems, including engineering design, feed-forward neural networks, parameter estimation, function optimization, and combinatorial optimization [89]. This bio-inspired algorithm follows the steps outlined in Fig. 5(b).

3.2.10. Artificial bee colony algorithm

The Artificial Bee Colony algorithm (ABC), based on the swarm intelligence algorithm, was proposed by Karaboga in 2005. It is based on a meta-heuristic technique that replicates the foraging activities of honey bees in search for food sources. The algorithm divides the bees into three groups: workers, observers, and scouts. Forager bees, also known as the employed bees, scout out each food source, and the observer bees select the food location using the data supplied by the employed bees. Next, scout bees look for unplanned food sources. A group of optimization parameters that correspond to the location of the food supply make up the search space for each solution. This population-based algorithm has been applied to manage and maintain the functions of MGs, control MG energy cost, and load frequency [90]. The phases of this algorithm are illustrated in Fig. 6(a).

3.2.11. Paddy field algorithm

The Paddy Field algorithm (PFA) is a revolutionary algorithm that is structured based on the reproductive principles of plant populations and their proximity to urban populations and multilateral solutions. This algorithm does not use coupled behavior or individual crossover, in contrast to evolutionary algorithms. Instead, it concentrates on the ideas of pollination and spread. Many optimization issues, including clustering, routing, and scheduling of MGs, can be solved using the technique. PFA consists of five fundamental steps shown in Fig. 6(b).

3.2.12. Whale optimization algorithm

The Whale optimization algorithm (WOA) is a MHOA inspired by hunting behavior of humpback whales, the largest mammal on Earth. The algorithm imitates the whale's process of finding and catching

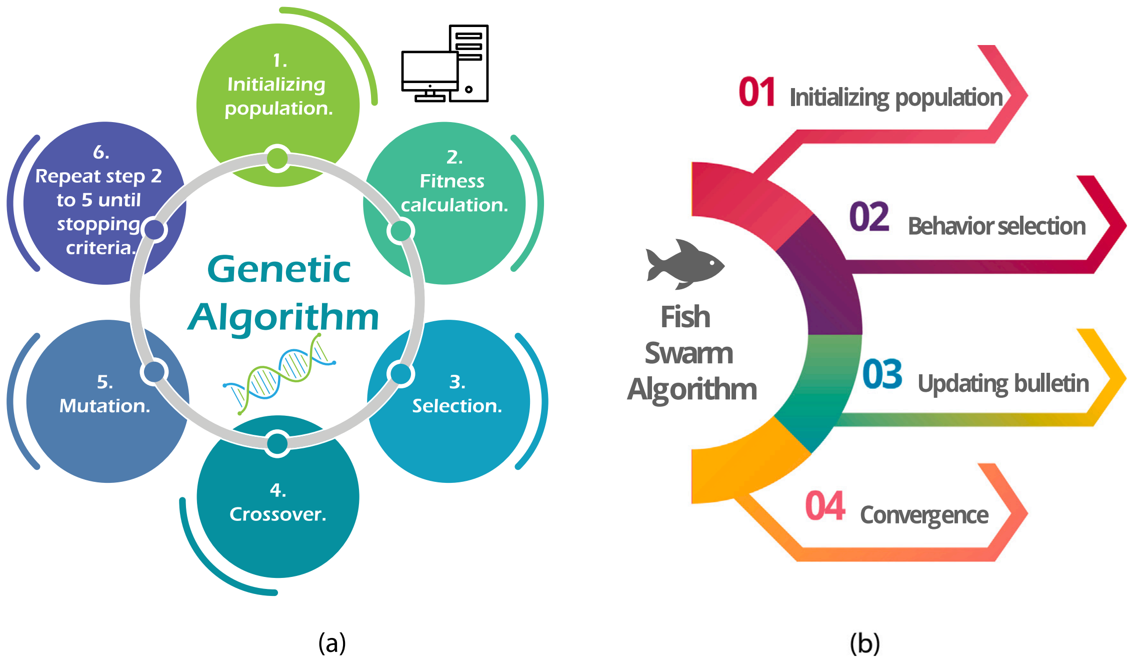

Fig. 5. (a) Genetic Algorithm (b) Fish Swarm Algorithm.

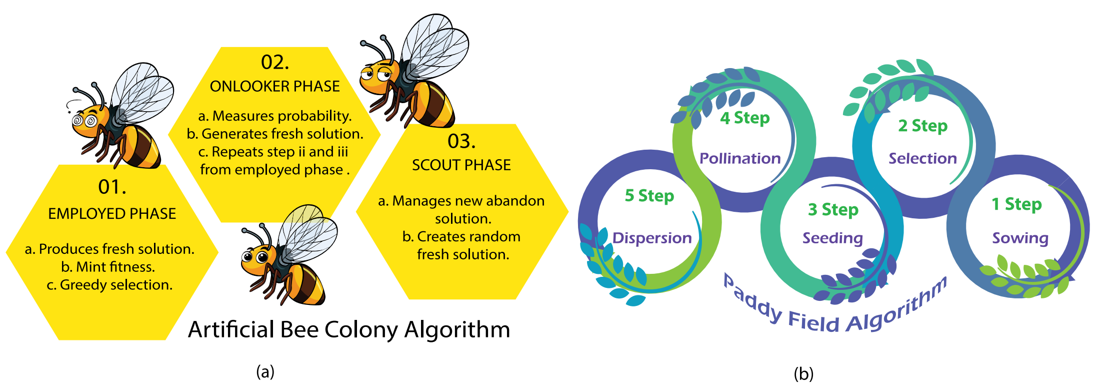

Fig. 6. (a) Artificial Bee Colony Algorithm (b) Paddy Field Algorithm.

prey. The whale creates a "bubble" and dives deep before launching an attack on its target and collecting food [56]. Several research works in recent years have suggested using WOA for MG optimization, such as determining the optimal size, power generation scheduling, scheduling of load demand, and optimizing ESSs in MGs. The design of this algorithm is done based on three stages visualized in Fig. 7(a).

3.2.13. *Ant colony optimization*

Ant Colony optimization (ACO) is another swarm-based algorithm proposed by Dorigo and Di Caro in 1999. This graph-based meta-heuristic algorithm, which is inspired by the behavior of actual ants, is used to solve complex issues involving pathfinding. The algorithm is probabilistic and inspired by how ants track down food. ACO can be used to locate the shortest path, maximize time, and detect voltage collapse conditions in MG networks. This technique is useful for designing power electronic circuits as well as energy and electrical networks [53]. The three optimization procedures of ACO are illustrated in Fig. 7(b).

3.2.14. *Artificial immune system algorithm*

The Artificial Immune System (AIS) algorithm is a population-based MHOA based on the clonal selection principle and inspired by the biological immune system [91]. The highly adaptable, parallel, and distributed adaptive system of the human immune response serves as the basis for this algorithm. The method combines several important qualities, such as immune consciousness, feature extraction, immune computation, impervious acknowledgment, variety, and solidity. AIS can be used for various applications such as artificial intelligence, multi-agent optimal dispatching, optimal scaling, and defect detection in MGs. The design of AIS follows the processes described in Fig. 8.

3.2.15. *Biogeography-based algorithm*

The Biogeography-based Optimization (BBO) approach is inspired by mathematical models of biogeography that study the distribution of species over time and space, including features like species mobility and emigration among natural habitats. It is based on two fundamental processes, migration and mutation, which allow information to be shared amongst potential solutions. Many optimization issues, such as frequency regulation, load frequency management, optimal scheduling, benchmark function optimization, power system optimization, and others can be addressed by using the BBO [92]. The design steps of this MHOA can be found in Fig. 9.

3.2.16. *Group search optimizer*

The Group Search Optimizer (GSO), shown in Fig. 10, is a nature-inspired population-based optimization algorithm focusing on the producer-scrounger model, in which individuals or groups search for

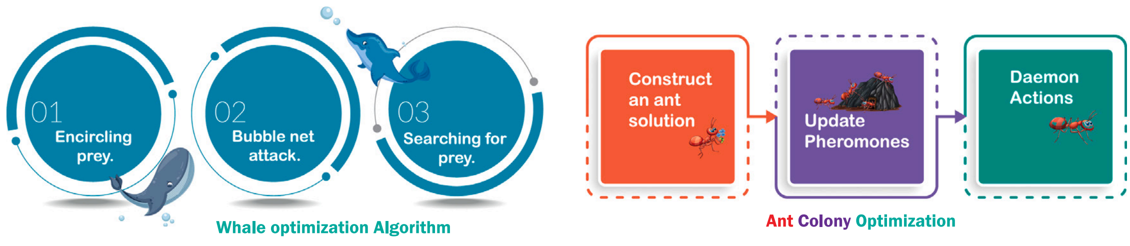

Fig. 7. (a) Whale Optimization Algorithm (b) Ant Colony Optimization.

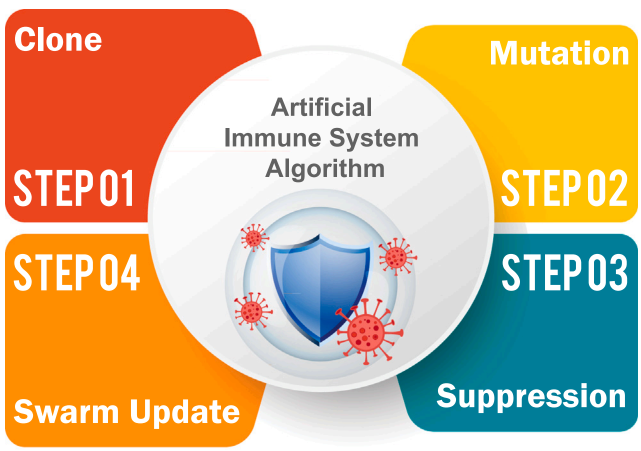

Fig. 8. Artificial Immune System Algorithm.

producer and scrounger opportunities. The program develops seeking techniques for ideal settings by using metaphorical animal tracking mechanisms. There are three types of GSO: basic, modified, and discrete. Each type has its own applications, including benchmark function optimization, categorization, networking, and engineering. Additionally, it can be used to solve various optimization problems, such as multi-objective optimization, condition monitoring, and optimal power flow [93].

3.2.17. *Shuffled frog leaping algorithm*

The Shuffled Frog Leaping Algorithm (SFLA) is introduced to address multidimensional optimization issues. It is a memetic, population-based MHOA that combines PSO and the Shuffled Complex Evolution algorithm. The population-based paradigm used by SFLA offers an evolutionary advantage. The algorithm was inspired by how frogs in the wild interact with one another to find food. Many optimization issues have been addressed with SFLA, such as the design of fuzzy controllers, multicast routing optimization, grid task scheduling, and efficient reactive power flow [94]. The phases of this algorithm are shown in Fig. 11.

3.2.18. *Firefly algorithm*

The Firefly algorithm (FA) is another population-based MHOA utilized for mathematical optimization that takes its cue from the flashing characteristic of fireflies. This algorithm uses multiple agents working in parallel to solve a problem using an iterative process and three idealized rules:

1. Fireflies are attracted to each other regardless of gender.
2. The brightness of a firefly attracts other fireflies, which decreases as the distance between them increases. If no brighter firefly is present, they move randomly.
3. The objective function's landscape determines the brightness of a firefly.

This algorithm can be used for a wide variety of tasks, such as digital image compression with little computational overhead, feature selection, antenna design optimization, multi-objective load dispatch issues, scheduling, reducing MG generation costs, power system optimization, and stabilization [74]. The algorithm's process is instructed in Fig. 12.

3.2.19. *Cuckoo search algorithm*

The behavior of the bird that lays its eggs in other birds' nests serves as the foundation for this program. Here, the host bird represents the best possible answer at the moment, while the cuckoo bird's egg represents a fresh possibility. The cuckoo bird's egg may be accepted or rejected by the host bird. If the host bird accepts the egg, it swaps out its own egg for the cuckoo's egg; if it rejects the egg, it keeps searching for a more effective solution. This process is repeated until a satisfactory solution is found [96]. This algorithm can be applied to optimize various aspects of MGs, including energy management, demand response, and control strategies. The process of the Cuckoo Search algorithm (CSA) is illustrated in Fig. 13.

4. Meta-heuristic optimization in microgrids: Trends and challenges

4.1. *Recent trends of MHOAs in microgrids*

4.1.1. *Load forecasting*

Load forecasting is a critical process that aims to predict consumer demand and ensure that the required amount of energy is produced efficiently. It involves collecting data from consumers and performing mathematical operations to determine future load requirements. This information is then used to reduce losses and maximize efficiency within the system. For an MG, load forecasting includes capacity optimization, load shedding techniques, load uncertainty, power forecasting, weather forecasting, risk forecasting, and cloud optimization. Several conventional statistical techniques were used previously to perform these operations, but their efficiency was limited due to a lack of sufficient information. This led to the development of new machine-learning techniques that are more accurate. However, some algorithms require system information that may not be available or difficult to obtain for certain infrastructures. To overcome this challenge, meta-heuristic algorithms have been created that are system-independent. Table 3 provides information on the currently used meta-heuristics in MGs for load forecasting. Current research in this arena indicates that these methods can be widely used in the future due to their dynamic approach to optimization [104].

In MGs, the application of MHOAs in load forecasting involves gathering past data on energy usage, selecting pertinent load-influencing characteristics, integrating meta-heuristics into forecasting models, and meticulously fine-tuning model parameters using the sophisticated methods. Essentially, the goal is to introduce flexibility into load projections so that they can adapt to changing load trends and the

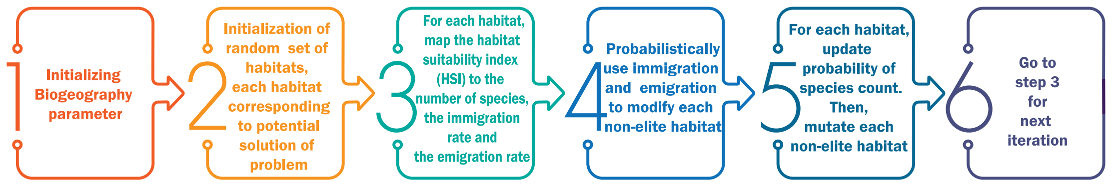

Fig. 9. Biography based algorithm.

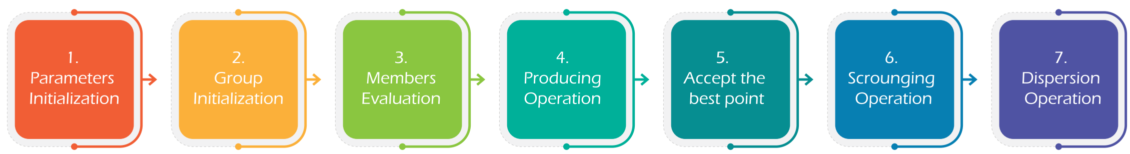

Fig. 10. Group Search Optimizer.

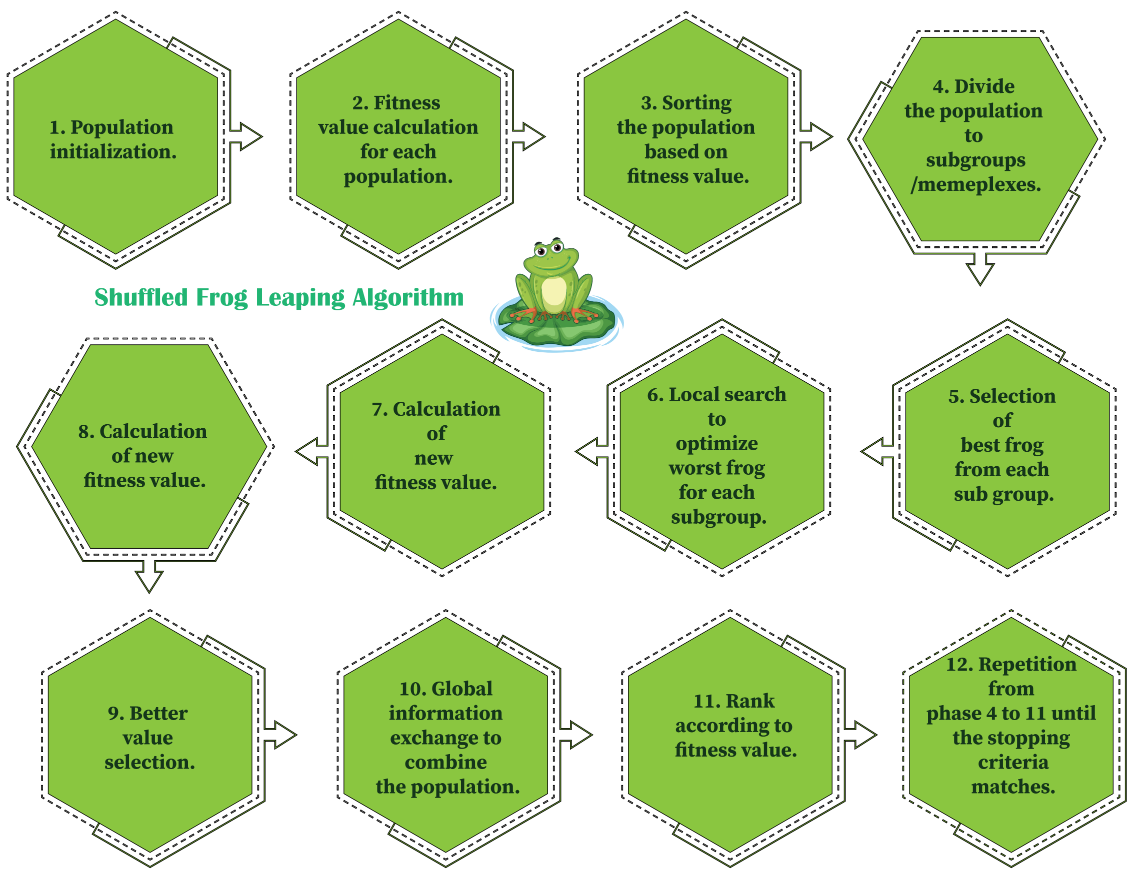

Fig. 11. Shuffled Frog Leaping Algorithm.

dynamic environment. The primary objective of this core mission is to enhance the quality and reliability of load forecasting, which, in turn, can improve load management and the overall efficiency of energy generation in MGs. Several advantages can be achieved by applying MHOAs in MG's load forecasting, as given below.

1. Improve forecasting precision by ensuring operating efficiency over non-convex optimization.

2. Mitigate the complexity inherent in successfully load forecasting environment by capturing the non-linear interactions.

3. Ensure accurate model performance by selecting necessary feature and preventing overfitting.

4. Adjust model performance with changing conditions in dynamic MG settings.

5. Confirm robust performance by handling uncertainty and ensure scalability.

6. Allow parallel processing speed to reduce computational burden.

7. Accept data fusion to combine data from many sources for ensuring load prediction validity.

4.1.2. Energy management

Energy management is a critical aspect of ensuring that every function within an MG is monitored, regulated, and enhanced. An MG's power output should be distributed in accordance with demand and utilized as effectively as possible. To this end, it is important for energy management to monitor power output, modify settings, and carry out necessary tasks. In earlier decades, electricity generation in MGs was only done using a few conventional methods, but they were

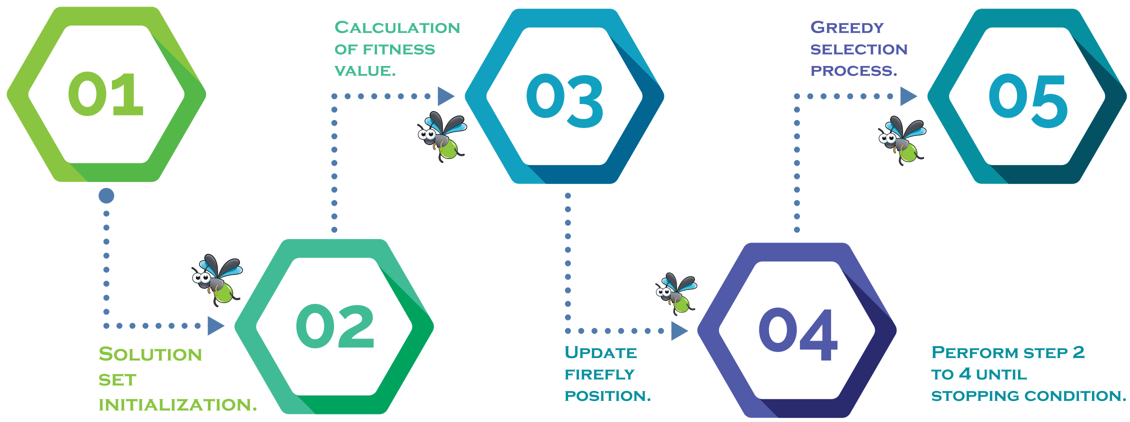

Fig. 12. Firefly Algorithm.

Table 3
Recently used MHOAs in MG load forecasting.

Paper	Year	Algorithm	Purpose	System
Ref. [26]	2018	DE	Microgrid capacity optimization	Grid-connected
Ref. [18]	2018	CABC, GA	Load forecasting	Hybrid
Ref. [95]	2018	FOA	Simulate the nonlinear system of a monthly electricity load (MEL) time series	Hybrid
Ref. [76]	2018	FAPSO	Optimal load shedding planning	Islanded
Ref. [76]	2018	FA, PSO	Optimize load shedding technique; voltage stability index	Islanded
Ref. [96]	2019	CSA, GWO	Load forecasting and capacity optimization	Islanded and grid-connected
Ref. [52]	2019	PSO	Load uncertainty	Grid-connected
Ref. [82]	2019	DE	Electric load forecasting	Hybrid
Ref. [84]	2019	GWO	Forecasting	Grid-connected
Ref. [97]	2019	PSO, SPSO	Combinatorial, non-linear, and NP-hard complex optimization	Islanded and grid-connected
Ref. [98]	2019	PSO	Load forecasting	Grid-connected
Ref. [93]	2020	GSA	Load pattern clustering	Hybrid
Ref. [99]	2020	NSFA	Dynamic load control	Islanded
Ref. [100]	2020	GA	Power forecasting	Islanded
Ref. [101]	2020	MILP	Day-ahead energy forecasting	Islanded and grid-connected
Ref. [102]	2021	GA	Forecasting	Grid-connected
Ref. [103]	2021	PSO	Load forecasting	Hybrid
Ref. [104]	2022	PSO	Forecasting	Islanded
Ref. [105]	2022	WWO	Responsive load participation	Grid-connected

not efficient enough. Deep learning algorithms along with optimization have been used to optimize systems and extract reliable and secure output. This has made it possible for meta-heuristic algorithms to function well. Table 4 provides examples of the implementation of meta-heuristic algorithms in the current scenario of MG energy management. Based on this knowledge, future research can be conducted to increase sustainability [101].

The utilization of MHOAs can act as a central role in MG energy management, following the same application principles applied to load forecasting. This intricate process is marked by an unwavering commitment to ongoing data surveillance and rigorous deep learning analysis. The application of MHOAs involves fine-tuning the intricate aspects of power distribution, load configurations, and operational parameters. In harmonious synergy, MHOAs elevate the overall efficiency and sustainability of MGs, paving the way for a future characterized by adaptable energy management and the realization of a more dependable and ecologically responsible energy distribution network.

In MG energy management, the MHOAs can provide the following advantages.

1. Properly predict the allocation of DERs in MGs while taking complicated restrictions into account. This leads to effective solutions that maximize stability and economy.

2. Improve grid resilience and minimize operating costs by making adaptive management decisions based on load demand, renewable energy availability, and system circumstances.

3. Reduce difference between the anticipated and real load by properly optimizing the allocation of energy sources.

4. Optimize demand response programs by providing exact control over load shifting or curtailment, which helps with peak load management and lowers costs.

4.1.3. Control operation

Optimizing the control operation of MGs can improve the efficiency of entire systems by adjusting a few parameters. This optimization improves the effectiveness of overall management and controls frequency, voltage, current flow, and other factors for the efficient operation of MGs. Traditionally, controllers like PID (Proportional–Integral–Derivative), Linear Quadratic Regulator, and Linear Quadratic Gaussian were used for certain processes where the controller parameters claimed optimization itself for the maximum and precise output. However, machine learning-based intelligent control techniques are now used, and algorithms like GBRBMs (Gaussian Bernoulli-restricted Boltzmann machines), BBPRBMs (Beta-Bernoulli process-restricted Boltzmann machines) and others have been employed to optimize the controller's parameters. The MHOAs have shown better performance due to their widespread application and independence from system knowledge. Table 5 provides a summary of current applications of meta-heuristic methods in MG control that highlight the potential for future growth in terms of system efficiency [50].

The application of MHOAs in the realm of MG control operations follows a structured approach. This process begins with identifying pivotal control parameters, transitioning from conventional controllers to adopting machine learning-driven intelligent control techniques. The

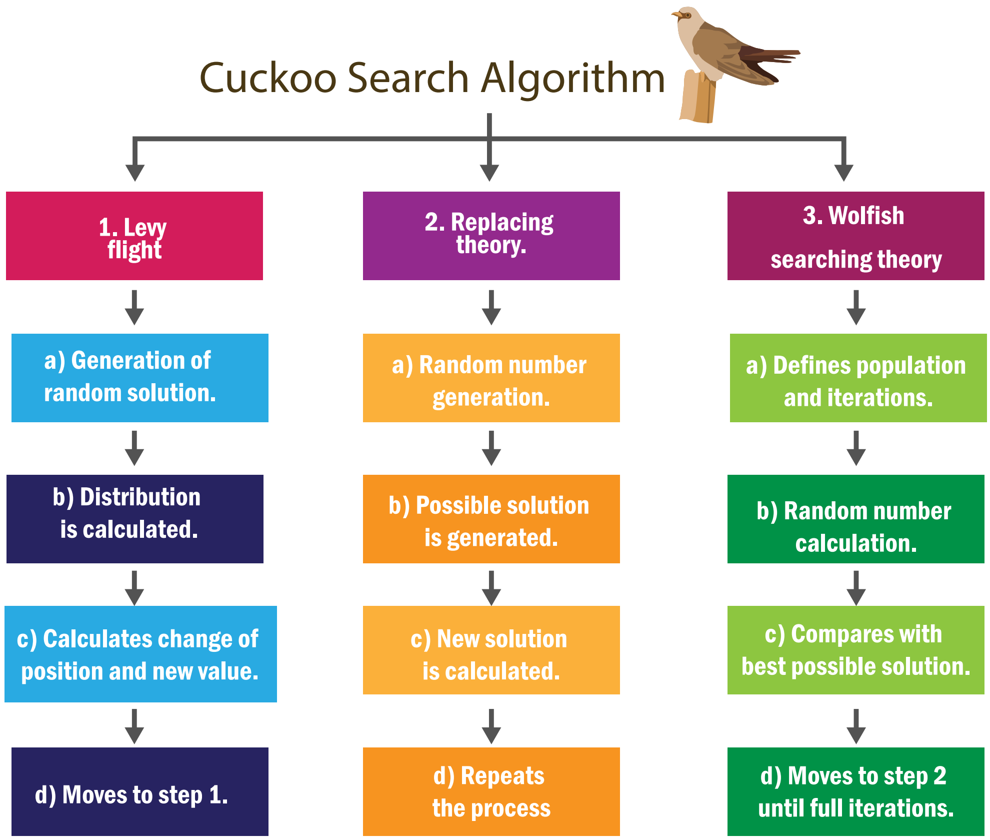

Fig. 13. Cuckoo Search Algorithm.

MHOAs continually fine-tune control parameters, ensuring the MG operates with peak efficiency while upholding stability and maintaining a degree of system agnosticism. The persistent assessment of the performance and the promising prospect of future advancements in system efficiency underscore the substantial role played by these techniques in enhancing MG control operations. The MHOAs can offer a list of benefit for MGs control, as outlined below.

1. With the use of metaheuristic algorithms, control techniques may be optimized in real time, allowing microgrid components to be dynamically adjusted for optimal functioning under changing circumstances.

2. Precisely coordinate and manage DERs, which maximizes their use and improves grid stability.

3. Demand response solutions are designed to maximize stability and economic benefits by achieving fine-grained control over load shifting or curtailment tactics.

4. Active management and optimization of frequency and voltage control ensures grid stability and power quality across a range of circumstances and disruptions.

5. Revenue and grid performance are maximized by grid service provision optimization, such as frequency management and peak shaving.

4.1.4. Anomaly analysis

Anomaly analysis is an empirical procedure that scans a dataset for potential incorrect data values, pieces of data, or information to identify malicious activity. Even within a regulated data analysis framework, it can be difficult to anticipate the various types of problems and faults that can arise in different datasets, especially when these datasets are reused for different purposes. Therefore, it is important to establish a benchmark evaluation procedure to assess the quality of a dataset before it is used, regardless of its downstream usage. Various algorithms such as Isolation Forest, Local Outlier Factor, Robust Covariance, and One-Class SVM are used for anomaly analysis [24].

Previously, heuristic algorithms were used for optimization in anomaly analysis, but these algorithms require complete knowledge of the system. However, with the introduction of meta-heuristic algorithms, the need for additional system information was eliminated as they operate based on the requirements of the task. Table 6 provides a brief summary of the implementation of meta-heuristic algorithms in anomaly analysis for MGs.

The integration of MHOAs with anomaly analysis for MGs follows a rigorous process. Collecting the data and selecting the right method, we might start how the model works in finding anomaly. The model is then thoroughly trained on past data, facilitating the identification of abnormalities and providing early warnings for prompt remedial action. An ongoing feedback loop ensures continuous system improvement, with benchmarking procedures carefully followed to assess and enhance the system's performance. This, in turn, strengthens the security and integrity of data analysis in MGs. The following are some advantages of using metaheuristic algorithms in the field of MG anomaly analysis.

1. Through improving anomaly identification accuracy and lowering false positives, metaheuristic algorithms optimize the parameters of anomaly detection models.

2. MHOAs can simulate intricate and non-linear data relationships, which makes it easier to identify minute irregularities and departures from anticipated patterns.

3. The capacity to adapt in real-time allows anomaly detection algorithms to be dynamically adjusted in response to evolving anomalies and shifting grid conditions.

4. MHOAs can provide operational integrity, protect the microgrid from cyber-attacks, and maximize the identification of anomalies connected to cybersecurity.

5. Effective anomaly analysis is aided by the integration of data from various sources using optimized data fusion techniques, which improve anomaly detection accuracy.

Table 4
Recently used MHOAs in MG energy management.

Paper	Year	Algorithm	Purpose	System
Ref. [92]	2013	BBO	Frequency regulation	Hybrid
Ref. [106]	2018	PSO	Optimal load dispatch	Hybrid
Ref. [107]	2018	PSO	Power management	Islanded
Ref. [80]	2018	PSO	Robust optimization	Grid-connected
Ref. [67]	2018	SSO	Reduce emissions, optimize energy resources	Islanded and grid-connected
Ref. [73]	2018	GWO	Energy storage sizing	Islanded
Ref. [55]	2019	GA	Optimize dispatching	Islanded
Ref. [108]	2019	SSO	Voltage and frequency regulation	Islanded
Ref. [109]	2019	PSO	Stochastic energy optimization	Grid-connected
Ref. [86]	2019	BFO	Power optimization	Islanded
Ref. [110]	2019	GWO	Control the size of the repository	Grid-connected
Ref. [70]	2019	PSO	Energy efficient management	Grid-connected
Ref. [111]	2019	GA	Multi-objective operation optimization	Grid-connected
Ref. [112]	2020	MOGOA	Energy management optimization	Islanded
Ref. [113]	2020	PSO	Energy management problem of DERs	Grid-connected
Ref. [8]	2020	MILP-PSO	Optimal scheduling of diesel generator, ESSs	Islanded
Ref. [114]	2020	GWO	Optimum battery ESSs size	Islanded
Ref. [115]	2020	PSO	Demand response optimization	Islanded and grid-connected
Ref. [116]	2020	BSO	Energy management	Islanded
Ref. [117]	2020	PSO	Optimize the power flow	Islanded
Ref. [118]	2020	PSO	Battery energy management strategies	Grid-connected
Ref. [119]	2020	PSO, SPSO	Minimization of power loss	Islanded and grid-connected
Ref. [120]	2020	GA	Energy exchange for maximizing profit	Grid-connected
Ref. [121]	2020	GOA	Determine optimal power generation	Islanded and grid-connected
Ref. [122]	2020	PSO	Maximize the net present value	Islanded
Ref. [87]	2020	WCA	To improve performance of a PV	Grid-connected
Ref. [72]	2021	GA	Energy management	Islanded and grid-connected
Ref. [123]	2021	GA, DE	Energy management	Grid-connected
Ref. [124]	2021	WOA	Automation	Islanded
Ref. [125]	2021	PSO, CSA and HHO	Distribution management	Grid-connected
Ref. [126]	2022	PSO	Energy management	Hybrid
Ref. [127]	2022	ABC	Energy management	Islanded
Ref. [128]	2023	GA, ACO, PSO	Energy management	Islanded and grid-connected
Ref. [129]	2023	GA, CSA, PSO	Demand response, load forecasting	Hybrid
Ref. [130]	2023	PSO, CSA	Energy management	Islanded
Ref. [131]	2023	HSO, SA, SMA, GSA, BHO, SCA, MVO, LSA	Energy management	Grid-connected
Ref. [132]	2023	MOGWO, MOPSO, MOGA, MOGOA	Energy management	Hybrid
Ref. [133]	2023	GA	Energy management	Islanded and grid-connected
Ref. [134]	2023	PSO	Energy management, demand response	Grid-connected
Ref. [135]	2023	GA-AWPSO	Forecasting, energy management	Islanded and grid-connected
Ref. [136]	2023	PPSO	Optimal operation of batteries	Islanded and grid connected
[137]	2023	ES	Solar energy management	Islanded and grid connected

6. MHOAs work on predictive maintenance by spotting anomalies that point to possible equipment and save downtime and maintenance expensive.

4.1.5. System resilience

Resilience refers to the capacity of a system to adapt and recover from anticipated or unexpected changes in the environment by applying risk management, operational planning, and resilience strategies. Resilient systems possess several key characteristics, such as being composed of multiple components, having strong relationships between the components, horizontal and vertical integration of modules, and high degrees of diversity to ensure backup in the event of equipment failure. Several strategies can be employed to enhance resilience, including warnings and alerts, circuit breaker patterns, back-off retry algorithms, concurrency techniques, antivirus software, elastic load balancing, fault isolation, fire detection and suppression systems, and line replaceable units. For MGs, resilience is a crucial aspect for evaluating risks, identifying hazards, and developing appropriate strategies to mitigate them [66]. Traditional algorithms face certain challenges in this regard, prompting the use of metaheuristic algorithms to overcome these limitations, as demonstrated in Table 7.

Strategically implementing MHOAs in MGs to enhance system resilience requires a methodical approach. The initial step involves identifying critical resilience factors, followed by the selection of appropriate meta-heuristic algorithms. Subsequently, these algorithms are integrated into resilience strategies, facilitating the optimization of dynamic parameters, enhancing fault isolation and recovery procedures, expanding system diversity, and enabling real-time adaptation to changing conditions. The intrinsic flexibility of meta-heuristics plays a crucial role in facilitating efficient risk evaluation and reduction, solidifying their status as essential instruments for fortifying MGs against expected and unanticipated modifications, thus ensuring the robustness of the system. The use of MHOAs can improve MG system resilience in a number of following ways.

1. In order to quickly react to changing conditions and increase grid resilience against shocks, metaheuristic algorithms allow for the dynamic reconfiguration of MG architecture and resource distribution.

2. Strong cybersecurity measures are designed and optimized by using MHOAs, strengthening the MG against cyberattacks and improving system resilience.

3. MHOAs offer adaptive control in real-time, allowing for quick responses to grid disruptions, efficient use of energy resources, and grid stability, all of which contribute to increased resilience.

4. Through enabling autonomous disengagement from the main grid during disruptions, islanding capabilities ensure continuous power delivery to important loads and enhance resilience.

5. Resilience considerations involving multi-objective optimization balance intricate techno-economic and resilience goals while maintaining grid robustness and cost-efficiency.

Table 5
Recently used MHOAs in MG control.

Paper	Year	Algorithm	Purpose	System
Ref. [138]	2018	Modified PSO	Voltage and frequency control	Grid-connected
Ref. [80]	2018	PSO	Robust optimization	Grid-connected
Ref. [107]	2018	PSO	Frequency and voltage control	Islanded
Ref. [56]	2018	WOA	Regulating the voltage and frequency	Islanded
Ref. [139]	2018	WOA	Power control	Grid-connected
Ref. [140]	2018	PSO	For optimizing PI controller of Hierarchical control	Grid-connected and islanded
Ref. [141]	2018	Water cycle algorithm	Voltage control	Islanded
Ref. [142]	2018	GSA	Voltage and frequency control	Islanded
Ref. [81]	2018	PSO,GWO	Frequency control	Islanded
Ref. [143]	2019	FA	Frequency control	Grid-connected
Ref. [144]	2019	GA	Robust control	Islanded
Ref. [108]	2019	Salp Swarm Optimization Algorithm	Voltage and frequency regulation; dynamic response enhancement	Islanded
Ref. [145]	2019	WCA	Frequency control	Islanded
Ref. [110]	2019	GWO	Control the size of the repository	Grid-connected
Ref. [91]	2019	AIS	Voltage control	Hybrid
Ref. [146]	2019	HMDA, BSA	Power flow control, load control	Grid-connected
Ref. [50]	2019	PSO	Load frequency control	Islanded
Ref. [25]	2020	HSO	Control technique for adjusting the voltage and frequency	Islanded
Ref. [90]	2020	ABC	Control of the system congestion	Islanded
Ref. [147]	2020	NSBGA-II	Regulate the power converters	Grid-connected
Ref. [99]	2020	NSFA	Dynamic load control	Islanded
Ref. [148]	2021	GWO	Load and frequency control	Islanded
Ref. [149]	2021	PSO	Voltage and frequency control	Islanded
Ref. [150]	2021	ACO	Voltage and frequency regulation	Islanded
Ref. [151]	2022	GWO	Frequency control	Islanded
Ref. [89]	2022	SFO	Frequency control	Islanded
Ref. [152]	2022	BFO	Frequency control	Islanded
Ref. [153]	2023	PSO	Optimal power flow	Islanded

Table 6
Recently used MHOAs in MG anomaly analysis.

Paper	Year	Algorithm	Purpose	System
Ref. [74]	2018	FA	Stabilization	Grid-connected
Ref. [67]	2018	SSO	Reduce emissions, increase reliability, and optimize energy resources	Grid-connected and islanded
Ref. [76]	2018	FA,PSO	Load shedding technique, voltage stability	Islanded
Ref. [52]	2019	PSO	Load uncertainty	Grid-connected
Ref. [154]	2019	PSO	Minimize the carbon emissions	Grid-connected
Ref. [155]	2019	ABC	Model order reduction	Grid-connected
Ref. [75]	2020	FA	Fault monitoring, relay coordination	Islanded
Ref. [8]	2020	MILP-PSO	Optimal scheduling of a diesel generator	Islanded
Ref. [156]	2020	PSO	Environmental emission mitigation	Hybrid
Ref. [157]	2020	A Gaussian PSO	Stability of the system	Grid-connected and islanded
Ref. [54]	2020	SSOA	Minimize a time integrating error	Grid-connected
Ref. [158]	2020	BAS	Inverse-time over-current protection, energy protection	Grid-connected and islanded
Ref. [66]	2020	Robust optimization	Risk-constrained scheduling	Islanded
Ref. [159]	2020	BMO-DE	Address the mixed integer nonlinear programming	Grid-connected and islanded
Ref. [160]	2020	MRCGA	Resolve each deterministic dilemma populated from first phase	Hybrid
Ref. [22]	2020	ACO	Operation and maintenance	Grid-connected
Ref. [161]	2020	DE	Minimize power loss, and voltage stability	Islanded
Ref. [24]	2023	GA, ABC, PSO	Fault diagnosis	Hybrid

6. Optimizing battery management for grid support improves overall resilience by strengthening energy storage systems' capacity to sustain themselves during disruptions like frequency regulation.

4.1.6. Techno-economic modeling

The techno-economic model is a strategy that aims to save costs while retaining maximum system efficiency. This paradigm balances market control with consumer and producer convenience. To achieve this balance, standard electrical, mechanical, and computational efficiency optimization has traditionally been used. However, machine learning approaches have been added to improve system efficiency, and algorithms like MILP, and Distribution Engineering Workstation (DEW) have been employed for effective optimization computation.

Heuristic approaches were initially introduced, however, they required a thorough understanding of the system to be optimized. The procedure has been transformed by the introduction of MHOAs because the system uses no longer needs any additional knowledge to operate this process. Table 8 presents a summary of recent uses of MHOAs to enhance techno-economic models for MGs. These algorithms are often utilized now and may offer a sustainable path for future research [162].

In techno-economic modeling for MGs, the integration of MHOAs constitutes a rigorous procedure designed to enhance system efficiency while maintaining cost-effectiveness. Seamlessly incorporating a suitable MHOA, such as PSO or GA, into the existing techno-economic model is crucial for optimizing critical variables like energy production, storage, and distribution while facilitating real-time adaptation. The dynamic investigation of solution spaces by MHOAs allows for the discovery of optimal configurations without requiring a comprehensive understanding of the system. The integration of machine learning functions to enhance the model, along with ongoing benchmarking, sensitivity analysis, and validation against historical data, contributes to the continuous improvement of the techno-economic model. By presenting a sustainable paradigm, this all-encompassing strategy effectively addresses the ever-changing requirements of MG systems.

Here, the MHOAs provide various techno-economic advantages:

1. Metaheuristic algorithms effectively address the challenging multi-objective optimization issues in MG design, striking a balance

Table 7
Recently used MHOAs in MG system resilience.

Paper	Year	Algorithm	Purpose	System
Ref. [54]	2020	SSO	Minimize a time integrating error fitness function	Grid-connected
Ref. [99]	2020	NSFA	Dynamic load control	Islanded
Ref. [66]	2020	Robust optimization	Risk-constrained scheduling	Islanded
Ref. [163]	2020	GA	Optimize the limits of the maximum plug setting multiplier for the overcurrent relays coordination	Islanded and grid-connected
Ref. [159]	2020	BMO-DE	Address the mixed integer nonlinear programming	Islanded and grid-connected
Ref. [160]	2020	MRCGA	Resolve each deterministic dilemma populated from first phase	Hybrid
Ref. [164]	2020	CSA	Provide ancillary services through the incorporation of plugin electric vehicles as fast-responsive storage	Hybrid
Ref. [71]	2020	DE	Reshape and smooth the load profile, and also provide reserve capacity along with dispatchable units	Islanded and grid-connected
Ref. [79]	2020	H-PSO-SCAC	Reduce system demand peak and subscribers bills for various loads	Grid-connected
Ref. [165]	2020	MOO	Minimize battery degradation	Islanded
Ref. [161]	2020	DE	Minimize power loss, and switching costs, and enhance voltage stability index, considering time-variations of loads	Islanded
Ref. [166]	2021	GA	Optimization to explore new efficient designs of electrical MG components	Islanded and grid-connected
Ref. [53]	2023	ACO	Load demand	Islanded
Ref. [167]	2023	WOA	Load demand	Grid-connected

between techno-economic trade-offs related to cost, efficiency, and grid reliability.

2. Allocate DERs optimally while taking limits into account, maximizing techno-economic performance through resource deployment optimization.

3. Offer dynamic, real-time control over MG operations, enabling adaptive decision-making to lower operating costs based on grid conditions and techno-economic goals.

4. In order to precisely limit or transfer load, metaheuristic algorithms optimize demand response systems. This lowers peak demand costs and enhances the techno-economic performance of microgrids.

5. Battery cycle life, energy cost reduction goals, and techno-economic considerations are all taken into account while optimizing energy storage systems.

6. MHOAs create strong control plans that improve cybersecurity, guard against online attacks, and guarantee the durability of techno-economic activities in MGs.

7. Techno-economic costs are minimized while preserving or improving grid performance through dynamic reconfiguration of MG architecture and resource use, especially in response to changing conditions.

4.2. Implementation challenges

A meta-heuristic algorithm is a system-independent optimization technique. It uses a trial-and-error method to find the best fitness value for certain operations in a system. However, this method requires the algorithm to generate a population-based iteration policy, which can lead to the following issues that may compromise efficiency.

4.2.1. High processing power

The trial-and-error method used by meta-heuristic algorithms involves a large number of iterations, which can consume significant processing power in a system. This can result in decreased computational efficiency and even complete system breakdown if the processing power is not sufficient. To address this issue, high-performance equipment can be introduced to provide the necessary processing power for optimization [140].

4.2.2. Large transient time

Performing high-level optimization with a large number of iterations can increase the transient time for optimization. This can be detrimental to the system, especially for those that require optimization within a specific time period. If the threshold time is exceeded, it can trigger severe alerts in the system and surrounding environment. To overcome this issue, fast processing components can be integrated into the system, which will be able to process big data within a short period of time, thus reducing the transient time for optimization [168].

4.2.3. Inaccurate system behavior prediction

As a universal algorithm, the MHOA is capable of predicting system behavior and adapting accordingly. However, the algorithm may encounter errors that can cause complete system malfunction if accurate behavior prediction is not achieved. To prevent system breakdowns, adjusting the declaration of population and number of iterations can optimize output and ensure accurate behavior prediction [75].

4.2.4. Data availability

MHOA requires data inputs such as load, weather forecast, and equipment availability, which may not be readily available in real-time or may be expensive to obtain. Thus, effective data management techniques must be employed to ensure data availability [18].

4.2.5. Large-scale optimization

MGs can have a large number of components including generators, ESSs, and loads, which can result in a large-scale optimization problem. The MHOA may struggle with the computational complexity of large-scale problems and may require parallelization or distributed computing to achieve the desired results [200].

4.2.6. Dynamic operation

MGs are subject to dynamic operation due to the changing conditions of demand and generation. The MHOA may need to be adapted to handle dynamic optimization problems, such as using online optimization techniques or model predictive control [108].

Table 8
Recently used MHOAs in techo-economic modeling of MG.

Ref	Year	Algorithm	Purpose	System
Ref. [168]	2018	CSA	REDG sizing	Hybrid AC/DC
Ref. [51]	2018	PSO	Economic emission dispatch	Islanded
Ref. [23]	2018	WOA	Cost minimization	Grid-connected
Ref. [83]	2018	GWO	Clustering, parameter optimization	Islanded
Ref. [169]	2018	ISA	Minimize the operating cost	Grid-connected
Ref. [85]	2018	MHS	Cost functions	Islanded
Ref. [170]	2018	WCA	Minimize the operating cost	Grid-connected
Ref. [171]	2018	GWO	Cost minimization	Grid-connected
Ref. [172]	2018	GA	Optimal sizing	Islanded
Ref. [173]	2018	ACO	Reduce cost, emissions, optimal sizing	Hybrid
Ref. [80]	2018	PSO	Cost minimization	Islanded and Grid-connected
Ref. [43]	2018	GA	Economic dispatch	Islanded
Ref. [174]	2018	PSO	Minimization of operational cost	Grid-connected
Ref. [94]	2018	SFLA	Load, optimal economic dispatch	Grid-connected
Ref. [175]	2018	JA	Optimal scheduling	Grid-connected
Ref. [176]	2018	GWO	Optimize the procurement costs of network	Grid-connected
Ref. [177]	2019	GOA	Optimal sizing	Islanded
Ref. [178]	2019	PSO	Optimal sizing	Islanded
Ref. [179]	2019	GA	Optimal sizing	Hybrid
Ref. [180]	2019	PSO	Optimal sizing	Grid-connected
Ref. [181]	2019	MFO	Optimal sizing	Islanded
Ref. [162]	2019	WCA	Techno-economic optimization	Islanded
Ref. [182]	2019	GA	Optimize economic, environmental factors	Islanded and grid-connected
Ref. [183]	2019	DE, PSO	Minimize operation costs and emissions	Grid-connected
Ref. [154]	2019	PSO	Minimize cost	Grid-connected
Ref. [184]	2019	CSA	Minimization of cost and emission	Hybrid
Ref. [185]	2019	PSO	Cost function	Grid-connected
Ref. [186]	2019	GA	Cost minimization	Islanded and grid-connected
Ref. [187]	2019	PSO, GA, FPA	Economic dispatch	Islanded and grid-connected
Ref. [188]	2019	PSO	Optimize the total cost and reliability	Hybrid
Ref. [88]	2020	EA	Optimal sizing	Hybrid
Ref. [156]	2020	PSO	Decrease the cost of generation	Hybrid
Ref. [10]	2020	PSO	Reduce cost and the number of iterations	Hybrid
Ref. [22]	2020	ACO	Minimize expenditure for fuel and operation	Grid-connected
Ref. [189]	2020	DE	Minimization of operating cost and pollutants	Islanded and grid-connected
Ref. [190]	2021	GOA	Optimal sizing	Islanded
Ref. [191]	2022	PSO, DE, WCA, GWO	Optimal sizing	Islanded
Ref. [192]	2022	GA, PSO, DE, FA	Cost reduction	Islanded and grid-connected
Ref. [193]	2022	PSO, SSA, COOT	Cost reduction	Islanded and grid-connected
Ref. [57]	2022	GWO	Cost minimization	Islanded
Ref. [194]	2023	FA, BA, ISA	Techno-economic	Hybrid
Ref. [195]	2023	DE, PSO	Techno-economic	Hybrid
Ref. [195]	2023	PSO, DE	Techno-economic	Hybrid
Ref. [196]	2023	PSO	Techno-economic	Grid-connected
Ref. [197]	2023	PSO	Optimal sizing	Islanded
Ref. [198]	2023	DE	Techno-economic	Islanded
Ref. [199]	2023	PSO, SFLA, DE	Optimal sizing	Hybrid

4.2.7. *Algorithm selection*

Selecting an appropriate MHOA for an optimization problem can be challenging due to factors such as problem- and algorithm-specific nature, strengths and weaknesses, performance evaluation, and computational resources. It requires a deep understanding of the problem and available MHOAs, as well as careful consideration of algorithm behavior, parameter settings, and available computational resources. Evaluating performance also requires appropriate performance metrics and statistical experiments to evaluate whether the observed performance differences are meaningful [35].

4.2.8. *Limited communication*

MGs may have limited communication between components, which can make it challenging to obtain real-time data or to control the operation of the MG. The MHOAs may require distributed optimization techniques or local control approaches to address these communication limitations [51].

5. Discussion

The operation of MGs largely depends on the nature of RESs and their precise integration. Additionally, economic losses, integration of ESSs with MGs, energy imbalance, cyberattacks, scalability, and forecasting may be responsible for degrading the operation and design efficiency of MGs. The use of proper optimization techniques in the MG domain paves the way to address these issues. Although several heuristic optimization algorithms are found in the existing literature for addressing the mentioned issues, local minima and the inability to find the global minimum limit the use of these techniques in large-scale problems. The emergence of MHOAs can be beneficial in these cases due to their capability of finding the global minimum.

In this paper, we study various MHOAs and review the recent trends of MHOAs in correspondence to the MG domain. The state-of-the-art summary in terms of load forecasting, management, control, anomaly analysis, system resiliency, and techno-economic modeling of MGs is presented in Section 4 to explicitly highlight the opportunities of MHOAs. This wide range of applications makes MHOAs a powerful option for researchers in the area of MGs, as they can address multiple objectives optimization problems, non-linear, and convex constraints. Because of these benefits, they can be a promising alternative to mitigating the current difficulties and restrictions of conventional optimization techniques. Additionally, we measure the utilization level of optimization techniques among the various studied MHOAs in the MG domain on a case-by-case basis. These results are analyzed based on the number of existing studies related to MHOAs, which may encourage

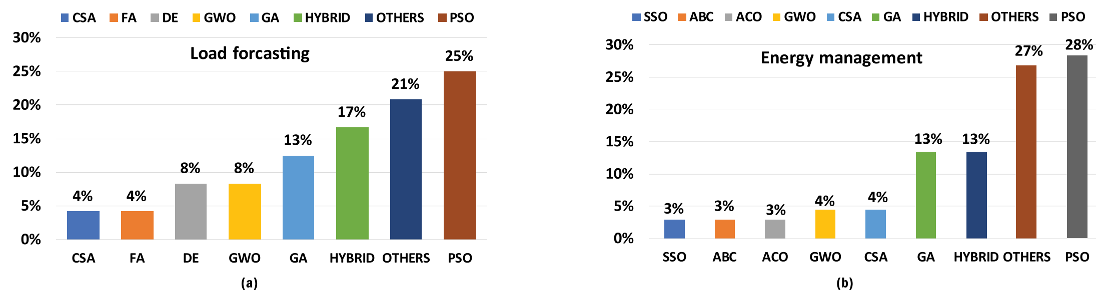

Fig. 14. Uses percentage of different MHOAs for MGs (a) Load forcasting (b) Energy management.

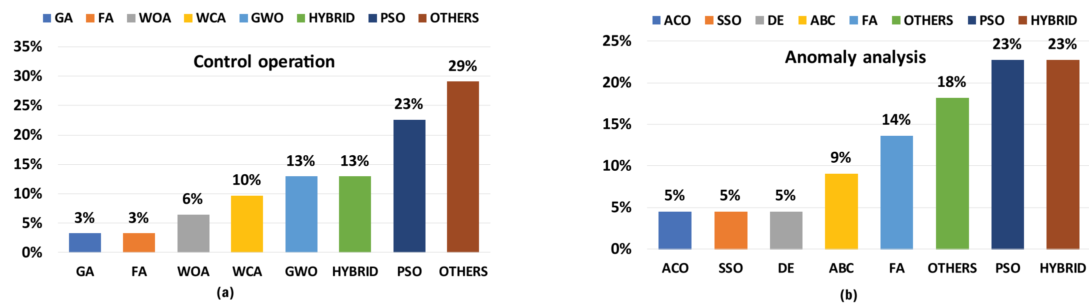

Fig. 15. Uses percentage of different MHOAs for MGs (a) Control operation (b) Anomaly analysis.

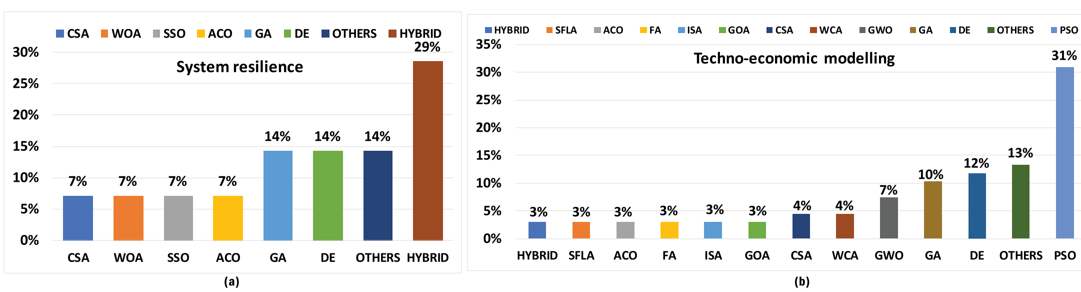

Fig. 16. Uses percentage of different MHOAs for MGs (a) System resilience (b) Techno-economic modeling.

new researchers to choose MHOAs for specific cases. The details of these results are as follows.

The implementation intensity of recently used MHOAs in MG load forecasting is illustrated in Fig. 14(a). This statistics is prepared based on the 15 studied papers collected from the literature. From the figure, it is found that nearly 4% of research work uses ACO and FA, 8% of research uses DE and GWO, and 13% uses GA for MG load forecasting. Again, the utilization of hybrid MHOAs is increasing gradually which nearly reaches the top of the intensity margin compared to other single MHOAs except PSO. Following Fig. 14(a), it can be seen that the PSO technique holds the highest value of MHOAs applied in MG load forecasting due to its simplicity, robustness and quick convergence to the optimal solution.

In Fig. 14(b), the degree of MHOA for MG optimizations in terms of energy management is reported, where only 3% of research work uses SSO, ABC, and ACO due to their premature convergence, lack of diversity, and limited scalability. The degree of level for MHOAs for others cases, i.e., control operation, anomaly analysis, resiliency, and techno-economic modeling can be found in Fig. 15(a), Fig. 15(b), Fig. 16(a) and Fig. 16(b), respectively. By analyzing all of the figures, it can be concluded that the PSO technique is widely applied in MG sectors because of its diverse opportunities.

6. Future recommendations

Future research in MHOAs for MGs should consider the unique characteristics of MGs when developing new meta-heuristic algorithms, such as their complex topology, non-linear generation and consumption, and the presence of various constraints. The integration of MHOAs with other techniques can improve the performance of the algorithms. Furthermore, research should focus on improving the efficiency and effectiveness of MHOAs in MGs by developing new search strategies and parameter tuning methods, and addressing the uncertainties inherent in MGs, such as the variability of load demand and RESs. Pursuing these research directions has the potential to significantly improve decision-making in the planning and operation of MGs, leading to greater economic, social, and environmental benefits. Here, some of the emerging future aspects of MHOAs in MGs are discussed below.

6.1. *Digital twin-based microgrids optimization*

MHOAs have a wide range of potential scopes in digital twin (DT)-driven MG applications. They can optimize the design of DT-based systems, including the selection of optimal modeling techniques and parameter values. They can also be applied to optimize the parameters of DT models using real-world data to improve their accuracy and reliability. Furthermore, these algorithms can optimize the scheduling of maintenance activities for DT systems by predicting when failures are likely to occur, and detect and diagnosis faults in DT systems by analyzing system data and identifying anomalies. These potential applications demonstrate the future scope of MHOAs in improving the efficiency, accuracy, and reliability of DT-based MG systems.

6.2. Hybridization of optimization algorithms

The hybridization of MHOAs presents a promising avenue for future research. As MGs become more prevalent and involve multiple energy sources, loads, and ESSs with varying operational constraints and objectives, it may become necessary to address their unique and complex characteristics. This complexity makes it challenging to find optimal solutions using a single algorithm. By hybridizing multiple algorithms, the strengths of each algorithm can be leveraged to address different aspects of the optimization problem and provide more efficient and effective solutions. This can lead to improved operation and management of MGs, allowing for better integration of RESs and enhanced energy security.

6.3. Distributed optimization

MHOAs can be used to develop distributed optimization algorithms that enable the optimization of MG operation in a decentralized manner. This approach can provide greater flexibility and resilience to MG systems, as well as reducing the risk of single points of failure. With the growing interest in decentralized energy systems, distributed optimization algorithms are likely to become an important area of research for MG optimization.

6.4. Quantum-based microgrids optimization

MHOAs may offer a broad range of scopes in quantum computing-based MG optimization, which is a rapidly evolving field with vast potential for optimization problems. Metaheuristic techniques can optimize quantum circuits, gates, and annealing processes for efficient and reliable quantum computation. They can also optimize the design and configuration of quantum computing architectures, including qubit selection, circuit routing, and error correction strategies. Quantum-inspired meta-heuristic algorithms can further enhance the efficiency and effectiveness of quantum computing, allowing for the solution of large-scale optimization problems that are difficult to solve using classical computing.

6.5. Enabling multi-objective optimization in IoT-enabled microgrids

One potential future prospect for MHOAs is the development of multi-objective optimization algorithms in IoT enabled MGs. These algorithms can handle multiple objectives simultaneously, such as maximizing efficiency, reducing costs, and minimizing emissions. With the increasing demand for sustainable energy solutions, MGs will require sophisticated optimization techniques to balance conflicting objectives.

6.6. Optimization of advanced emerging technologies

MHOAs can be integrated with other emerging technologies, such as blockchain, to create a more efficient and secure MG system. Here, blockchain can be used to enable peer-to peer energy trading among MG participant.

7. Conclusion

This paper reviewed the role of meta-heuristic optimization techniques in improving the MG's performance as well as ensuring their sustainability across various modes of operation. Firstly, we discussed the essential framework of MGs and highlighted some potential issues for the needs of optimization. The scopes of applying optimization techniques in the MG domain were then explored and presented through a brief discussion. Additionally, this paper can support the researchers and practitioners by serving the following useful information.

- Highlighted the fundamentals of MG optimization that can inspire researchers to work more in this arena.
- Discussed several MHOA frameworks and their benefits in MG optimization that may serve as the foundation knowledge for new researchers in optimization. This may also encourage the development of new MHOAs for future MGs through the hybridization of multiple MHOAs.
- Summarized recent trends of MHOAs in the MG domain in terms of various applications, enabling researchers to track the progress of MHOAs in MG sustainability and potentially attract more researchers to this field.
- Explored some implementation challenges of MHOAs and future research areas in which researchers can conduct their future research to address them.

Considering the above points, it can be concluded that this paper may provide extended support for engineers and researchers to understand how optimization confirms the sustainable operation of MGs. However, this work does not cover issues like how objective functions of MHOAs are sensitive to MG parameters and configurations, as well as the potential computational burden they might impose, especially in larger and more intricate MG systems. Additionally, it does not discuss the difficulties encountered when translating MHOA theories into real-world applications, which include hardware limitations, communication protocols and regulatory factors. Exploring the solution of these issues, mapping the MHOAs in reducing MG problem difficulty level and showing the comparison between MHOAs and other alternative optimization techniques such as AI/DL/ML and Data Science could be an area to conduct future research.

Abbreviation

ALOA	Antlion optimizer algorithm
ASA	Artificial sheep algorithm
BA	Bat Algorithm
BAS	Beetle antennae search
BFBA	Bacterial foraging-based algorithm
BHO	Black Hole Optimization
BMO-DE	Bird Mating Optimization-Differential Evolution
BSA	Bat Search Algorithm
BSO	Backtracking search optimization
CABC	Chaotic Artificial Bee Colony
CBA	Coot Bird Algorithms
CE-VNDEPSO	Cross-Entropy Variable Neighborhood Differential Evolutionary Particle Swarm Optimization
COOT	Coot optimization algorithm
CRO	Coral Reefs Optimization
DEEPSO	Differential Evolutionary Particle Swarm Optimization
EMA	Exchange market algorithm
ER-WCA	Evaporation rate water cycle algorithm
FAPSO	Fuzzy Adaptive Particle Swarm Optimization

FOA	Fruit fly optimization algorithm
FPA	Flower pollination algorithm
GA-AWPSO	Genetic algorithm–adaptive weight particle swarm optimization
GSA	Gravitational Search Algorithm
HMDA	Hybrid modified dragonfly algorithm
HMOMFO	Hybrid multi-objective moth flame optimization
H- PSO-SCAC	Hybrid Particle Swarm Optimization algorithm with Sinusoidal and Cosine Acceleration Coefficient
Hybrid BBF	Hybrid Bare Bones Fireworks
Hybrid HHO-FNN	Hybrid Harris hawks' optimization-based feed-forward neural network
ILP	Integer linear program
ISA	Interior search algorithm
HMGSG	Hybrid Modified GWO/SOS/GA algorithm
IMOBA	Improved multi-objective bat algorithm
JA	JAYA algorithm
KHA	Krill Herd algorithm
LSA	Lightning Search Algorithm
MBEO	Modified bat evolutionary optimization
M-CSA	Modified Cuckoo Search Algorithm
MFO	Moth–Flame Optimization
MGWOSCACSA	Modified grey wolf optimizer, sine–cosine algorithm and crow search algorithm
MHS	Modified harmony search algorithm
MIDACO	Mixed Integer Distributed Ant Colony Optimization
MILP	Mixed integer linear programming
MINLP	Mixed Integer Nonlinear Programming
MOGOA	Multi-objective grasshopper optimization algorithm
MOEA	Multi-objective evolutionary algorithm
MOGA	Modified Optimized Genetic Algorithm
MOGWO	Modified Optimized Grey Wolf Optimization
MOO	Multi-objective optimization
MOPSO	Multi-objective particle swarm optimization
MRCGA	Modified real-coded genetic algorithm
MVO	Multiverse optimization
NSBGA	Nondominating sorting binary genetic algorithm
NSBGA-II	Nondominating sorting binary genetic algorithm-II
NSFA	Nondominated sorting firefly algorithm
NSGA-II	Non-dominated sorting genetic algorithm-II
PEM	Point estimate method
PPSO	Parallel Particle Swarm Optimization
PSOGSA	Hybrid particle Swarm-Gravitational Search Algorithm
REDG	Renewable Energy Distributed Generators
RF	Random Forest
RMO	Radial Movement Optimization
SA	Search algorithm
SA	Simulated Annealing
SBBA	Satin bower bird algorithm
SCA	Sine-Cosine Algorithm
SFO	Sailfish Optimizer
SHO	Spotted Hyena Optimizer
SMA	Slime Mold Algorithm
SOGSNN	Gravitational search algorithm (GSA)-based artificial neural network (ANN) and squirrel search algorithm (SSA), SOS and GA
SPSO	Selective Particle Swarm optimization
SSO	Social Spider Optimization
SSOA	Salp Swarm Optimization Algorithm
TL	Teaching Learning
WCA	Water Cycle Algorithm
WWO	Water wave optimization
MODEA	Multi-objective differential evolutionary algorithm

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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