Heuristic Evolutionary Optimization for Control and Management of Renewable-Based Hybrid Microgrids

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***Abstract*—The surge in renewable energy and distributed generation necessitates advanced control systems for network performance enhancement. However, the lack of a standardized evaluation framework hampers comparisons, especially in complex hybrid networks. Hybrid energy systems offer greener and more reliable networks but require sophisticated control methods. To address this challenge, research explores novel linear and nonlinear techniques. This overview focuses on heuristic evolutionary optimization methods for Microgrids, covering AC, DC, and hybrid AC-DC systems, highlighting current research and future control requirements.**

***Index Terms*—Microgrids, Energy Storage Devices, Uncertainty, Optimization, Control, Management System.**

Nomenclature

ABC	Artificial Bee Colony
AC	Alternating Current
ACO	Ant Colony Optimization
CHP	Combined Heat and Power
CSA	Crow Search Algorithm
DC	Direct Current
DDPG	Deep Deterministic Policy Gradient
DER	Distributed Energy Resource
DQN	Deep Q-Networks
EBCO	Enhanced Bee Colony Optimization
EMS	Energy Management System
ESS	Energy Storage Systems
GA	Genetic Algorithm
HBMO	Honey Bee Mating Optimization
HVDC	High-Voltage DC Transmission
MCSA	Modified Crow Search Algorithm
MG	Microgrid
MILP	mixed-integer programming
MINLP	mixed-integer nonlinear programming
OPF	Optimal Power Flow
PLL	Phase-Locked Loops
PSO	Particle Swarm Optimization
RES	Renewable Energy Resource
RL	Reinforcement Learning
WOA	Whale Optimization Algorithm

I. Introduction

Microgrids (MGs) consist of distributed energy resources (DERs), energy storage systems (ESS), and loads, operating as a unified unit relative to the utility [1]. They connect to the utility via multiple points and operate in grid-tie or islanded mode. MGs can be DC, AC, or hybrid, integrating both AC and DC sources, as shown in Fig. 1 [2]. Hybrid AC-DC MGs offer improved power flow control, management, and reliability [3]. However, synchronizing AC and DC buses complicates grid architecture, necessitating further research into coordinated control strategies [3]. Control strategies for DC sub-MGs focus on voltage regulation, while AC sub-MGs regulate voltage and frequency [4]. Various hierarchical and distributed control schemes have been proposed for AC-DC MGs [5]. Researchers are exploring novel control strategies to ensure stable operation under diverse conditions [6].

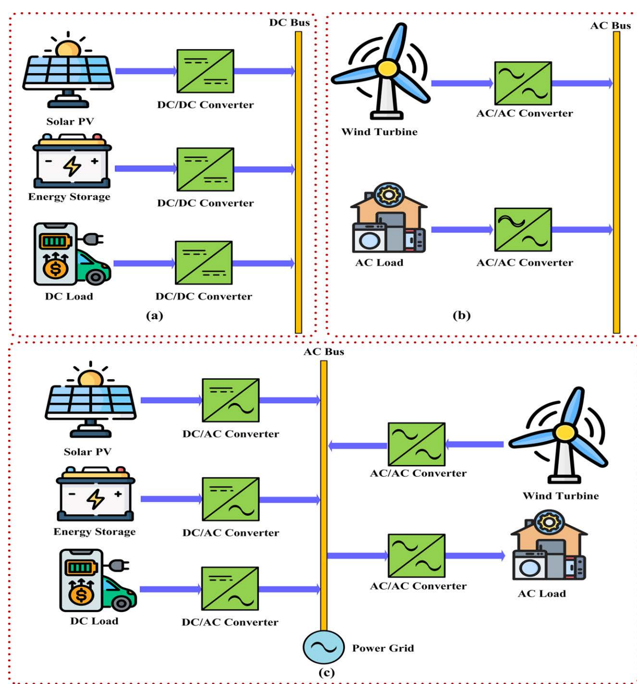

Fig. 1. MG architectures: (a) DC MG [7], (b) AC MG [8], (c) hybrid MG [9]

Resilience-centric planning for interconnected MGs is understudied. Xie et al. propose an optimal sizing framework for energy storage units [10], focusing solely on battery sizing and relying on EMSs, potentially leading to inaccurate outcomes. Wang et al. present a resilience-driven operational model for hybrid AC/DC MGs [11], integrating grid-connected and islanded modes. Cao et al. handle MG planning using chance-constrained stochastic models [12], primarily emphasizing MG islanding. Barnes et al. propose a resilient design for networked MGs [13], overlooking uncertainties. Robust methods are needed to ensure MG's resilience and alignment with realism and efficiency. Several studies overlook extreme events, focusing solely on line faults or MG islanding. The control and management systems of MGs have attracted significant attention, employing mixed-integer nonlinear programming (MINLP) and mixed-integer linear programming (MILP) methods across centralized, decentralized, and distributed themes [9]. MINLP methods use evolutionary-based optimization for exploring optimal solutions under nonlinear constraints [14], while MILP focuses on optimal source utilization within linear constraints [15]. Yet, assessing the performance of these methods is crucial for real-time applications.

Taking inspiration from the above discussions, this paper reviews various control and management systems, highlighting challenges, features, advantages and disadvantages, simplicity, ease of implementation, and effectiveness. This analysis of heuristic population-based optimization techniques and their applications lays a foundation for future research aimed at enhancing centralized EMSs and improving power network reliability and quality.

Section II introduces different layers of MG control systems, focusing on centralized approaches. Section III discusses state-of-the-art techniques for single and multi-objective problems. Section IV addresses detailed formulation and structural challenges of evolutionary algorithms for specific MG types. Finally, Section V concludes the paper.

II. Configurations of Control and Management

Designing an effective management system for an MG involves analyzing its components: generation, loads, and storage devices [16]. Optimization tools in EMSs are crucial for finding optimal solutions, considering factors like scalability and placement strategies of DGs, storage devices, and loads. The decision-making module optimizes available sources and loads to enhance power quality [17]. MG stability is maintained through economic dispatching. RESs aim to maximize grid efficiency. MG control systems adopt a hierarchical structure with three control loops: tertiary, secondary, and primary. Primary-level control regulates power converters in AC/DC bidirectional converters [18]. Power-sharing based on bus voltage and frequency eliminates bus voltage deviations in DC MGs [7]. A decentralized spatial repetitive controller stabilizes the MG system by controlling each DG [19]. Tertiary control focuses on optimal energy exchange between MGs and the upstream network, optimizing set points for DGs. A real-time management algorithm for AC-DC hybrid MGs aims for fast load matching and long-term load buffering [20].

A. Decentralized Configuration

The distributed nature of MGs, characterized by scattered DERs, poses challenges for centralized control systems. Decentralized control and operation management offer solutions to address these issues [21]. Hierarchical management for multi-agent-based MGs enhances resiliency during natural disasters by including load shedding as per emergency load priorities [22]. A droop control scheme classifying DGs into reliability and flexibility classes addresses basic issues such as damping filter fluctuations, and DC voltage offset prevention [23]. Guerrero et al. ensure harmonic current-sharing reliability by leveraging the non-linearity of loads [24]. Power-angle droop control controls source voltage phase angles proportional to system timing references [25]. Yet, voltage and frequency variations during islanded operation pose challenges and need restoration. Stability analysis of radial MGs has received attention, but meshed network stability remains an open research area [26]. Due to the limitations of droop methods, recent research trends towards centralized schemes.

B. Centralized Configuration

The centralized control and management framework is crucial for optimizing MG operation and determining equipment size, capacity, and limitations [27]. Researchers extensively explore this framework, addressing grid-tied and islanded operation modes. Particle swarm optimization (PSO) is employed in [27] to assess robustness under load and disturbance variations. Similarly, intelligent algorithms like PSO enhance power supply quality through real-time control parameter self-tuning [28]. Energy exchange and DG/demand scheduling are focal points for optimal energy management. Probabilistic frameworks like 2m Point Estimation Method (2m PEM) model uncertainty due to aggregated RESs, minimizing operational costs [29]. Economic dispatching for combined heat and power (CHP) based MGs is discussed in [30], while optimal sizing and technology deployment are explored in [31] to minimize loss and emissions. Nonlinear optimization problems from power electronic devices, generators, and loads in large-scale networks are addressed using approaches like direct search methods [32] and isolation niche immune genetic algorithms (INIGA) [33].

C. Distributed Configuration

Distributed control within MGs allows DERs to autonomously make decisions based on local measurements and limited inter-device communication. Unlike centralized control, which assigns fixed setpoints to DERs at intervals, distributed control can dynamically update setpoints in response to local conditions. Although distributed control may not match the speed of decentralized control, it offers faster response times compared to centralized methods. Advances in primary control include droop-free control, which communicates with neighboring sources to adjust power supply until all DERs reach a shared target, maintaining system frequency and voltage [34].

In the secondary control layer, distributed models vary from dense communication setups, where each DER shares states with all others, to sparse pathways prioritizing nodes with larger deviations [35]. Fully distributed tertiary control models enable DERs to interact based on incremental cost functions or marginal prices, converging to a consensus MG-wide power price [36]. While most distributed control models utilize neighboring communication to reduce burdens, increasing DER numbers may elongate convergence time [37].

TABLE I
COMPARISON OF VARIOUS CONFIGURATIONS [37]

	Centralized	**Decentralized**	**Distributed**
Speed	Low	High	Medium
Accuracy	High	Low	Medium/High
Economic	Medium	Low	Medium/High
Complexity	High	Low	Low
Communication Burden	High	Low	Medium/High
Stability	Low	High	Medium
Scalability	Medium	High	Medium

III. APPLICATIONS OF EVOLUTIONARY-BASED OPTIMIZATION METHODS FOR CONTROL SYSTEM

This section explores heuristic optimization methods for EMS applications, focusing on optimal solutions for AC, DC, and AC-DC hybrid MGs while addressing practical implementation barriers. Various methods, including GA, PSO, and GSA, have been utilized in MG optimization [38]–[43]. GA has been applied to allocate capacitors, place energy storage devices, and optimize power generation system design. Modifications like matrix real-coded GA and practical constraints have enhanced its efficacy. PSO has been employed for economic load dispatch, optimal operation of AC MGs, and ESS allocation. Adaptive variants of PSO and its combination with fuzzy logic have improved power loss and voltage profiles in distributed generations. GSA addresses uncertainties in renewable energy sources, achieving better MG operation under market price and load variations. Other methods like MCSA and ACO combined with ABC have also shown promise [44]–[48]. Further investigations are needed to ensure their effectiveness in practical applications with nonlinear constraints. EBCO is employed for economic dispatch in low-voltage MG systems, while HBMO introduces a Pareto optimal solution for large power networks. MCSA is explored for hybrid AC-DC MG optimization, demonstrating superiority over other algorithms. ACO combined with ABC is utilized for optimal DG sizing and location, while a hybrid PSO-HBMO approach minimizes power losses in radial networks.

Overall, these evolutionary-based optimization methods offer fast energy management solutions, but their performance under practical conditions requires thorough evaluation. These studies showcase the versatility of evolutionary-based optimization methods in addressing various challenges in MG optimization, paving the way for more efficient and reliable EMSs.

IV. STRUCTURE OF EVOLUTIONARY OPTIMIZATION METHODS

Various EMS approaches discussed in prior research offer improved optimization performance over conventional strategies. However, evolutionary-based optimization algorithms have drawbacks depending on their rules and parameters. Selection of the appropriate optimization algorithm hinges on factors like its ability to handle complex and nonlinear problems, convergence speed, and multi-objective functionality. Each evolutionary optimization method operates based on its set of parameters, directly impacting convergence speed and solution quality. However, the most efficient algorithm may not always be the most suitable for specific applications. Real-time applications demand algorithms that can adapt to momentary changes effectively. Thus, it is vital to evaluate the computational capabilities of each method for MG control and management and determine the most suitable approaches.

A. Genetic Algorithm (GA)

The GA employs character strings to represent chromosomes, manipulating them to find solutions to assigned problems. Typically, GA involves six key parameters: selection (genetic operators), crossover operator, crossover probability, mutation operator, mutation probability, and replacement operator, as shown in Fig. 2 [49]. Selection and crossover operators identify predefined solution sets and generate new solutions, respectively. Mutation operators enable the algorithm to avoid local minima issues. Variants of GA have emerged, like the chaotic quantum GA [50], which combines GA with a chaotic algorithm-based local search quantum probability model. Another variant, the non-dominated sorting GA (NSGA), manages constrained multi-objective problems effectively [51]. GA has shown efficacy in escaping local minima for RES sizing problems in MGs. However, its computational time and coding complexity increase with problem dimensionality. Ref. [52] proposes a two-stage iterative strategy to tackle the optimal sizing challenge of hybrid AC-DC MGs. It uses a custom GA in the first stage to address optimal sizing, followed by a nonlinear solver in the second stage to resolve operational issues based on the design and investment decisions acquired in the first stage. Integrating a detailed power flow algorithm capable of capturing technical aspects ensures precise solutions and effectively addresses MG operational hurdles.

B. Particle Swarm Optimization (PSO)

The PSO is an iterative agent-based evolutionary approach that relies on the collective swarm movements in a specific area. Each particle in the moving swarm presents an intelligent solution that depends on its own, as well as its group's behavior and displacement. There are two position values, P_{best}, and G_{best}, which stand for the previous experience of the i^{th} particle (objective) that has been attained so far and the best particle among the entire population, respectively. The particles' locations are updated based on their velocity, which addresses their displacement (Fig. 3). In other words, P_{best}, G_{best} depend

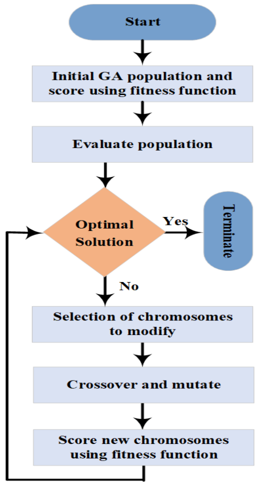

Fig. 2. Schematic diagram of GA [49].

on an acceleration V_i^{k+1}, which is a weighted random integer. The acceleration moves the particles' position as follows:

$$\begin{aligned} V_i^{k+1} &= \omega \times V_i^k + C_1 \times \text{rand}_1(.) \times (P_{best_i} - \mathrm{X}_i^k) \\ &\quad + C_2 \times \text{rand}_2(.) \times (G_{best_i} - \mathrm{X}_i^k) \qquad (1a) \\ X_i^{k+1} &= X_i^{k+1} + V_i^{k+1} \qquad (1b) \end{aligned}$$

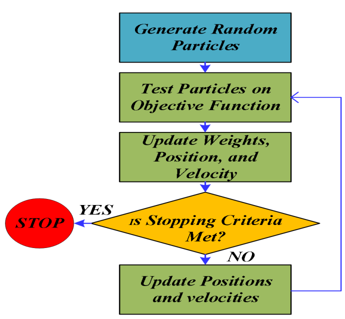

Fig. 3. Flowchart of PSO algorithm [53].

C. Gravitational Search Algorithm (GSA)

The GSA is among the popular biological-inspired optimization methods. It draws inspiration from Newton's law of gravity, where each mass (particle) exerts a force attracting other masses towards it (Fig. 4). The gravitational force $F_{je}^{k,t}$ between two masses depends on their distance and the product of their masses. The acceleration of the masses (particles) is determined by their total force and mass. Each mass's position represents a solution to the optimization problem. The GSA formulation, represented in (2a), includes the gravitational constant (G^k) at each iteration, which depends on two setting parameters, ω and G_0, crucial for escaping local minima. The mass of each particle is determined based on its fitness value. Subsequently, the particles' positions $X_{new,i}^{k,t}$ and velocities $V_{new,i}^{k,t}$ are updated using (2c) and (2d) [42]:

$$F_{je}^{k,t} = G^k \times \left(\frac{M_j^k \times M_e^k}{R_{je}^k + \epsilon} \right) \times (x_i^{k,t} - X_e^{k,t}) \qquad (2a)$$

$$G^k = G_0 \times exp \left(\overline{\omega} \times \frac{Itr}{Itr_{max}} \right) \qquad (2b)$$

$$V_{new,i}^{k,t} = a_i^{k,t} + r \times V_{old,i}^{k,t} \qquad (2c)$$

$$X_{new,i}^{k,t} = X_{old,i}^{k,t} + V_{new,i}^{k,t} \qquad (2d)$$

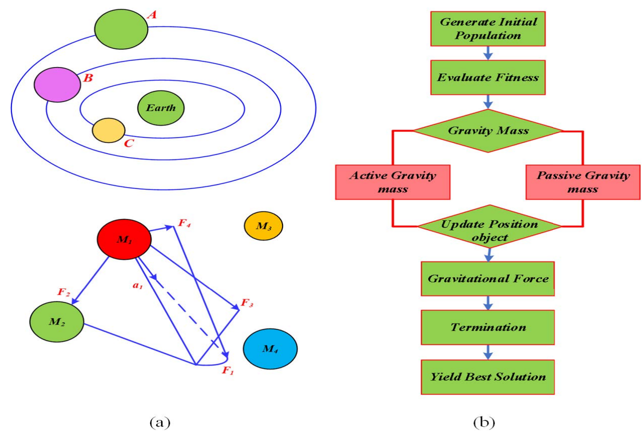

Fig. 4. GSA algorithm; (a) Processing: (b) Flowchart [54].

GSA's major drawback is its memory-less feature, meaning particles don't utilize information from previous iterations [55]. The mutation technique should incorporate GSA's best solution to address this, making it suitable for MGs optimization [56]. Despite handling greater complexity than PSO with fewer control parameters, GSA's lack of memory remains a significant limitation among evolutionary-based techniques.

D. Honey Bee Mating Optimization (HBMO) Algorithm

The HBMO algorithm introduces a novel approach inspired by the collaborative behavior of bees within a colony. The bee colony comprises a queen, drones, and workers. HBMO leverages the queen's and drones' mating process, offering a probabilistic methodology [57] applicable to optimization tasks. In each mating process, the sperm is stored in the queen's spermathecal, decreasing the queen's speed to a specific value. After each new solution is generated in the optimization process, workers are tasked with protecting the brood. The generation process iterates as better-situated broods are produced. The new solution replaces the previous queen (representing the previous solution in optimization), forming a new generation. This cycle continues until the best queen (representing the best solution) is obtained (Fig. 5) [48], [58]. In the original HBMO, the first generation of brood [39] is produced by a single queen (X_{queen}), which mates with a population of drones.

$$X_{\text{broad},i} = X_{\text{queen}} + \gamma \times (X_{\text{queen}} - S_{pi}) \qquad (3)$$

Here, S_{pi} represents the queen's spermathecal matrix, with a size of NS_p, while γ denotes the first control parameter, taking a random variable within the range of $[0, 1]$. In the modified HBMO algorithm, following the generation of the queen's spermathecal, the generation proliferation process undergoes modification. This involves selecting three individual queens from the repository (memory), along with the mean value of the repository and the fuzzy membership function. Subsequently, two individual queens are chosen as new drones for the generation proliferation process.

$$\Delta X_{qk,Dm} = r_k \left(X_{q,k} - T_F . X_{D,m} \right), k = 1, 2, 4, m = 1, 2 \tag{4}$$

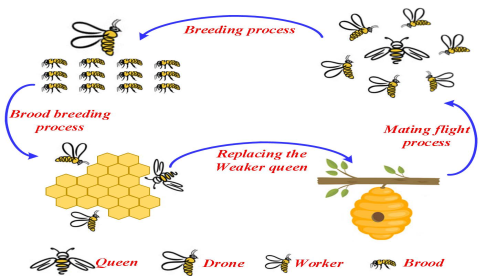

Fig. 5. Schematic of HBMO algorithm [58].

In [59], r_k and T_F denote the second and third control parameters, respectively, both being random values. T_F heuristically determines the mean value changes. $X_{D,m}$ represents the m^{th} newly generated drone, while ΔX_{qk} stands for the k^{th} new queen for the breeding process modification. While HBMO shares three control setting parameters with GSA, its convergence speed, especially in stochastic analysis, is slower than other evolutionary techniques with the same number of control parameters [43], [54]. HBMO is classified as a memory-based biologically inspired algorithm. In [58], evaluating the modified HBMO in an IEEE 30-bus system as a low-voltage MG, operational planning goals were pursued by minimizing costs and maximizing reliability. ACO combined with ABC has been explored in [45] for optimal location and sizing of DERs, leveraging ABC's global search advantage and ACO's local search capability simultaneously. Similarly, in [46], a hybrid framework of PSO and HBMO has been proposed, improving the optimization tool's performance compared to simple HBMO for DG placement and voltage profile enhancement in MGs.

E. Crow Search Algorithm (CSA)

The CSA emerges as a promising heuristic approach to address the limitations of existing evolutionary-based optimization techniques in MG control and management. CSA draws inspiration from crow behavior when foraging for food [60]. Crows are known for their intelligence, including their ability to remember food cache locations, communicate effectively, and predict each other's behavior regarding food. These traits make CSA a viable population-based metaheuristic method for solving optimization problems in a d-dimensional environment with N crows and their positions at each iteration in the search space. In MG control and optimization problems, crows represent feasible solutions, with each crow's elements representing optimal values or statuses for variables such as DGs and the main grid, as expressed in (5):

$$X_i^{Itr+1} = X_i^{Itr} + r_i \times fl_i^{Itr} \times (M_i^{Itr} - X_i^{Itr}) \tag{5}$$

Where M_j denotes the position of the crow's hiding place, representing the best position that crow j has achieved thus far. Fig. 6 illustrates a schematic diagram of the algorithm. In this diagram, small values of fl guide the CSA toward local search, focusing on the neighborhood of X_i, while large values of fl facilitate global search, directing the algorithm far from X_i. If crow X_j becomes aware that it is being followed by crow X_i, it will alter its flight path to deceive X_i and protect its nest from potential attack. This adjustment in flight path is determined by a constant value Γ denoting the awareness of crow X_j about being followed, as follows:

$$X_i^{Itr+1} = \begin{cases} X_i^{Itr} + r_i . fl_i^{Itr} . (M_i^{Itr} - X_i^{Itr}) & r_j \geq \Gamma_j^{Itr} \\ X_{\text{rand}} & r_j < \Gamma_j^{Itr} \end{cases} \tag{6}$$

In CSA, Γ balances intensification and diversification during optimization. Unlike PSO and GA, CSA requires only two parameters: flight length and awareness probability (fl, Γ), simplifying parameter tuning and enhancing convergence speed. Additionally, CSA operates as a non-greedy algorithm, promoting population diversity more effectively than greedy algorithms like GA and PSO. This feature enhances the optimization process by exploring a wider solution space.

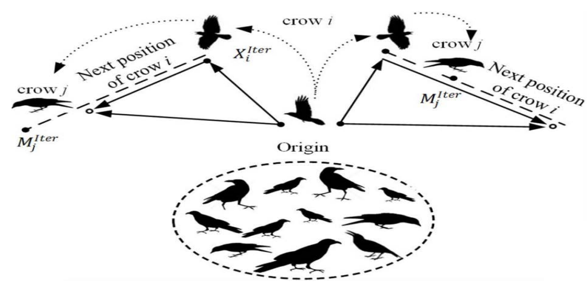

Fig. 6. Schematic diagram of the crow search improvement stage [60].

F. Ant Colony Optimization (ACO)

The ACO is a metaheuristic algorithm based on ant foraging behavior. Ants find the shortest paths to food and leave pheromone trails, which draw more ants to these paths due to higher pheromone density. Ants choose paths with stronger pheromone scents, while evaporation prevents getting stuck in local minima. Pheromone levels are updated in each iteration.

$$X_{ij}^k = \begin{cases} \frac{(\tau_{ij})^\alpha (\eta_{ij})^\beta}{\sum_{m=1}^{N_i^k} (\tau_{im})^\alpha (\eta_{im})^\beta} & j \in N_i^k \\ 0 & otherwise \end{cases} \tag{7}$$

The probability that an artificial ant k moves from node i to node j is represented by P_{ij}^k and can be calculated using a specific equation. This probability depends on several factors. The strength or intensity of the pheromone trail left between nodes i and j, denoted as τ_{ij}. Pheromones are chemical signals used by real ants to mark paths. N_i^k is the set of neighboring nodes that ant k has not visited yet and can potentially move to next. η_{ij} is a heuristic function that guides the ant's movement based on problem-specific information or rules. α and β are parameters that determine the relative importance given to the pheromone trail intensity versus the heuristic information when deciding the next move. The ACO algorithm has fast convergence speed and high accuracy. These properties make it well-suited for solving optimization problems in MGs, such as finding the optimal configuration of distributed generation sources to minimize costs and reduce environmental pollution from power generation [61].

G. Whale Optimization Algorithm (WOA)

The WOA draws inspiration from the remarkable hunting strategies employed by humpback whales [62]. Initially, the humpback whales encircle their prey, and since the optimal solution is yet to be determined, WOA utilizes the objective prey or a nearby point as the best candidate solution. Subsequently, the whales form an encirclement around the prey, and the best location is updated using the equations (8a) and (8d). In these equations, $X(t)$ represents the current position vector, while $X^*(t)$ denotes the position vector of the best solution obtained thus far. The variable D signifies the distance between the whale i i and the prey.

$$D = |CX^*(t) - X(t)| \tag{8a}$$
$$X(t+1) = X(t) - AD \tag{8b}$$
$$A = 2a.r - a \tag{8c}$$
$$C = 2.r \tag{8d}$$

After encircling the prey, humpback whales use one of two ways to attack: the shrinking encircling technique or the spiral updating position. For the shrinking encircling technique, the value of a is gradually decreased from 2 to 0, causing A to fall within the range [-1, 1]. This allows the newly updated position $X(t+1)$ to be anywhere between the current position $X(t)$ and the best solution obtained so far for the position vector, $X^*(t)$. The spiral updating position condition is applied between the position of the humpback whale and its prey, according to (9). Here, b is a constant used to model the shape of the logarithmic spiral, and l is a random value in the range [-1, 1].

$$X(t+1) = X(t) + De^{bl}\cos 2\pi l \tag{9}$$

The probability of the whales selecting either of the above-mentioned ways is 50% [62], as depicted by (10) in which p is an arbitrary value in the interval [0,1].

$$X_{ij}^k = \begin{cases} X(t+1) = X(t) - AD & p < 0.5 \\ X(t+1) = X(t) + De^{bl}\cos 2\pi l & p \geq 0.5 \end{cases} \tag{10}$$

WOA utilizes (11a) and (11b) to search for prey. X_{rand} is a random position vector or a random whale chosen from the whale population. WOA is a very efficient optimization algorithm that benefits from having a limited number of parameters while most of the important parameters are self-tuned in the iteration process [63]. Advantages such as optimization accuracy and fast convergence make it possible for WOA to ensure optimum management of MGs and DERs [64]. The WOA employs the equations (11a) and (11b) to facilitate the search for prey, which represents the optimal solution. In these equations, X_{rand} denotes a random position vector or a randomly selected whale from the population. WOA is renowned for its efficiency as an optimization algorithm, benefiting from having a limited number of parameters, while most of the crucial parameters are self-tuned during the iterative process [63]. Its advantages, such as high optimization accuracy and rapid convergence, make WOA well-suited for ensuring optimal management of MGs and DERs [64].

$$D = |CX_{rand} - X(t)| \tag{11a}$$
$$X(t+1) = X_{rand} - AD \tag{11b}$$

H. Reinforcement Learning (RL) Methods

The dynamic nature of hybrid MGs, which integrate renewable energy sources, energy storage systems, and fluctuating loads, poses significant challenges for traditional control methodologies. However, recent advancements in machine learning algorithms, particularly in the field of RL, have emerged as well-suited approaches for controlling these diverse systems. RL offers a promising data-driven approach for MG control, enabling the system to learn and adapt to evolving conditions [65]. These RL algorithms are particularly advantageous for MG control due to their adaptability, robustness, and ability to handle multi-objective optimization problems. They can effectively learn and optimize control policies based on the dynamic interactions between the MG components, renewable energy sources, and varying load demands. However, the application of RL in MG control also presents challenges, such as computational complexity, the exploration-exploitation trade-off, and safety considerations. The paper explores these challenges and discusses strategies to address them, ensuring RL techniques' effective and reliable implementation in MG optimization. Overall, the integration of RL methods in MG control systems offers a promising approach to effectively manage the complexities of hybrid MGs, enabling efficient and sustainable energy management while adapting to changing conditions and optimizing multiple objectives simultaneously.

1) Q-Learning: Q-Learning is a fundamental model-free RL technique where an agent learns an optimal policy through trial-and-error interactions with the environment. In MG control applications, Q-Learning enables the system to make decisions based on the rewards received, such as power dispatch. While Q-Learning offers a straightforward implementation, its scalability to complex MGs with numerous state variables can be challenging [66].

2) Deep Q-Networks (DQN): The DQNs extend the capabilities of Q-Learning by leveraging deep neural networks to approximate the Q-table, allowing the handling of high-dimensional state spaces. This makes DQN suitable for complex MGs with multiple variables, such as voltage and power flow. DQN exhibits faster learning and better generalization compared to traditional Q-Learning methods [65].

3) Deep Deterministic Policy Gradient (DDPG): The DDPG belongs to the class of actor-critic algorithms, combining the advantages of policy-based and value-based RL approaches. DDPG excels in continuous control problems, making it suitable for MG tasks involving power setpoints or converter modulation ratios. It efficiently balances exploration and exploitation while learning complex control policies [67]. RL techniques offer several advantages for MG control, including adaptability to changing conditions, robustness against uncertainties, and multi-objective optimization capabilities. However, challenges such as computational complexity, the exploration-exploitation trade-off, and safety and security considerations need to be addressed for real-world deployment [68].

V. Conclusion

EMSs offer a reliable approach for controlling and managing MG operations, particularly when paired with optimization tools. This paper explores current intelligent evolutionary methods, providing insights into their potential for future power distribution infrastructures. We summarize various control and management systems, highlighting challenges, features, merits and demerits, simplicity, ease of implementation, and effectiveness. This analysis of heuristic population-based optimization techniques and their applications lays a foundation for future research aimed at enhancing centralized EMSs and improving power network reliability and quality.

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