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An advanced meta metrics-based approach to assess an appropriate optimization method for Wind/PV/Battery based hybrid AC-DC microgrid

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ABSTRACT

This paper discusses the growing influence of renewable energy and distributed generation, emphasizing the need for smart control systems to maximize benefits and optimize network performance. However, the absence of a standardized evaluation framework makes it challenging to compare different control systems effectively, especially in large-scale hybrid networks with both AC and DC components. While hybrid energy systems show promise for greener and more reliable power networks, they introduce complexity to control methods. Researchers are exploring innovative approaches, including linear and nonlinear techniques, to leverage renewable energy sources effectively in hybrid grids. The paper provides an overview of heuristic evolutionary optimization methods for microgrids (AC, DC, and hybrid AC-DC), highlighting promising techniques such as Crow Search Algorithm, Modified Crow Search Algorithm, Particle Swarm Optimization, and Genetic Algorithms. Comparative analysis suggests that the Modified Crow Search Algorithm performs best across various evaluation criteria, indicating its potential for optimizing microgrids effectively.

1. Introduction

Energy demand's potential increase of 53% by 2035 has been steadily increasing the trend toward renewable energy resources (RESs) usage over the past decade to solve acute sustainability issues, environmental concerns, and reliable energy problems [1]. As defined by the US Department of Energy and certain European institutions, a microgrid comprises a network of distributed energy resources (DERs), energy storage systems (ESS), and interconnected loads, distinctly partitioned by electrical boundaries, functioning as a unified, controllable unit relative to the utility [2]. These microgrids connect to the utility via multiple points of common coupling (PCC) and operate either in grid-tie or islanded mode, contingent upon grid supply availability and operational parameters [3,4]. Microgrids (MGs) can be DC, AC, or hybrid, integrating both AC and DC sources, as shown in Fig. 1 [5].

A hybrid AC-DC microgrid, where AC/DC sources supply respective AC/DC buses, operates in grid-tied mode and can function independently even when no power is transferred from the utility grid, referred to as islanded mode [5,9]. Any surplus or deficit power can be exchanged with the utility for grid-tied mode, while islanded mode includes intentional (planned) and unintentional (unplanned or accidental) islanding. Intentional islanding encompasses service maintenance and scheduled outages, while unintentional islanding results from short circuits, faults, or component malfunctions, posing more challenging control issues. Interconnection and interoperability of DERs with associated ESSs and ICs can be implemented as per IEEE standard IEEE-1547 [10]. With advancements in renewable energy sources and power electronics, DC generation and transmission via high-voltage DC transmission (HVDC) lines have gained popularity alongside traditional AC generation and high-voltage AC transmission (HVAC). Recognizing the benefits of both AC and DC microgrids, researchers have developed hybrid AC-DC microgrids, aiming for enhanced power flow control, management, stability, reliability, energy management, and economic efficiency. Directly integrating DERs, ESSs, and AC/DC loads in hybrid AC-DC microgrids reduces the need for converters, lowering system losses and expenses. However, the synchronization requirement between AC and DC buses complicates the grid architecture compared to independently operating AC and DC microgrids [11]. This necessitates

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further research into coordinated control strategies (centralized, decentralized, and distributed) for DC and AC microgrids operating independently of the utility. The architectural intricacies and challenges of hybrid AC-DC microgrids are reviewed in [11]. Additionally, employing interfacing converters for the combined operation of AC and DC microgrids results in advanced hybrid AC/DC microgrids, leveraging both AC and DC energy sources [12–14]. Nonetheless, such hybrid microgrids require relatively complex control strategies [15,16]. Control strategies for DC sub-microgrids typically focus on bus voltage regulation without considering reactive power control or frequency synchronization, while AC sub-microgrids regulate AC bus voltage and frequency [17–19]. Hierarchical control strategies are often suitable for AC-DC microgrids [20–22], while distributed control strategies can ensure stable operation and smooth transitions in active distribution networks [23,24]. Coordinated control schemes for AC-DC microgrid control are extensively discussed in [25–27]. Presently, researchers are proposing various new control strategies for hybrid AC-DC microgrids to ensure stable and seamless operation under diverse operating conditions [28].

In the literature, resilience-centric planning challenges for interconnected Microgrids (MGs) have yet to receive comprehensive attention. A notable contribution in this realm, outlined in [29], proposes an optimal sizing framework for energy storage units to bolster resilience and reliability. However, this approach solely focuses on battery sizing and relies on Energy Management Systems (EMS) for modeling MG operation, potentially yielding inaccurate outcomes. Moreover, it addresses resilience through single-line faults, a scenario that might lack realism as resilience evaluations ideally should account for $N-K$ contingencies.

Ref. [30] introduces a resilience-driven operational model, integrating two operational modes (grid-connected and islanded), and incorporating intricate technical aspects such as voltage-related operational limitations, to fortify the resilience of a hybrid AC/DC MG. A meticulous AC optimal power flow (OPF) algorithm accounts for operational constraints and power exchanges between AC and DC subgrids. demand response strategies are implemented to mitigate load shedding during emergency scenarios. In [31], a two-stage chance-constrained stochastic conic model is introduced to tackle MG planning issues, incorporating multi-site investments and dual-mode operations. Similarly, Ref. [32] develops a risk-averse mixed-integer conic model for designing MGs, emphasizing reorganizing MG boundaries. Yet, these studies primarily hinge on MG islanding as the primary external contingency. Additionally, Ref. [31] adopts a single-bus system to represent each MG, which may oversimplify the network's intricacies. Furthermore, fixed capacities for DER sizing problems, as employed in [31], could lead to excessive investments. Another approach, detailed in [33], proposes a resilient design considering line hardening, redundancy, and networked MGs to mitigate power outages during extreme events. While this paper considers line faults as potential contingencies, it overlooks uncertainties and relies on fixed capacities for sizing backup generators.

Often simplifies Optimal Power Flow (OPF) algorithms and resorts to stochastic programming for uncertainty modeling, potentially compromising solution accuracy. However, when employing detailed nonlinear AC OPF, ensuring computational efficiency and solution feasibility becomes uncertain. Hence, robust methods are needed to ensure MG resilience in worst-case scenarios, aligning with realism and efficiency in planning considerations. Moreover, several studies only account for line faults [29,33] or MG islanding [31,32] as contingencies, which might not adequately capture the extensive impacts of extreme events, such as those examined in [34].

Control and management systems of MGs and smart grids have received significant study attention in the past decade, with numerous articles available in the literature [8]. These studies are carried out for mixed-integer nonlinear programming (MINLP) and mixed-integer linear programming (MILP) techniques, considering three general themes [8]: Centralized, Decentralized, and Distributed.

The MINLP for a centralized fashion involves advanced evolutionary-based optimization techniques for exploring the optimal solution of the grid management system associated with all nonlinear constraints [35]. Optimization techniques and tools based on evolutionary computations have recently become popular due to their capability to solve nonlinear problems [27]. The heuristic nature of the algorithms that inspired evolutionary techniques makes them good candidates for multi-objective or Pareto functions applications [36]. The MILP focuses on developing the grid's source utilization optimal solution on the linear environment limits [37]. But, based on the functionality of the control and energy management system, the performance evaluation framework for comparative analysis is required. The impact of such comparative analysis of control systems results in a full understanding of each methodology's feasibility and reliability for real-time applications.

Therefore, taking a cue from the above discussions, this paper addresses the above-mentioned issues as follows:

- A comprehensive review and discussion of the weight modification process using various heuristic evolutionary optimization techniques, as well as their past roles in MGs.
- A proposed metric-based evaluation of heuristic evolutionary-based optimization strategies to discern what optimization techniques are the most well-suited to control various grid parameters across a spread of grid objectives.
- A review of the qualitative centralized nonlinear methods to find a cost-effective set of solutions or even the highest attainable

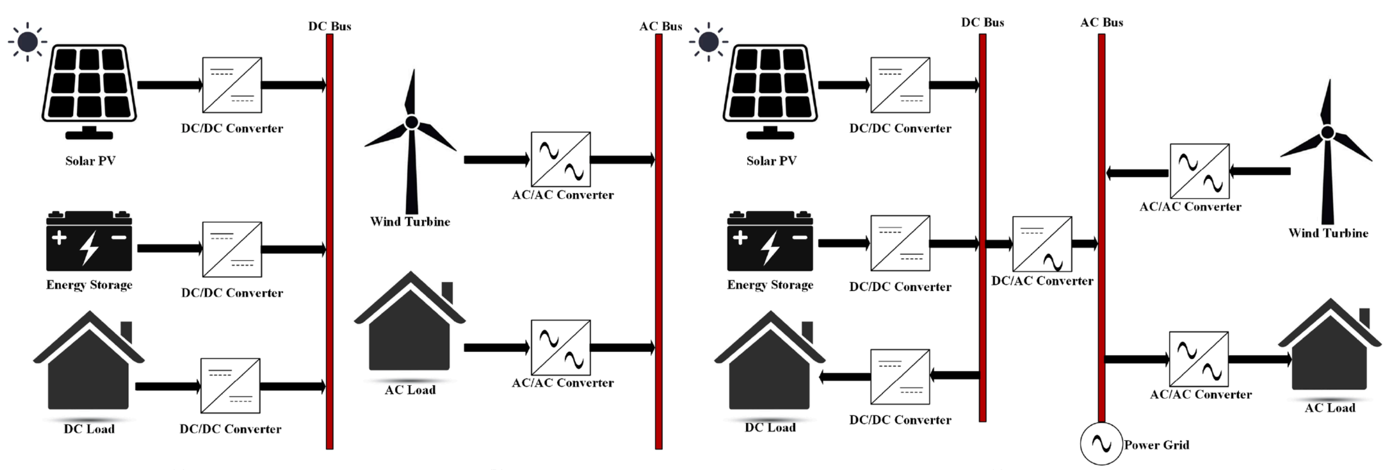

Fig. 1. Architecture of MGs (a) DC MG [6]; (b) AC MG [7] (c) Hybrid MG [8].

performance for AC, DC, and AC-DC hybrid MG, as well as their control-performance assessment.

The organization of the paper is given as follows. In Section 2, different layers of MG control and management systems are introduced, and centralized control and management approaches for various types of MGs are presented. Section 3 provides state-of-the-art techniques for single and multi-objective problems. Detailed formulation and structural challenges of each proposed evolutionary algorithm to control and manage specific kinds of MGs are addressed in Section 4. The proposed metrics evaluation to assess control methodologies on potential applications is presented in Section 5. Section 6 concludes the research requirements for current applications and future development.

2. Configurations of control and management

Designing a proper management system for an MG relies on an exhaustive analysis of components such as generations, loads, and storage devices. Moreover, the corresponding optimization tools and approaches utilized in the EMSs play roles in exploring the best possible solution depending on scale, setting points, and placement strategies of DGs, storage devices, and loads. Scalability deals with DGs' capacity and type. Setting points deals with DG placement in the distribution networks so that the control and management are configured to minimize the loss, maximize profit, and increase performance. Many studies have focused on two different aspects, centralized and decentralized, for management configuration by implementing various optimization tools based on MG's types and consisting of parts [38–44].

In other words, the decision-making module of the control and energy management system makes the optimization method leverage the available sources and loads optimally and provide better power quality in the time horizon. Also, MG stability controlled by economic dispatching plays a vital role in ensuring the generation, load, and storage are stable within power networks [45]. Optimal operation of RESs has also strived to attain maximum efficiency in grids. From a control structure perspective, MG control systems are often implemented in a hierarchical manner, as depicted in Fig. 2, with three control loops:

- Tertiary loop, which is responsible for power exchange.
- Secondary loop, which aims to keep the grid's electrical operating points at nominal values and
- Primary loop, which provides device-level control for power converters.

In some studies [47–49], a control and management configuration at the primary level is implemented to control power converters for a fully controlled AC/DC bidirectional converter. In [6,50] and [51], power-sharing based on bus voltage and frequency of the load and grid managed to eliminate bus voltage deviations in DC MGs by droop control for maximizing profits. A decentralized spatial repetitive controller based on the signature frequency-voltage injection method is proposed in [49] for each DG to stabilize the overall MG system. The grid simulates without any presence of mutual communication among MG components and operates under different types of sudden transients. Since this work's primary focus is on the steady-state analysis of the AC, DC, and AC-DC hybrid MGs, tertiary control is discussed regarding optimal energy exchange between the MGs and upstream network depending upon the optimal set point for DGs. Mohamed et al. [52] proposed a real-time management algorithm for AC-DC hybrid MGs consisting of supercapacitors for fast load matching in long-term load buffering and aims to control energy in power networks by using nonlinear regression. An operation management frame aims to determine the optimum and best solution in the multidirectional state for the above-mentioned applications.

2.1. Decentralized configuration

Distributed structural features of MGs rely upon distributed energy resources (DERs), scattered over a wide area, which creates some issues for the centralized control and management system. Decentralized control and operation management would help cope with centralized problems [53]. In reference [54], hierarchical management for multiagent-based MGs is investigated to increase the resiliency level under difficulties caused by natural disasters. Their approach covered load shedding, which depends upon what kinds of loads are vital in the situation of emergency. They also developed a software-based MG simulator to evaluate, sustain, and recover the necessary power for loads through utility disturbances. Several basic issues have been addressed in [55], such as damping filter output fluctuations and preventing the DC voltage offset by inverter control.

A droop control scheme is proposed by classifying the DGs into three classes to achieve a high reliability and flexibility level. Another work [56] extended the droop control concept to guarantee a harmonic current-sharing relay on the non-linearity of the loads. The suggested approach, as shown in Fig. 3, provides initial control signals from sources into the network, and phase-locked loops (PLL), in related remote units investigate for information and adjust the output. In further investigations [57–59], researchers introduced power-angle droop control to regulate the source voltage's phase angle proportional to a system timing reference that depends upon its droop law. The voltage and frequency variation of MGs based on a change in load in the islanded operation mode is counted as the main drawback of such control approaches. Furthermore, there should be a restoration mechanism for bringing voltage and frequency to their nominal values. However, problems such as stability issues and a lack of synchronizing signals must be addressed in the methodology. By far, most previous works focused on stability analysis [60–62] of radial MGs, while meshed networks stability analysis is still an open research area. Due to the dominance of radial power networks and the drawbacks of droop-based control and management methods, most recent research focuses on a centralized management scheme.

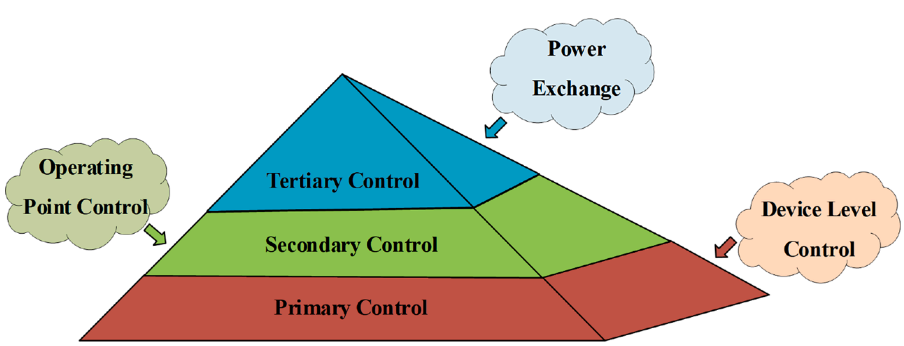

Fig. 2. MG Hierarchical control and management block diagram [46].

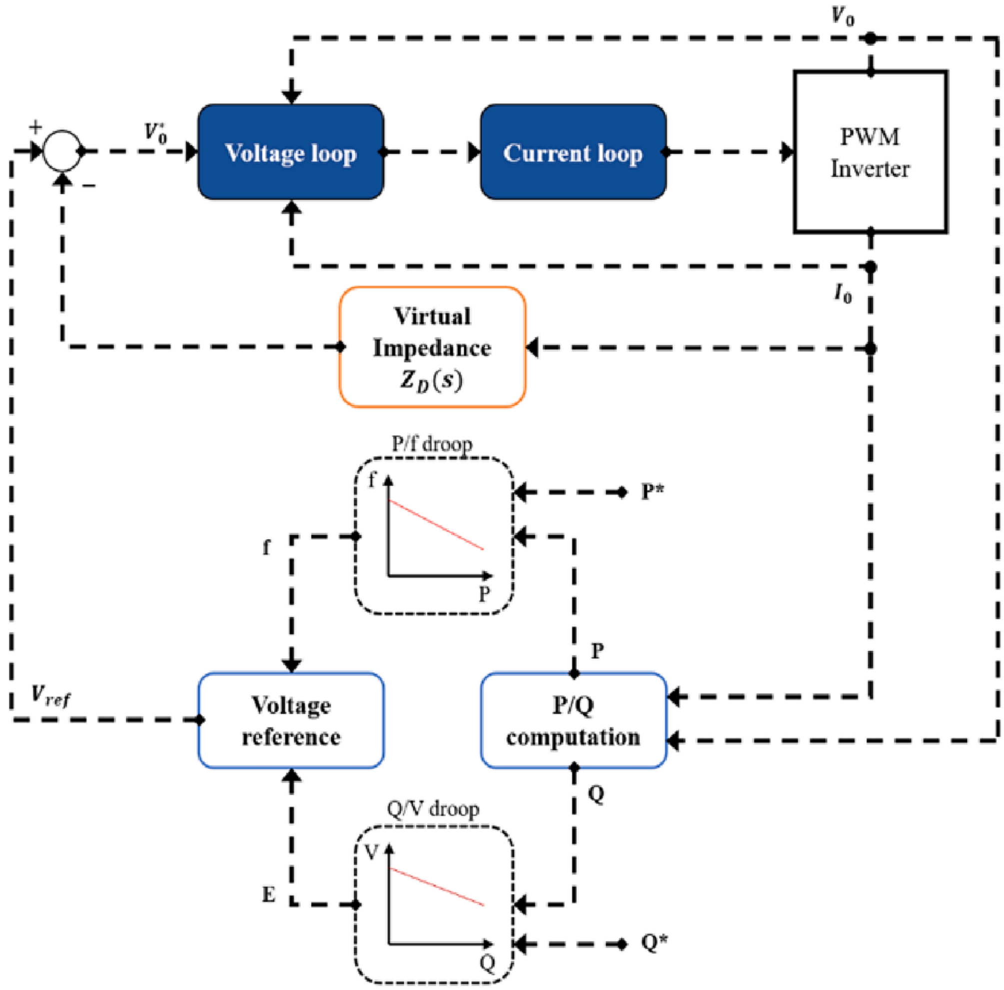

Fig. 3. General diagram of droop control as secondary control loop [52].

2.2. Centralized configuration

As a core decision-maker, the centralized control and management framework plays an essential role in the network's economy after defining the size, capacity, and limitation of equipment and components integrated into power sub-grids. This section reviews the centralized control framework for optimizing MGs' operation, and different researchers have discussed it in grid-tied or islanded operating modes. An optimization problem was analyzed in [63] to consider the MG's dynamic nature in grid-tied and islanding modes, which rely on optimal controller parameters. While in autonomous mode, under load, and facing disturbance variations, the control and management system's robustness is assessed where particle swarm optimization (PSO) is employed. The power supply's quality improvement is explored using intelligent algorithms (PSO) in [64] to self-tun control parameters in real-time. Real-time analysis of controller setting parameters for voltage source inverter-based DGs was also investigated to realize the minimum integral time absolute error when the MG test system switches from interconnected to islanding operation mode as well as a similar power-sharing approach between MGs and the main-grid that was considered in other works [65,66] under both steady-state and dynamic analysis.

Another major focus on energy exchange and DG/demand scheduling has been considered to offer optimal energy management for various conditions. A probabilistic framework [67] based on the 2m Point Estimation Method (2m PEM) is investigated to model uncertainty due to RESs aggregated to MGs to minimize operation cost. In a different scheme, economic dispatching of combined heat and power (CHP)-based MG was discussed in [68] and similarly [69] deploys optimal size and location, as well as technologies to minimize loss and emissions depending upon the type of DER. A dynamic programming formulation is proposed to determine an optimal mixture of CHP-based MG resources based on the reliability criterion for time-varying generation and load [70]. A quantum genetic algorithm (GA) has been explored for superior economic dispatch for smart MG heat-balancing while considering power supply reliability and quality [71]. A chaotic coding through hybrid GA has also increased the algorithms' diversity, so the novel economic dispatch improved MGs' performance.

The nonlinear nature of these problems comes from various power electronic apparatus, generators, and loads, making a complex problem specifically in a large-scale network. Thus, some studies focus on a non-convex problem state to investigate the feasibility and functionality of optimization tools in nonlinear/non-convex environments. A direct search method (DSM) approach is considered to determine the optimal wind turbine capacity in the form of wind-thermal mixture coordination dispatch for commercial users' time-of-use rate, thus simplifying the nonlinear problem [72]. Liao et al. [73] presented an isolation niche immune genetic algorithm (INIGA) to deal with the multi-peak model function for developing a dynamic unit commitment of AC MG under nonlinear constraints. Therefore, heuristic evolutionary-based optimization algorithms show high compatibility with such problem states for single and multi-objective applications. However, the critical challenge is identifying the best strategy among the most recently used optimization methodologies for the control and management systems associated with renewable and sustainable energy resources.

2.3. Distributed configuration

Distributed control within microgrids empowers DERs to autonomously make decisions based on local measurements and limited inter-device communication. In contrast to centralized control, where MGCC assigns setpoints to DERs at fixed intervals, distributed control can dynamically update DER setpoints in response to local conditions, whether through measurement or communication alterations. Consequently, the response speed of distributed control is anticipated to exceed that of centralized control, albeit lagging behind communication-free decentralized control. Ideally, distributed control leverages local coordination to stabilize the system and converge DER operating states to desired values, although this may introduce control oscillation during the convergence process. The comparision of centralized, decentralized, and distributed configurations on the basic of few parameters is summerized in Table 1.

Historically dominated by decentralized methods, primary control has seen recent advancements with neighboring communication-based droop-free control, potentially challenging decentralized control's dominance [74]. Droop-free control operates on voltage source inverters akin to droop control but differs in its communication with neighboring sources to adjust power supply until all DERs reach a shared target, maintaining system frequency and voltage [75]. In the secondary control layer, two common distributed control models exist. One relies on dense communication, where each DER shares operating states with all others [76,77]. Conversely, sparse communication pathways prioritize nodes with larger deviations to achieve even frequency and voltage distributions [78,79].

In fully distributed tertiary control models without MGCC coordination, DERs interact based on incremental cost functions or marginal prices, converging to a consensus microgrid-wide power price [80–82]. All in all, most distributed control models utilize neighboring communication to reduce communication and computational burdens, offering plug-and-play properties. However, as DER numbers increase, convergence may require more iterations, potentially elongating the settling time of distributed control.

Ref. [83] presents a detailed comparison of the above-discussed methods in terms of responding speed, accuracy, economic performance, complexity, computational burden, stability, and scalability.

3. Applications of evolutionary-based optimization techniques for control system

This section will describe the heuristic optimization methods structure for EMS applications, investigating optimal solutions for AC, DC, and AC-DC hybrid MGs. Some of the practical barriers to implementing the optimization methods in real time are also discussed. Several well-known optimization methods have been introduced in several scientific works to solve problems in different conditions and applications. The first well-known optimization method for applications such as capacitor allocation and energy storage device placement in MGs is GA. These applications rely on the GA method to solve large-scale and complex optimization problems. Chen et al. [84] developed smart energy management (SEMS) for economic load dispatch and optimal DG operation based on matrix real-coded GA. A new version of GA can be found in [85] in which the following practical constraints are considered: feeder loading, voltage violation, and the reactive power compensation level to optimize reactive power sources using capacitor banks. The authors also evaluated the performance of their proposed control approach for two case studies (9-bus and 24-bus AC MGs) in both island and grid-tied operation modes. Another methodology has been developed for energy storage systems (ESS) in [86] to investigate the economic analysis of ESS allocation into MGs. For the sake of performance increment of MGs in optimal ESS arranging and allocation, a 2-D real number matrix GA was presented to verify that the effective net present value (VPN) of ESS depends on their size and type. Due to extensive research on RESs such as PV and WT to bolster their position as promising power infrastructures, authors in [87] applied GA to design an optimal power generation system that leverages stand-alone hybrid PV/WT for residential applications. Their proposed method's defining characteristic is its comprehensive system design, containing several batteries, the PV array's tilt angle, and WT's corresponding installation height, significantly affecting the production level, maintenance, and installation cost. Zhao et al. [88] presented a methodology based on a non-dominated sorting genetic algorithm (NSGA-II) to consider the batteries' lifetime characteristics to minimize the generation cost and maximize energy storage devices' lifetime in the stand-alone mode of MGs. The optimum configuration of hybrid solar-wind systems associated with battery banks to satisfy the supply probability loss requirements has been investigated by [89] using GA to search for the optimal configuration dynamically. A configuration in [89] contains five decision variables: 1) number of PV modules, 2) number of wind turbines, 3) battery slope angle, 4) PV slope angle, and 4) wind turbine installation height for a typical low-voltage MG.

Comparing the GA algorithm utilized in the above-mentioned studies, the limitations found in the GA method are low convergence speed, inability for multi-objective functions, and large-scale problems. Another well-known optimization technique known as PSO has been utilized in the literature to improve the EMS performance in MGs to cope with the GA's problems. In [90], an adaptive modified PSO was developed for optimal operation of a notional AC MG, accompanied by a backup hybrid power source, e.g., microturbine, fuel cell, and battery. A combination of the chaotic local search (CLS) mechanism and fuzzy self-adaptive (FSA) structure is utilized to analyze more accurate and practical mathematic models for RES dynamic stability characteristics. Lan et al. [91] used the PSO algorithm to improve power loss and voltage profiles for DGs, particularly RESs. To show the effectiveness of their proposed optimization algorithm for best ESS allocation in a distributed control system, based on decreasing the risk of voltage instability, the authors in [91] validate their method on the IEEE 34-bus system associated with different load types. Bevrani et al. [92] have discussed using fuzzy logic and PSO to ensure that generation-load balance requirements meet the necessary criteria. Because of the classic control and management systems' issues regarding RES uncertainty in large-scale MGs, intelligent management design methodologies have more potency than pure fuzzy PI Ziegler-Nichols PI methods. Wang and Singh [93] developed a multi-criteria design utilizing the PSO method to derive a more rational evaluation for a hybrid generation system consisting of AC and DC networks. The performance of a hybrid power network based on cost, reliability, and emission criteria was considered to obtain trade-off solutions that offer various design alternatives to the operators for maximizing profits of the local distribution system. In another resource [94], a joint optimization approach consisting of wind farm reactive power control and distribution network reconfiguration is proposed based on binary and hybrid PSO with wavelet mutation. This modified PSO method incorporates the GA's evolutionary operation of mutations.

Another stochastic framework for energy and operation management of AC MG based on a gravitational search algorithm (GSA) is

Table 1
Comparison of centralized, decentralized, and distributed configurations [83].

	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

investigated to consider the uncertainty effect of RESs at different levels, such as market price and loads [95]. Niknam et al. in [95] employed Rosenblueth's 2m point estimate method (2m PEM) to optimize an MG operation by probabilistic modeling of the uncertainty in the RESs power generation, market, and load demands. An intelligent stochastic energy management system in [96] is proposed to solve the unit commitment problem for handling the corresponding constraints of the thermal units associated with large-scale wind farms on the test system, which depends upon binary GSA. Further investigation in Ref. [97] was done by implementing an opposition-based self-adaptive GSA for optimal voltage control and a 30-bus AC test system's reactive power. The combined operation management of DGs and demand response (DR) is addressed in [98] and relies on multi-period GSA in the MG-islanded operation mode. Their real-time analysis is validated over IREC MG to evaluate the accuracy and effectiveness of MGSA.

Moreover, a meta-heuristic algorithm founded on bats' echolocation behavior has been explored in [99] to provide nonlinear single and multi-objective optimization problems for power networks. Other investigations in [99,100] inspired by the dolphin echolocation optimization algorithm (DEOA) explore renewable MGs' stochastic scheduling. The proposed multi-objective approach aims to minimize the net cost and emission level of the MGs, considering its forecasting variables, i.e., a day ahead of renewable energy availability and load data from National Renewable Laboratory technical reports. The studies above have provided a fast approach to energy management compared to well-known PSO and GA strategies. However, their performance in practical applications with nonlinear constraints should be investigated to ensure their effectiveness. Lin et al. [101] employed an enhanced bee colony optimization (EBCO) to solve the typical low-voltage MG system's economic dispatch problem in both islanded and grid-tied operations. Using the EBCO procedure, the self-adaption repulsion factor has been utilized to improve the bee swarm pattern behavior and increase its accuracy and effectiveness, particularly in high dimensions. In [102], another Pareto optimal solution based on the honeybee mating algorithm aims to minimize the active power losses, total cost, and voltage deviations. The induced algorithm based on modified honeybee mating optimization (HBMO) is introduced to offer a set of non-dominated solutions for the nonlinear optimization problem in large power networks consisting of 32- and 85-bus AC distribution test systems. An interactive HBMO approach in [103] simultaneously reduces power loss in peak load and voltage deviation.

Papari et al. [104] explore a modified crow search algorithm (MCSA) for hybrid AC-DC microgrid optimization given a stochastic load flow for an IEEE standard test system. MSCA implements a modification process that aims to increase the search area of the potential optimal solution, as well as increase the diversity of the solution swarm. Simulation results illustrate MCSA's superior performance over PSO, GA, and crow search algorithm (CSA) in terms of energy losses, cost, voltage deviation, and computation time over a 24-hour period.

For realistic analysis, a fuzzy stochastic long-term modeling associated with the uncertainties of DERs is employed to illustrate the performance and credibility of the proposed approach in the IEEE 30-bus radial test system. Kefayat et al. [105] employed a combination of ant colony optimization (ACO) with artificial bee colony (ABC) for optimal size and location of DGs by modeling uncertainty in the distribution level. The hybrid ACO-ABC method's potential is demonstrated in the IEEE 33-and 69-bus case studies, comparing its performance against other evolutionary-based techniques. To enhance the performance of evolutionary-based optimization techniques for optimum DG sizing and location in the local distribution system, authors in [106] use a hybrid approach consisting of PSO and HBMO. By applying a deterministic analysis that depends upon the hybrid optimization method, the total power losses in radial networks were minimized, and the voltage profile was improved.

4. Structure of evolutionary optimization techniques

The above-stated research works to provide a wide variety of EMS approaches that increase optimization performance compared to conventional strategies [1]-[6]. However, these kinds of heuristic and iterative algorithms suffer from different downsides depending on their rules. Each evolutionary-based optimization tool controls and manages MGs depending on their ability to solve complex and nonlinear problems. The determinative factor for choosing the proper optimization algorithm is the number of control parameters associated with the structural nature of the evolutionary techniques. Control parameters influence optimization algorithms in different ways, such as the algorithm's capability for finding the optimal solution, the convergence speed, and multi-objective functionality. The functionality of each evolutionary technique relies on its setting parameters. The number of setting parameters differs for different methods and directly affects the algorithm's convergence speed. Also, sometimes, the most efficient optimization tool may not be the most appropriate approach for specific applications. For instance, real-time applications need optimization approaches that are functional and compatible with momentary changes. Hence, the aim here is to consider each optimization tool's computational potential for operational control and management of MGs and to find suitable approaches. The detailed structural information of some well-known optimization techniques is as follows.

4.1. Genetic algorithm

As a basic evolutionary method, GA is inspired by Darwin's theory and uses character strings to represent the chromosomes. The strings are manipulated and tested for their fitness in solving the assigned problem. Generally, GA's setting parameters include six main processes: selection (genetic operators), crossover operator, crossover probability, mutation operator, mutation probability, and replacement operator [107]. The selection and crossover operators select and find predefined sets of solutions and new solutions, respectively (Fig. 4).

The mutation operator gives the algorithm the capability to escape from the local minima problem. Some GA variations have evolved in previous works, such as in [71], which use a chaotic quantum genetic algorithm by combining GA with a local search quantum probability model based on chaotic algorithms. Another kind of GA named non-dominated sorting GA (NSGA), was introduced by [108] to solve constrained multi-objective problems effectively. NSGA was investigated by other scholars as well [88,109,110]. In all the mentioned research works, GA demonstrated the ability to escape a local minimum for RES sizing optimization problems in MGs. However, the algorithm's functionality time and coding complexity increase proportionally to the problem due to higher space dimensions.

Study [111] aims to devise a suitable combinatorial optimization method to address the optimal sizing dilemma of hybrid AC-DC microgrids. It introduces a novel two-stage iterative strategy: firstly, employing a meta-heuristic approach grounded in a custom GA to address the optimal sizing predicament, followed by deploying a non-linear solver in the second stage to resolve operational issues based on the acquired design and investment decisions. The proposed method furnishes precise solutions by integrating a detailed power flow algorithm capable of capturing technical aspects like voltage and frequency, thus effectively tackling microgrid operational hurdles.

4.2. Particle swarm optimization

PSO is an iterative agent-based evolutionary approach that depends on the collective swarm movements in a specific area. James Kennedy and Russell Eberhart developed the idea behind PSO to solve a multi-objective function problem. 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},

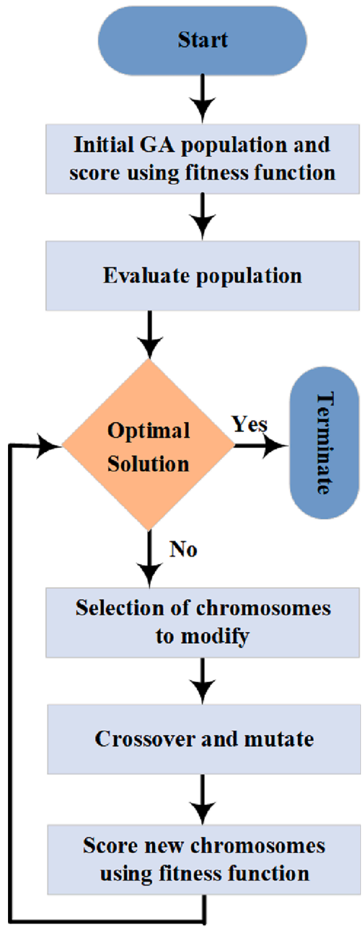

Fig. 4. Schematic diagram of Genetic Algorithm (GA) [107].

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. 5). In other words, P_{best}, G_{best} depend on an acceleration V_i^{k+1}, which is a

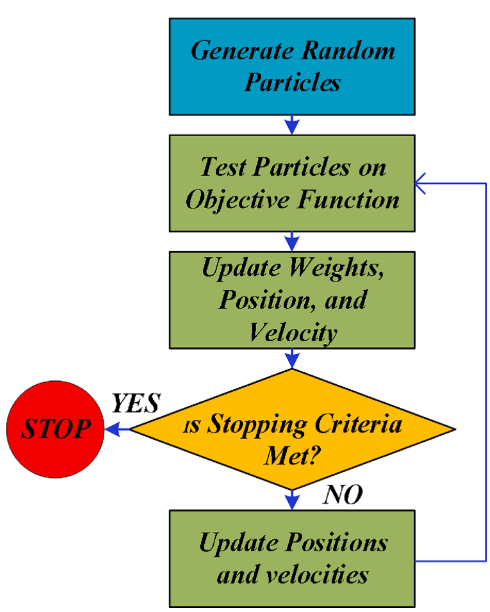

Fig. 5. Flowchart of particle swarm optimization (PSO) algorithm [90].

weighted random integer. The acceleration moves the particles' position as follows:

$$V_i^{k+1} = \omega \times V_i^k + C_1 \mathrm{rand}_1(.) \times \left(\mathrm{Pbest}_i - X_i^k\right) + C_2 \times \mathrm{rand}_2(.) \times \left(\mathrm{G_{best}} - X_i^k\right) \tag{1a}$$

$$X_i^{k+1} = X_i^{k+1} + V_i^{k+1} \tag{1b}$$

4.3. *Gravitational search algorithm*

The third favorite method among biological-inspired algorithms for optimization is GSA. GSA, inspired by Newton's law of gravity, was proposed in 2007 by Formato [112]. GSA's basic concept is based on the gravitational force $\left(F_{je}^{k,t}\right)$ of mass behaving in a way such that each mass attracts the other one (Fig. 6). Therefore, the gravitational force between two masses is related to their distance and their masses' product. Moreover, the acceleration of the masses (particles) only depends on their overall force and mass. Each mass position is a solution to the concerned problem. The GSA formulation is given in (2a). The gravitational constant $\left(G^k\right)$ at each iteration shown in (2b) depends upon two setting parameters, ω, and G_0, which must be tuned accurately for the algorithm to escape the local minima. The mass of each particle is computed by mapping their fitness value. Then, the particles' position $\left(X_{new}, j_k, t\right)$ and velocity $\left(V_{new}, j_k, t\right)$ must update through (2c) & (2d), which are denoted as the updating equations [95,113].

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

$$G^k = G_0 \times exp\left(\varpi \times \frac{Iter}{Iter_{max}}\right) \tag{2b}$$

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

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

GSA's main disadvantage is its memory-less characteristic. This means the particles will not use information from previous iterations [114]. Hence, the mutation technique needs to insert the information about the GSA's best solution so that it makes GSA appropriate for MGs optimization applications. The GSA setting parameters interleaved in (3) and (4) are ϵ, G_0, ϖ [115]. GSA handles more complexity than PSO by using a smaller number of control parameters, making it more efficient in convergence speed. However, the lack of memory counts as a negative point for such evolutionary-based techniques.

4.4. *Honey Bee Mating (HBMO) optimization algorithm*

The honeybee mating optimization (HBMO) algorithm exhibits a new approach based on the synergy between bees in a colony. The bee colony consists of a queen, drones, and workers. The mating process between the queen and drones offers a probabilistic methodology [48] for optimization applications. After each mating process, the sperm is stored in the queen's spermathecal, and the queen's speed decreases to a particular value. The worker's duty is to protect the brood after each new solution in the optimization process. The generation process will iterate when the better-situated broods are generated. The new solution will then take the place of the previous queen (previous solution in optimization) to provide a new generation. This trend will continue until the best queen (best solution) is obtained (Fig. 7) [102,103]. In the original HBMO, the first generation of brood [85] is produced by one queen (X_{queen}), which mates with the population of drones.

$$X_{\mathrm{broad},i} = X_{\mathrm{queen}} + \gamma \times \left(X_{\mathrm{queen}} - S_{pi}\right) \tag{3}$$

S_{pi} is the queen's spermathecal matrix, which is size NS_p, and γ stands

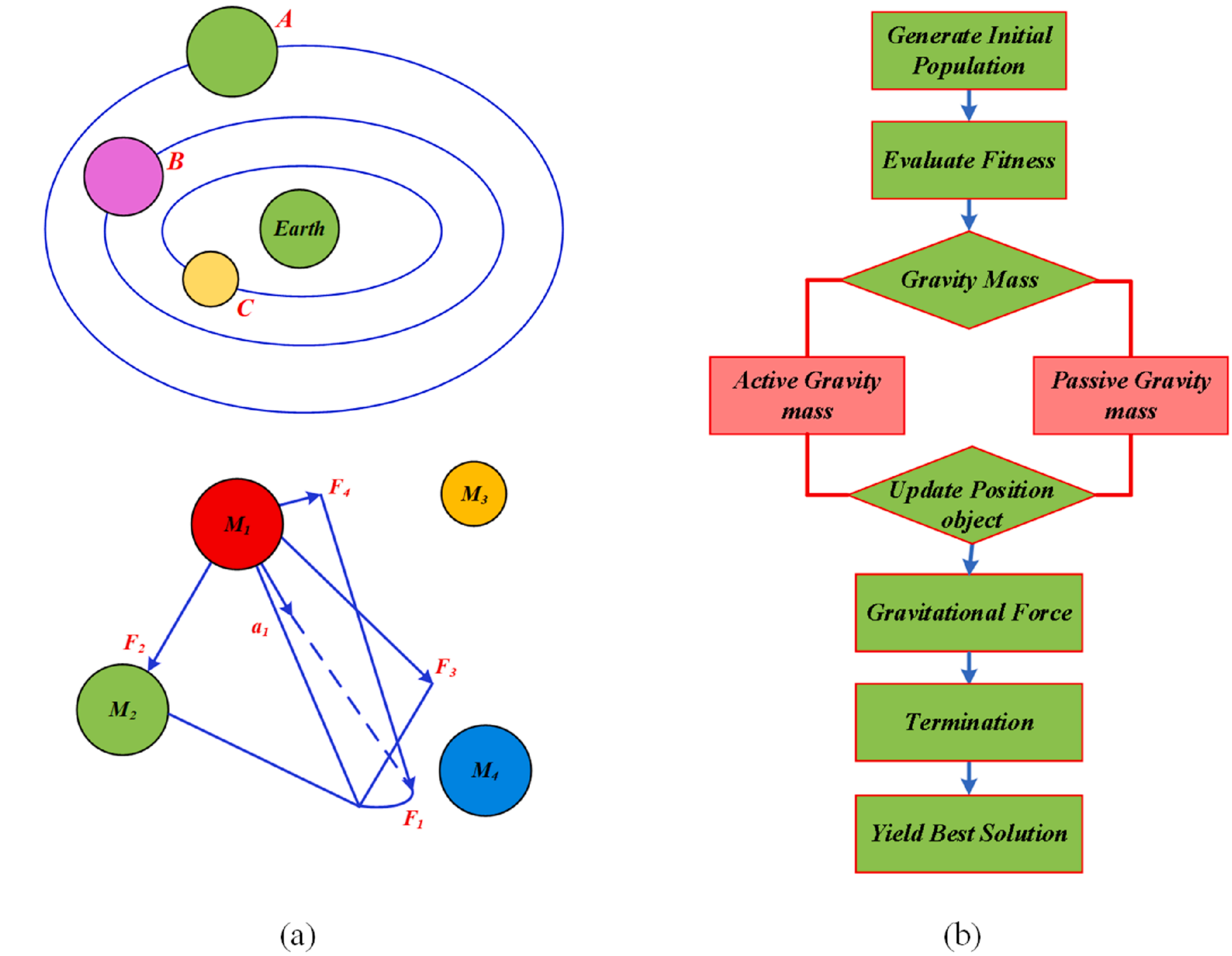

Fig. 6. GSA algorithm; (a) Processing: (b) Flowchart [112].

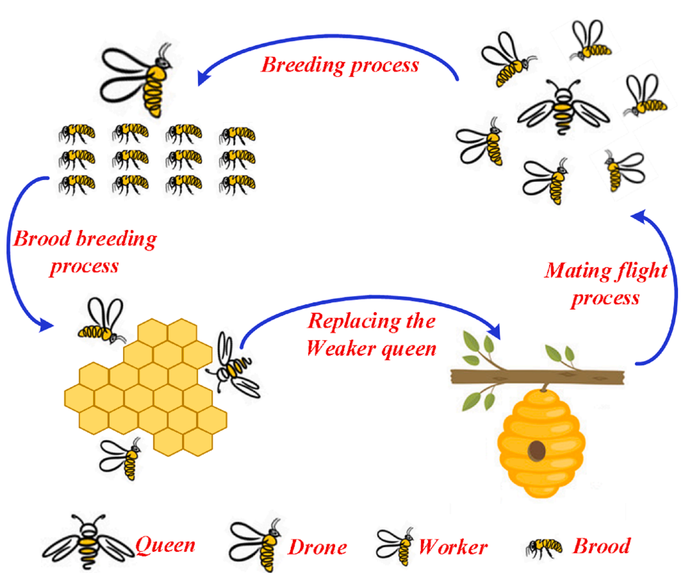

Fig. 7. Schematic of HBMO algorithm [103].

for the first control parameter with a random variable in the range of [0, 1]. In the modified HBMO algorithm, after the queen's spermathecal generation, the generation proliferation process is modified by selecting three individual queens from the repository (memory), the mean value of the repository, and the fuzzy membership function. Then, two individual queens are chosen as new drones for the generation proliferation process.

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

In [100], r_k, and T_F are the second and third control parameters. They are random values where T_F heuristically determines the mean value changes. $X_{D,m}$ is the generated mth new drone, and ΔX_{qk} stands for the k^{th} new queen for the breeding process modification. While the HBMO algorithm includes three control setting parameters similar to GSA, the convergence speed of HBMO, particularly in stochastic analysis, is less than other evolutionary techniques with the same numbers of control parameters [96,112]. HBMO counts as a memory-based biologically inspired algorithm. Authors in [103], pursuing operational planning goals by minimizing costs and maximizing reliability, evaluated the modified HBMO in the IEEE 30-bus system as a low voltage MG. Ant colony optimization (ACO) combined with artificial bee colony (ABC) has been investigated in [105] for optimal location and sizing of DERs to attain the global search advantage of ABC and the local search capability of ACO simultaneously. Similarly, in [106], a hybrid framework of PSO and HBMO has been proposed that improves the optimization tool's performance compared to the simple HBMO for DG placement and voltage profile improvement in MGs.

4.5. Crow search algorithm

To improve upon the shortfalls of the above-mentioned evolutionary-based optimization techniques in MG control and management, the crow search algorithm (CSA) would be the ideal potential heuristic algorithm. CSA, as a novel search technique developed in 2016 by Alireza Askarzadeh (electrical engineer) [116], mimics crow behaviors while searching for food. All evidence demonstrates that crows' families are intelligent and have a good memory for faces and food caches. Additional signs of intelligence include their ability to communicate in sophisticated manners and their recollection of their food's location. They are known to steal food from their congener and predict each other's behavior concerning their own food's hiding spot. These interactions indicate CSA would be a population-based metaheuristic method in a d-dimensional environment that includes N number of crows and the crow's position at each time (iteration) in the search space. Each crow is a vector in which each element shows a possible optimal value/status for the corresponding variable. In MG control and optimization problems, the optimal value and status of DGs and the main grid form each crow's elements. The crow population provides feasible solutions for the concerned optimization problem (5).

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

In [117], M_j is the position of the crow's hiding place, which is the best position that crow j has obtained so far. Fig. 8 shows the schematic diagram of the above algorithm. According to Fig. 8, small values of fl guide the CSA towards the local search (in the neighborhood of X_i), and large values of fl lead to the global search (far from X_i). If the crow X_j knows that a crow X_i is following it, it will change its flight path to fool the crow X_i and protect its nest from attack. Considering a constant value Γ for the awareness of crow X_j about being followed, it will change its flight path using the equation below:

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

In CSA, the parameter Γ is used to balance the intensification and diversification that occurs during the optimization process. Technically, CSA has some significant features that can distinguish it from other well-known evolutionary-based optimization algorithms, such as PSO and GA. First, it should be noted that parameter setting is a significant issue in optimization algorithms. Owing to the complexity and time-consuming effects of parameter setting, algorithms with fewer parameters are preferable. CSA uses only two parameters, i.e., flight length and awareness probability (fl, Γ). When compared to the other mentioned optimization algorithms, the small number of parameters makes CSA a pioneer in convergence speed and searchability. Second, in contrast to the GA and PSO, which are greedy algorithms, CSA is considered a non-greedy algorithm. In other words, CSA will move a crow to the new position generated by another crow even if that new position is not better than its current position. From a mathematical perspective, non-greedy algorithms can increase population diversity in new generations more than greedy algorithms. This effectively improves the optimization process.

4.6. Ant colony optimization

Ant Colony Optimization (ACO) is a population-based metaheuristic algorithm that utilizes real-world ant foraging behavior. Ants search for food and find the shortest paths between the food source and their nest. When an ant discovers a food supply, it returns some to its colony and leaves a trail of a chemical substance known as pheromone as it walks along pathways [118]. Shorter pathways generate more pheromone trail density and attract more ants, resulting in a larger number of ants than longer paths. Ants can detect the existence of pheromones through the sense of smell, and between two paths, ants select the path that has the higher pheromone concentration. Evaporation depletes pheromone trails over time and prevents the chances of being stuck at a local minimum. However, the pheromone values are updated at the end of each iteration [105].

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

P_{ij}^k, the probability of ant k moving from node i to node j can be expressed by (7). The intensity of the pheromone left in the path between nodes i and j is denoted by τ_{ij}. N_i^k is the set of feasible neighborhoods that ant k has not visited yet, η_{ij} is the heuristic function and α and β parameters represent the relative importance of pheromone concentration and heuristic information, respectively. The ACO algorithm's high convergence speed and high accuracy make it suitable for microgrid optimization problems, such as finding an appropriate pattern for distributed generation to minimize the costs and environmental pollution resulting from electrical power generation [119].

4.7. Whale optimization algorithm

Whale Optimization Algorithm (WOA) is inspired by the hunting techniques used by humpback whales [120]. First, the humpback whales surround the prey, and since the optimal point is not determined yet, WOA uses the objective prey or its nearby point as the best candidate point. After that, the whales encircle the prey, and the best location is modified using (8a) and (8d). $X(t)$ is the current position vector and $X^*(t)$ is the position vector of the best solution obtained till now, and D represents the distance between the whale i and the prey.

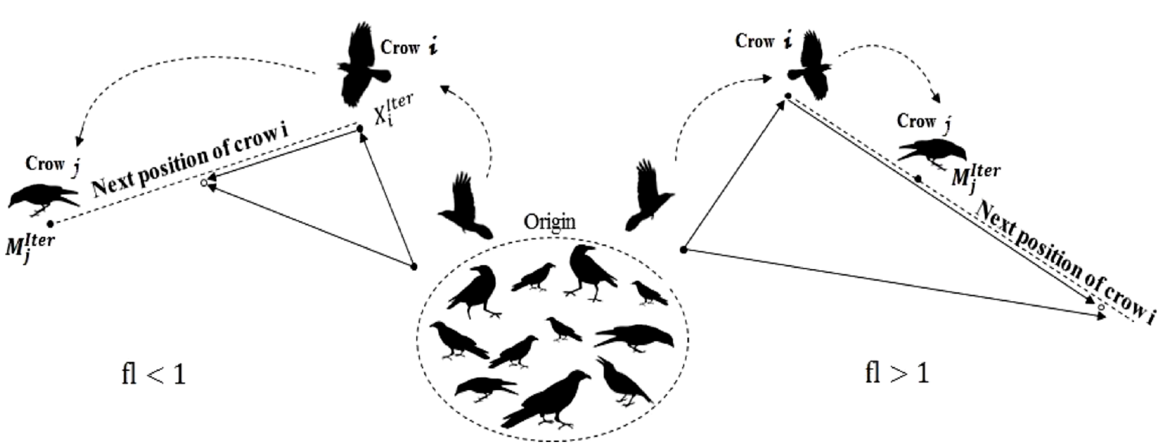

Fig. 8. Schematic diagram of the crow search improvement stage [116].

$$D = |CX^*(t) - X(t)| \tag{8a}$$

$$X(t+1) = X(t) - AD \tag{8b}$$

$$A = 2a.r - a \tag{8c}$$

$$C = 2.r \tag{8d}$$

After surrounding the prey, the whales employ one of two techniques: the shrinking encircling technique or spiral updating to attack their prey. For the shrinking encircling technique, the value of a is decreased gradually from 2 to 0 such that A falls in the range [-1, 1]. This enables the newly updated position $X(t+1)$ to be anywhere between the current position $X(t)$ and the best solution for the position vector till now, $X^*(t)$. The spiral updating condition is applied between the humpback whale's position and the prey according to (9). Here, b is a constant used to model the state of logarithmic winding, 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 choosing either the shrinking encircling and the spiral movement to update their position is 50% [120] and is expressed by (10). Here, 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 [121]. Advantages such as optimization accuracy and fast convergence make it possible for WOA to ensure optimum management of microgrids and DERs [122].

$$D = |CX_{rand} - X(t)| \tag{11a}$$

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

4.8. Reinforcement learning techniques

Hybrid microgrids pose significant challenges for traditional control methodologies due to their dynamic nature resulting from the integration of renewables, energy storage, and fluctuating loads. In the preceding sections, various control methods have been discussed, each with its unique set of strengths and weaknesses. However, recent advancements in machine learning algorithms have emerged as particularly well-suited approaches for controlling diverse systems. Notably, hybrid microgrid systems stand out as beneficiaries of these developments. Reinforcement Learning (RL) offers a promising data-driven approach for microgrid control, enabling systems to learn and adapt to evolving conditions [123]. This section provides an overview of prominent RL methods applied in microgrid optimization. Different algorithms, like Q-Learning, Deep Q-Networks (DQN), and Deep Deterministic Policy Gradient (DDPG) algorithms, are explained, highlighting their applicability, advantages, and challenges. Additionally, this paper explores the adaptability, robustness, and multi-objective optimization capabilities of RL for microgrid control while also addressing computational complexity, exploration-exploitation tradeoffs, and safety considerations.

4.8.1. Q-Learning

Q-Learning is a fundamental model-free RL technique where the agent interacts with the environment to learn an optimal policy through trial and error. In the context of microgrid control, Q-Learning enables the system to make decisions, such as power dispatch, based on received rewards. While Q-Learning offers a straightforward implementation, its scalability to complex microgrids with numerous state variables can be challenging [124].

4.8.2. Deep Q-Networks (DQN)

Deep Q-Networks (DQN) extend Q-Learning by leveraging deep neural networks to approximate the Q-table, enabling the handling of high-dimensional state spaces. This makes DQN suitable for complex microgrids with multiple variables such as voltage and power flow. DQN exhibits faster learning and better generalization compared to traditional Q-Learning methods [123].

4.8.3. Deep deterministic policy gradient (DDPG)

Deep Deterministic Policy Gradient (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 microgrid tasks involving power setpoints or converter modulation ratios. It efficiently balances exploration and exploitation while learning complex control policies [125].

RL offers several advantages for microgrid control, including adaptability to changing conditions, robustness against uncertainties, and multi-objective optimization capabilities. However, challenges such as computational complexity, exploration-exploitation tradeoffs, and safety and security considerations need to be addressed for real-world deployment [126].

5. Comparative analysis

5.1. Numerical analysis

Several heuristic optimization methods discussed in the previous section were developed in the literature to solve MGs' operational control and management problems. Mathematical formulations and parameter adjustments of these optimization tools affect their performance. The theoretical comparison of the control method explained in this study is highlighted in Table 2. In this section, some of these mentioned optimization algorithms are compared to evaluate the optimization power of the proposed CSA without a biased conclusion. The optimal energy management design problem of a notional MG is considered and solved to examine the optimizations mentioned above according to the number of their adjusting parameters. The complete data and single-line test system diagram of the case study can be found in [90].

Regarding managing the operational cost of MG efficiently and economically, some well-known optimization techniques and approaches have been implemented. A simple scenario is defined in which all DGs are active, and the battery state of charge is full at the beginning of the day to decrease the total cost of energy and minimize computational burden in the distribution system's EMS. Although there are several complicated scenarios for MGs' operation, a basic one was chosen to demonstrate the functionality and computation burden of the selected methods. Table 3 indicates the overall performance of several optimization tools for the above-mentioned problem. The comparative analysis of several optimal values of the objective function (net cost) for MG energy management is summarized in Table 3. The control parameters in Table 3 reflect different controlled variables for an MG.

As shown in Table 3, CSA and the modified version of CSA (MCSA) produced promising results on base scenarios compared to the other MG operational control and management system. According to the results, GA and PSO algorithms with maximum numbers of control parameters (six and four numbers, respectively) had longer processing times and higher (total operation) costs. Moreover, several modified versions of PSO algorithms have been compared with CSA's statistical results over 50 trials. The performance of modified PSO, which has been investigated in [127], still could not compete with CSA as the most optimal MG cost or computational burden. To allow the widespread comparison, other optimization tools, such as GSA and modified GSA (MGSA), proposed by Niknam et al., are placed in the same scenario and produce poor results

Table 2
Advantages and Disadvantages of Control Algorithms for Microgrid Systems.

Algorithm	Advantages	Disadvantages
Genetic Algorithm [71,88,109–111]	• Effective for global optimization: Genetic algorithms are well-suited for exploring large search spaces and can efficiently find near-optimal solutions. • Can handle non-linear and complex problems: Genetic algorithms are capable of optimizing non-linear and complex objective functions.	• Convergence rate may be slow: Genetic algorithms may require a large number of iterations to converge, particularly for complex problems or large search spaces. • Requires fine-tuning of parameters: Genetic algorithms often have several parameters that need to be fine-tuned for optimal performance, which can be time-consuming.
Particle Swarm Optimization [64, 90–94]	• Simple implementation: PSO has a simple structure and is easy to implement. • Efficient for continuous optimization: PSO excels in optimizing continuous objective functions due to its iterative nature.	• May converge to local optima: PSO is prone to converging to local optima, especially in multimodal or deceptive optimization problems where the global optimum is not easily reachable. • Sensitivity to parameter settings: PSO's performance can be highly sensitive to the choice of parameters such as inertia weight, cognitive, and social parameters.
Gravitational Search Algorithm [95–98, 112,113,115]	• Efficient for optimization in continuous search space: GSA is well-suited for optimizing continuous objective functions.	• May require more computational resources: GSA may require more computational resources compared to simpler algorithms due to its computational complexity. • May converge slowly: GSA's convergence rate may be slower compared to other algorithms.
Honey Bee Mating Optimization Algorithm (HBMO) [85,96,100,102,103, 105,106]	• Inspired by natural behavior: HBMO is inspired by the mating behavior of honey bees and effectively mimics the process. • Parallel search process: HBMO employs a parallel search strategy, allowing for efficient search space exploration. • Can handle multi-modal optimization: HBMO is capable of exploring multiple optima simultaneously, making it suitable for multimodal optimization problems.	• Limited scalability: HBMO may have limited scalability when applied to large-scale optimization problems or problems with high-dimensional search spaces. • May get stuck in local optima: Similar to other nature-inspired algorithms, HBMO can get trapped in local optima, particularly in complex or multimodal problems. • Performance highly dependent on parameter tuning: Achieving optimal performance with HBMO often requires careful tuning of parameters such as colony size, mutation rate, and selection criteria.
Crow Search Algorithm [104,116, 117]	• Efficient global search: Crow Search Algorithm (CSA) is designed to efficiently explore the search space for global optima. • Balanced exploration and exploitation: CSA strikes a balance between exploring new solutions and exploiting known good solutions, leading to effective optimization performance.	• Complexity in implementation: CSA can be complex to implement due to its multi-agent approach and parameter tuning requirements.

compared with CSA in terms of convergence when finding the concerned problem's solution. Also, MCSA shows better performance than MGSA in a similar way.

As a result, the main drawback of heuristics-based optimization tools is the setting parameters, where any fault in their adjustment can cause premature convergence. This creates a trap at a local optimum point. Therefore, the algorithm with less control and adjusting parameters is preferable and shows a faster response than the nonlinear constrained applications. Thus, CSA with a minimum of two control parameters is expected to provide a better convergence time. In contrast, approaches based on PSO and GA with four and six setting parameters have higher convergence times, respectively. However, these algorithms may benefit specific optimization problems with high complexity and non-convex constraints.

On the other hand, unlike PSO and GA, CSA is a non-greedy algorithm that would move to the new position generated by a crow even if that new position is not better than its current position. This means that the non-greedy algorithm by population diversity increases more than the greedy algorithm in the new generations and effectively improves the optimization process. The simulation results demonstrate the superiority of CSA compared to the other population-based evolutionary techniques. Whereas each scenario has a different nature of decision variables and constraints, the CSA approach would handle all nonlinear constraints without the penalty seen in other methods.

5.2. Meta-metrics analysis

To better illustrate each optimization algorithm's differences, a multi-metric performance evaluation technique, denoted as Meta-Metrics (MM) analysis [128,129], is used in this section to compare each optimization algorithm. MM is a linear combination of normalized performance metrics with their associated weights, representing the optimization's performance. GA, PSO, CSA, and MCSA are cumulatively evaluated using three performance metrics: cost, voltage deviation and power loss. MM has a dual structure where metrics are either normalized in the MM frame based on their improvement relative to an initial condition, denoted as the tuning plane, or normalized based on their stability around an operating point, denoted as the stabilizing plane. Since the tuning frame is selected for all three metrics, the initial performance condition is defined by when the system runs with all DGs and RESs turned ON and set to their minimum capacity and their daily forecasted power, respectively.

Furthermore, metric weights are determined via a two-step process: 1) user input in the form of linguistic commands and 2) an automatic adaptive algorithm that balances the weights considering the stability and performance level of their respective metrics. The algorithm is designed to shift the focus toward least-performing and least-stable metrics while respecting the user's boundaries. The normalization process in MM analysis transforms cost, voltage, and power loss measurements into one per-unit index, denoted as the MM variable, representing the optimization's global performance goodness. The cost formulation is given below.

$$m_1 = \frac{1}{\| \vec{P} \|_1}\left[\sum_{i=1}^{N_g} u_i(t) f_i p_i(t) \qquad + \sum_{j=1}^{N_r} u_j(t) f_j p_j(t) + C_{\text{grid}}(t) + P_{\text{grid}}(t)\right] \tag{12a}$$

Table 3
Comparison among cost objective functions for different scenarios (50 trials).

	Method	Best solution (€ct)	Worst solution (€ct)	Average (€ct)	Standard deviation (€ct)	Mean simulation time (Sec)	Numbers of control parameters
First Scenario	**GA**	277.74	304.58	290.43	13.44	N.R.	6
	PSO	277.32	303.37	288.87	10.18	N.R.	4
	FSAPSO [127]	276.78	291.75	280.68	8.33	N.R.	N.R.
	CPSO-T [127]	275.04	286.54	277.40	6.23	N.R.	N.R.
	CPSO-L [127]	274.74	281.11	276.33	5.96	N.R.	N.R.
	AMPSO-T [127]	274.55	275.09	274.98	0.32	N.R.	N.R.
	AMPSO-L [127]	274.43	274.73	274.56	0.09	N.R.	N.R.
	GSA [67]	275.53	282.17	277.80	2.92	0.78	3
	SGSA [67]	269.76	269.76	269.76	0	0.36	N.R.
	CSA	270.88	275.39	272.22	3.11	0.026	2
	MCSA	264.76	264.76	264.76	0	0.019	N.R.

N.R: Not Reported in the paper.

$$m_2 = \sum_{i=1}^{N_b} |1 - V_i(t) \tag{12b}$$

$$m_3 = \sum_{i=1}^{N_b}\sum_{j=1}^{N_b} \frac{\left(V_i(t) - V_j(t)\right)^2}{Z_{ij}} \cos\left(\theta_{ij}\right) \tag{12c}$$

Here, m_1 denotes cost performance, U denotes the on or off status, P represents active power output, and C_{grid} entails the cost concerning the acquisition of grid power. Voltage deviation performance is defined by (12b), where V represents the difference between actual RMS voltage and the nominal voltage value, and m_2 depicts voltage deviation performance.

Power loss performance is characterized by (12c). Here, m_3 defines power loss performance, and Z_{ij} and θ_{ij} are the magnitude and phase of impedance, respectively.

A set of 25 non-repetitive permutations of weighting modes (Table 4) is used as a variable for MM to capture the effects of varying weighting preferences. The best results obtained in 10 sample runs are shown in heat maps (Fig. 9). Examining Fig. 9, it is seen that MM is at its maximum for all optimization algorithms at the 17^{th} hour of the day with the 23^{rd} weight mode choice. Also, the maximum MM values, i.e., 22.16%, 27.72%, 27.79%, and 27.58% for GA, PSO, CSA, and MCSA, respectively, are within 5% proximity of each other, with GA having the worst performance. This relative uniformity in the MM results shows that all the algorithms pursue similar improvement goals with respect to cost, voltage deviation, and power loss. However, the same uniformity does not apply to the minimum MM values, as each optimization's weakest point has a different coordinate. This observation shows that GA, PSO, CSA, and MCSA have different weaknesses in the context of their MMs. The presence of negative MM values in some hours means that there are times when the optimization deteriorates the performance with respect to the base condition. The root of this problem is traced back to the fact that all four algorithms search for solutions with the best performance summed over the entire 24-hour period and not at each hour. The problem can be solved by integrating MM into the optimization decision-making process. MM-optimization integration is reserved for future research endeavors. Overall, MCSA proves to perform more reliably with respect to MM than other methods because it had: 1) the shortest MM score variance (-5.199% to 27.58%) across time and 25 different weight modes, 2) the highest minimum MM score and 3) the highest lumped MM score summed over the entire day.

6. Conclusion and future directions

The EMSs are identified as a viable and reliable systematic approach to control and manage the operation of MGs. Optimization tools used as a core component of EMSs enhance the feasibility and reliability of the control and management system. This paper has briefly reviewed current intelligent evolutionary techniques to investigate the promising potential approach for future power infrastructures at the distribution level. A summary of the different control and management systems, as well as their challenges, has been provided, along with a proposed approach for fulfilling current methods. The proposed control metric evaluation examines a metrics evaluation of several approaches.

Among various optimization tools with different functionality and decision variables, this research considers their different benefits in the concerned application and offers an appropriate method. As a proposed approach, CSA and MCSA allow further operation control and management improvements because of their straightforward structure, easy implementation, and comprehensive functionality. In CSA, the two adjusting parameters include awareness probability and flight length and project minimal computational burden for finding the best solution. A comparison of the results indicates the dominance of the CSA approach compared to the most commonly used optimization

Table 4
Weighting modes for meta metrics analysis.

Weight ranges associated with each linguistic input: D: 0-25%, C: 25-50%, B: 50-75%, A: 75-100%

Sequence of metrics: {cost, voltage deviation, power loss}

Weight Mode (#)	Combination n	Weight Mode (#)	Combination n	Weight Mode (#)	Combination n
1	{A, A, A}*	11	{B, D, A}	21	{D, A, C}
2	{A, B, C}	12	{B, D, A}	22	{D, B, A}
3	{A, B, D}	13	{B, D, C}	23	{D, B, C}
4	{A, C, B}	14	{C, A, B}	24	{D, C, A}
5	{A, C, D}	15	{C, A, D}	25	{D, C, B}
6	{A, D, B}	16	{C, B, A}		
7	{A, D, C}	17	{C, B, D}		
8	{B, A, C}	18	{C, D, A}		
9	{B, A, D}	19	{C, D, B}		
10	{B, C, A}	20	{D, A, B}		

*Note: When all three elements are equal, weight mode preference is indifferent; in other words: {A, A, A} = {B, B, B} = {C, C, C} = {D, D, D}.

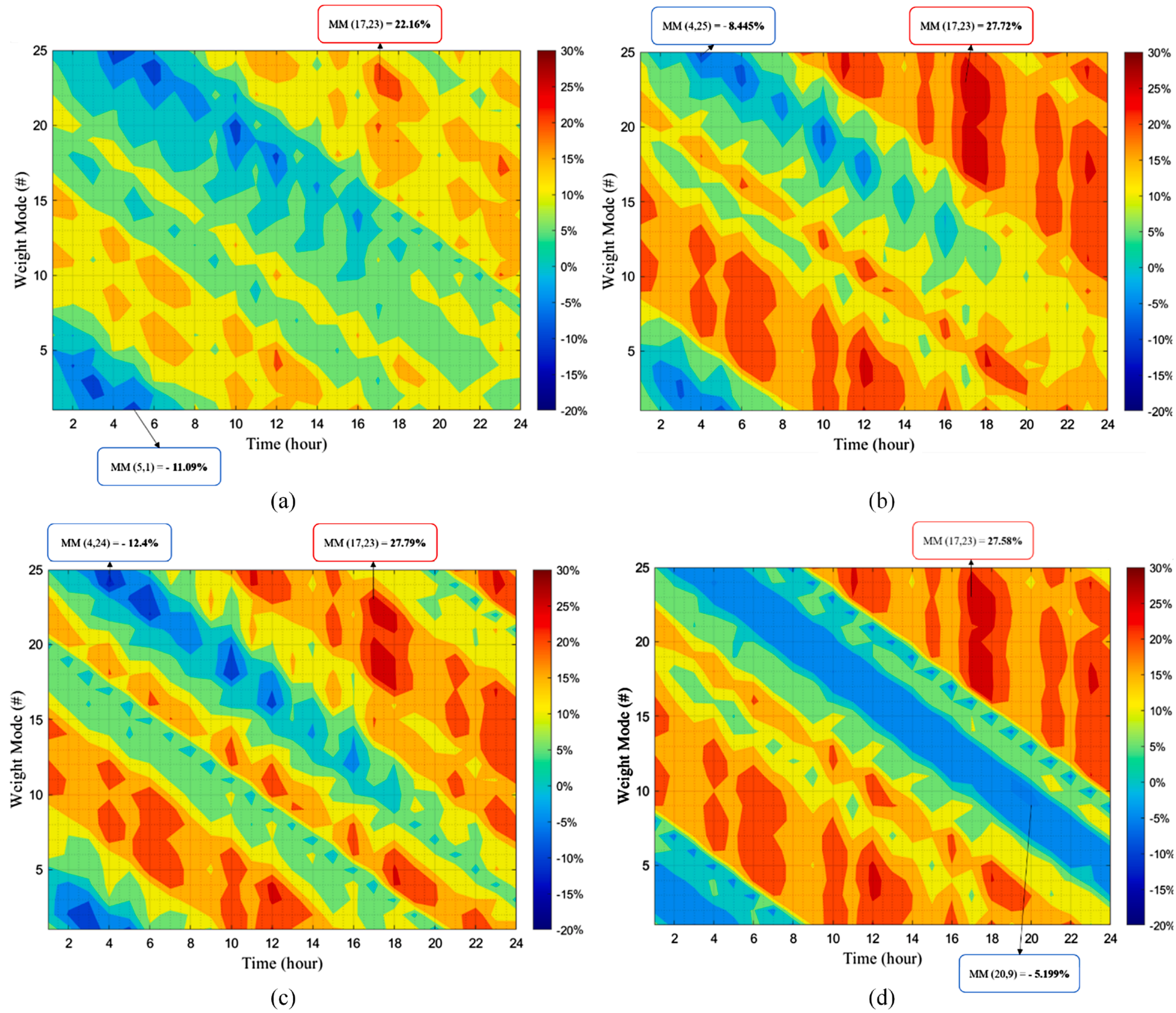

Fig. 9. MM performance contours, (a) GA, (b) PSO, (c) CSA, and (d) MCSA.

approaches, such as GA, PSO, and GSA. The effectiveness and usefulness of the proposed MCSA are demonstrated by solving the optimization problem for a notional single-line MG schematic. Simulation results based on the MM approach prove that CSA and MCSA are more diligent in comparison with the other studied algorithms. This conclusion is drawn from the algorithm's respective MM scores. MCSA had the smallest variance, largest summed score, and highest maximum scores compared to the other algorithms. Hence, literature reviews of heuristic population-based optimization techniques, their applications, and their challenges have been analyzed and presented to explore potential points for discovering probable future methods for serving novel and practical centralized EMSs. Meanwhile, further research regarding the open-ended problems in this field will assist EMSs by improving the power network's reliability and quality.

Field trials and controller hardware-in-the-loop (CHIL) experiments can be conducted to validate the effectiveness of evolutionary algorithms in real-world microgrid applications. With the increasing penetration of renewable energy sources, it is necessary to include modifications in the implementation of optimization algorithms so that uncertainties in renewable generation can be taken into consideration. Advanced control strategies can be developed by integrating machine learning techniques together with optimization algorithms to adapt to the dynamic conditions of microgrids. Furthermore, future research can include addressing the cyber security of microgrid operations against potential cyber-attacks.

CRediT authorship contribution statement

Behnaz Papari: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Resources, Methodology, Formal analysis, Data curation, Conceptualization. **Laxman Timilsina:** Writing – review & editing, Writing – original draft, Visualization, Data curation. **Ali Moghassemi:** Writing – review & editing, Writing – original draft, Supervision, Investigation, Formal analysis. **Asif Ahmed Khan:** Writing – review & editing, Validation. **Ali Arsalan:** Writing – review & editing, Writing – original draft, Resources. **Gokhan Ozkan:** Writing – review & editing, Writing – original draft, Resources, Supervision, Investigation, Data curation. **Christopher S. Edrington:** Writing – review & editing, Writing – original draft, Validation, Supervision, Formal analysis, Conceptualization.

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

No data was used for the research described in the article.

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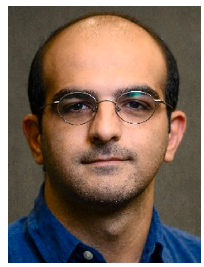

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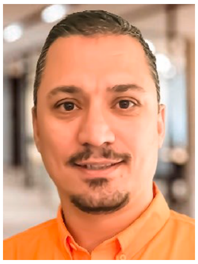

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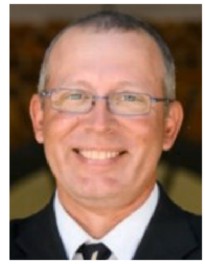

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