

## RESEARCH

# Advances in Mountain Gazelle Optimizer: A Comprehensive Study on its Classification and Applications

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## Abstract

The Mountain Gazelle Optimizer (MGO) is a newly emerging nature-inspired metaheuristic algorithm based on mountain gazelles' regionally and adaptively directed behavior. It is intended to solve complex optimization problems with an effective balance of exploration and exploitation. The MGO has several benefits: it is scalable, adaptable, parameter-free, capable of multi-objective optimization, and offers real-world application opportunities. The drawbacks of MGO include susceptibility to premature convergence, high computational complexity, and limited scalability to solve higher dimensional problems. The focus of the work is to investigate the development of MGO in the optimization field thoroughly. This review addresses the capabilities and limitations and express its growing relevance across applications. The investigation will refer to 89 studies published on MGO, categorized into four headings: adapted, variants, hybrid, and enhanced, contributing 37, 3, 33, and 27%, respectively, of all studies. This review is to supply researchers and practitioners with a comprehensive overview of potential optimization strategies. The review will compile and synthesize relevant studies to portray potential development opportunities for MGO and practical applications.

**Keywords** Mountain gazelle optimizer · Metaheuristic algorithm · Classification · Hybrid methods · Improved performance

## 1 Introduction

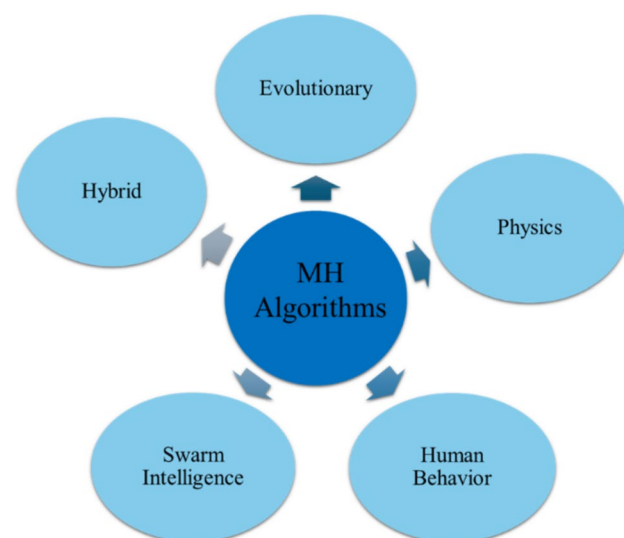
Metaheuristic (MH) algorithms have rapidly become indispensable optimization tools over the last few decades, especially for problems defined in nonlinear, high-dimensional, and multimodal search spaces [1, 2]. These algorithms are competent substitutes for traditional gradient-based methods, often impeded by slow convergence, entrapment in local optima, and high computational costs. MH algorithms search for better solutions in different ways by exploiting and exploring the search space [3, 4]. Random processes make it easier to search over substantial search spaces, making them well suited to engineering, energy systems, industrial processes, and so on [5–8]. Over the last 20 years, methods inspired by nature have been successfully used as they explore vast solution spaces efficiently and provide nearly optimal solutions. MH algorithms work well because they strike the right balance between exploration and exploitation. This means that they explore new areas to search for better solutions and converge in an area that holds promise. The balance afforded by this combination of interaction,



exploration, and exploitation allows algorithms to adapt to various problem structures and reach high-quality solutions within complex problem spaces. However, it should also be emphasized that in the field of metaheuristics, an increasing number of “new” algorithms are emerging that, despite their success, are inspired by metaphors, such as animal behavior or natural phenomena and do not make significant contributions to optimization theory. Sörensen [9] argues that many of these metaphor-based algorithms, while gaining popularity, are essentially rebrands of existing methods, offering little in terms of innovation. For instance, recent critiques by Camacho-Villalón et al. [10] expose the lack of novelty in popular algorithms, such as the Whale Optimization Algorithm (WOA) and the Grey Wolf Optimizer (GWO), both of which, despite their claims of novelty, closely resemble well-established algorithms like Particle Swarm Optimization (PSO). These metaphor-based algorithms, while seemingly innovative, often rely on familiar components from older techniques, such as PSO and evolutionary strategies, repackaged under new terminologies. In [11], the WOA, despite its popularity, suffers from significant shortcomings, including the lack of shift invariance, which hinders its ability to generalize to various problem domains. Another study [12] critiques the Arithmetic Optimization Algorithm (AOA), specifically pointing out its structural bias due to the algorithm’s heavy reliance on problem bounds, which creates a center-bias operator. This leads to artificially high accuracy when solving standard benchmark functions but poor performance when applied to shifted benchmarks. Similarly, another study [13] argues that the Chimpanzee Optimization Algorithm (ChOA) suffers from similar inherent biases, resulting in poor performance on more complex, real-world problems. These limitations highlight the need for algorithms that can adapt to a broader range of optimization tasks. On the other hand, per the No Free Lunch (NFL) theorem [14], no optimization algorithm is better than any other on average. Moreover, several studies have been presented to improve the understanding of MHs. In this regard, there is a valuable theoretically based study [15]. This study discusses how complex network theory has recently been employed to enhance the understanding and performance of metaheuristic-based algorithms, which have traditionally lacked solid theoretical foundations. By applying network theory to model the population structures and interactions within these algorithms, researchers have gained more profound insights into their dynamics, leading to more robust and efficient algorithms. Thus, there is a need to continuously produce and improve new MH algorithms to solve other optimization problems.

Metaheuristic algorithms are split into five classifications: Evolutionary Algorithms (EA), Physics-based Algorithms (PA), Human Behavior-based Algorithms (HB), Swarm Intelligence-based Algorithms (SI), and Hybrid-based Algorithms (HA). These categories are presented schematically in Fig. 1. EAs are used for optimization problems based on biological evolution, which involves selection, mutation, and crossover. PAs are grounded in physical phenomena, emulating natural principles to improve solution exploration. Research in this category is more difficult to develop compared to the other four categories, as the sources of inspiration are more restricted.

**Fig. 1** A categorization of MH algorithms



HB-based algorithms imitate human activities, such as driving training, political election processes, combat tactics, and game strategies, among others. Essentially, their core principle is to model individuals' interactions, learning processes, or problem-solving techniques, and apply them to optimization tasks within a mathematical framework. SI algorithms emulate natural swarm behavior to address complex problems without centralized oversight collectively. These algorithms are designed to address issues autonomously by simulating the interactions and collaboration among individuals inside a swarm. Although each individual adheres to fundamental laws, their combined actions result in the formation of a complex system. They fundamentally include an ongoing process of exploration and adaptation, influenced by the knowledge individuals get from other swarm members and their surroundings. This method facilitates efficient resolutions for intricate issues that would be challenging for an individual to address independently. HA algorithms integrate the advantages of established approaches to enhance performance. Some studies in the literature in these categories are presented in [16–22]. These algorithms have made significant contributions to solving various complex problems in many application areas [23–28].

Among the MH algorithms, the MGO, introduced in October 2022, has garnered interest as a potent optimization method owing to gazelles' hierarchical and adaptive locomotion within their environment [29]. This algorithm is developed based on its particularly equitable social and territorial, exploitative/exploratory, behavior that emulates that of a mountain gazelle. The main advantage of this hierarchical structure is the ability to use search strategies for various optimization problems in a more dynamic way, as this hierarchy can represent the exploration and exploitation phases using different herds of gazelles. The results demonstrated good convergence speed and performance with solution accuracy. Moreover, the MGO is unique, because it is scalable and can be adapted to large, complex, high-dimensional, and multimodal optimization problems with ease. Importantly, MGO does not have a tedious number of parameters that need tuning, thereby making it more versatile and practical in real-world usage. Therefore, it competes with the best MH algorithms, such as PSO [30], Artificial Rabbits Optimization (ARO) [31], Snow Ablation Optimizer [32], Crow Search Algorithm (CSA) [33], Genetic Algorithm (GA) [34], Sand Cat swarm Optimization (SCSO) [35], and African Vultures Optimization Algorithm (AVOA) [36]. Hence, it has many applications in power and energy systems, control engineering, structural optimization, AI-assisted modeling, and predictive analysis. Various research groups have taken an interest in the algorithm's flexibility, which led to the development of its variants, hybrid models, and enhanced versions to improve their scalability, convergence speed, and adaptability for real-time applications [1, 37–39].

## 1.1 Motivation and Contribution

The Mountain Gazelle Optimizer (MGO) emerged in response to the growing need for more robust and adaptable metaheuristic algorithms capable of solving complex optimization problems. Because of their sluggish convergence rates and vulnerability to local optima, traditional optimization algorithms (in particular, gradient-based approaches) frequently have trouble with nonlinear, high-dimensional, and multimodal problem spaces. Because of these constraints, more adaptable and practical MHs needed to be created to manage the growing complexity and unpredictability of real-world issues. Previous surveys on MH optimization emphasize classical methods or globally accepted algorithms [40–46], but there is no comprehensive survey of MGO yet. MGO was created expressly to tackle several significant issues in the MH domain:

- **Premature Convergence:** A prevalent challenge in metaheuristics is the premature convergence to poor solutions, particularly in high-dimensional or multimodal situations. Numerous conventional techniques sometimes converge prematurely to local optima, resulting in an inadequate exploration of the entire solution space. MGO, influenced by the adaptive movement and social behavior of mountain gazelles, achieves a balance between exploration and exploitation, enabling the algorithm to investigate new regions of the search space while concurrently optimizing potential solutions. This hierarchical and adaptive technique addresses the issue of premature convergence by constantly modifying the exploration and exploitation stages.

- **Scalability in High-Dimensional Problems:** Conventional optimization algorithms frequently encounter difficulties when utilized for high-dimensional or large-scale optimization challenges. Nearly all algorithms exhibit a decrease in efficiency when the number of variables escalates. The MGO algorithm was engineered for scalability, allowing it to address high-dimensional and multimodal challenges without a considerable efficiency loss. The hierarchical structure in MGO, inspired by the social groupings of gazelles, enhances its adaptability to complicated issues by preserving variation within the population and efficiently exploring extensive solution spaces.
- **Parameter Sensitivity:** Numerous established metaheuristic algorithms exhibit significant sensitivity to parameter adjustment. The efficacy of these algorithms might fluctuate considerably depending on the selection of parameters, like population size, crossover rate, or mutation rate. MGO, conversely, is a parameter-free method, minimizing the necessity for substantial parameter adjustment and facilitating its implementation in practical applications. This distinctive feature renders MGO an appealing option for addressing optimization problems in contexts where little parameter adjustment is preferred.
- **Computational Complexity:** The escalating intricacy of real-world issues frequently results in computationally intensive optimization endeavors. Numerous metaheuristic algorithms encounter inefficiencies while addressing large-scale problems, as the quantity of search agents and iterations increases. The computational burden of these methods restricts their use in real-time, and large-scale applications. MGO mitigates this deficiency by preserving computing efficiency, particularly in the resolution of extensive optimization problems. Nonetheless, its efficacy in extremely high-dimensional spaces necessitates enhancement to rival other algorithms regarding speed and computational expense adequately.
- **Adaptability to Dynamic and Noisy Environments:** Conventional optimization techniques generally presume a static environment in which the optimization landscape remains constant throughout time. In numerous practical applications, the issue environment is dynamic and noisy, necessitating algorithms capable of adapting to fluctuating conditions. The dynamic character of MGO, influenced by the gazelles' adaptability to different settings, renders it especially appropriate for these challenges. The hierarchical framework of MGO facilitates adaptable modifications, allowing it to excel in dynamic environments characterized by an evolving search space or uncertainty in the data at hand.
- **Application in Varied Domains:** Although most MH algorithms have been widely employed in numerous fields, MGO remains relatively novel and has not been well investigated over a broad spectrum of applications. Notwithstanding its potential, there has been insufficient thorough investigation into MGO's application to particular real-world optimization challenges in domains, such as energy systems, machine learning, engineering design, and biomedical applications. A comprehensive investigation into the applicability of MGO and its enhancements in these domains constitutes a notable deficiency in the existing research.

In summary, the motivation behind the development of MGO lies in its ability to overcome several limitations of traditional MH algorithms. While MGO does not exhibit superior performance across all evaluation criteria, it is still regarded as one of the promising and relatively recent MH algorithms that has gained acceptance in the field. Its unique combination of exploration–exploitation balance, parameter-free design, scalability, and adaptability to dynamic environments positions MGO as a powerful tool for solving a broad spectrum of optimization problems. It also carries the "new" algorithm definition described above, and is based on NFL theory. Consequently, this survey has the potential to resolve a gap in the current corpus of research. This paper aims to provide a thorough discussion of the evolution of MGO, its classifications, hybrid models, and real-world applications, focusing on the strengths and weaknesses of MGO and existing studies based on MGO. We aim to emphasize the growing importance of MGO in a diverse array of optimization disciplines and to offer valuable insights. This survey provides the following contributions:

- A review of MGO categorization in Adapted, Variants, Hybrid, and Improved groups.
- A review of the statistics of MGO-based studies published by different publishers.

- A review of the role and achievements of the MGO algorithm in various applications and problems.

This paper combines the latest activities on MGO, making it a useful starting point for using MGO in advanced optimization research. In the following sections, we explore the importance and future potential of MGO in advanced engineering, artificial intelligence, and scientific computing.

The operational concepts of the MGO algorithm are examined in the subsequent section. Section 2 offers a detailed examination of the working mechanism of the MGO algorithm. Section 3 presents an array of statistical analyses pertaining to MGO. Sections 4 and 5 elaborate on the MGO algorithm classes and its application domains, providing detailed descriptions of each technique. Section 6 presents a quantitative examination of several MGO variations. Section 7 examines the broader context of the strengths and potential challenges and limitations of the MGO algorithm. Section 8 of the paper presents the conclusions, findings, and prospective research directions.

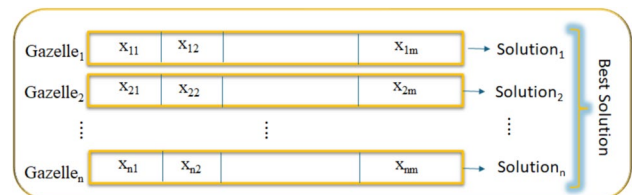
## 2 Mountain Gazelle Optimizer

The Mountain Gazelle Optimizer (MGO) is a new optimization algorithm inspired by mountain gazelles' social behavior and movement. MGO mimicking the hierarchy and adaptive migration of gazelle herds achieves a good trade-off between exploration and exploitation, making it a competent optimization tool against other evolutionary, herd-based MHs. Gazelles travel a long distance to find food, adjust to a new environment, and fight for land. The MGO optimization model mathematically formulates these hierarchical, adaptive behaviors, enabling effective search of the solution space and avoiding premature convergence. Different Gazelle groups and their functions are explained below. Structure of the algorithm—these gazelles are divided into three types of herds. Natal Herds consist of female gazelles and their calves. Bachelor herds are young males, which are the herds that compete for dominance and try to establish territory. Dominant males stay in their region and fight with rival males to pass on their genes. The MGO algorithm updates search agents (gazelles) using four primary mechanisms, each corresponding to different real-world gazelle behaviors. Using these mechanisms, the investigations and empirical verifications occur in parallel, and the search can remain global or local according to the needs. The first phase of this algorithm is the Initialization phase. This section of the paper summarizes the MGO algorithm's strategies using mathematical formulations.

### 2.1 Initialization Phase

In this phase, like several SI methods [47, 48], the beginning population of the MGO algorithm is the initialization phase. The mathematical expression of the randomly placed individuals in the population at initialization is presented in Eq. 1. Each group member (a gazelle) attempts to find an optimal solution to the target problem through a specified fitness function. In every iteration, the agent with the most promising solution will influence the movement and behavior of the other agents, so that the whole population will go toward a better solution over time. Equation 2 describes the relationship between agents and the fitness function. The MGO algorithm is structured in a way that works on a two-dimensional matrix (see Fig. 2) where rows are agents and columns are problem variables

Fig. 2 Initialization of the MGO algorithm



$$X = [X_1, X_2, \dots, X_i \dots X_n]^T = \begin{bmatrix} X_{11} & \dots & X_{1m} \\ \vdots & X_{ij} & \vdots \\ X_{n1} & \dots & X_{nm} \end{bmatrix} \tag{1}$$

$$F_X = \begin{bmatrix} f(X_{11} \dots X_{1m}) \\ \vdots & X_{ij} & \vdots \\ f(X_{n1} \dots X_{nm}) \end{bmatrix}_{n \times m} = \begin{bmatrix} f_1 \\ f_2 \\ \vdots \\ f_n \end{bmatrix}_{n \times 1} \tag{2}$$

Here, ‘*n*’ denotes the number of gazelles, while ‘*m*’ refers to the number of dimensions in the problem space. The term ‘*X<sub>i,j</sub>*’ specifies the location of the *i*<sup>th</sup> agent along the *j*<sup>th</sup> dimension, and the vector [*X<sub>i1</sub>*, *X<sub>i2</sub>*, ..., *X<sub>id</sub>*] defines the complete position of agent ‘*i*’ across all dimensions.

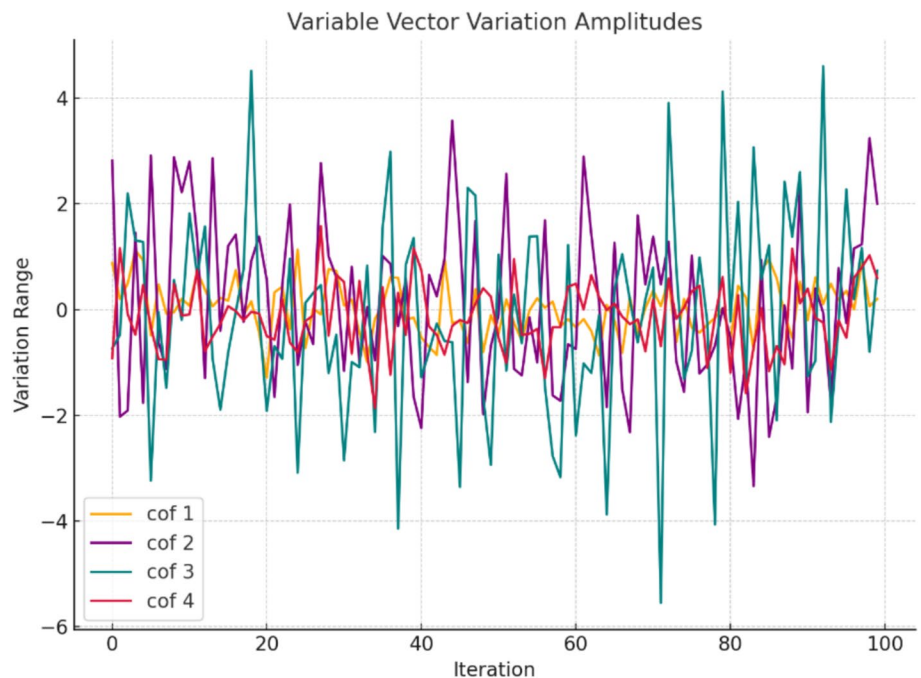
### 2.2 Territorial Solitary Males (TSM)

The best possible solution on a global level is represented by the most capable lone male gazelle within the MGO. It ultimately defends its territory and takes on the role of leader. Each search agent must adjust its position relative to the leader, which is considered the phase of exploitation. Its mathematical model and definition are represented formally in Eq. 3, where ‘male gazelle’ symbolizes the best-known solution

$$TSM = \text{male}_{\text{gazelle}} - |(r_{i1} \times BH - r_{i2} \times X(t)) \times F| \times \text{Cof}_r \tag{3}$$

The parameters ‘*r<sub>i1</sub>*’ and ‘*r<sub>i2</sub>*’ symbolize two random scaled integers of 1 or 2. The variable BH is a vector coefficient of the young male herd, as defined in Eq. 4. The ‘*F*’ is an adaptive scaling factor that governs exploration processes indicated in Eq. 5. Moreover, the abstract term ‘*Cof<sub>r</sub>*’ is a randomly chosen coefficient that affects the direction of motion. It is also calculated in an arbitrary directional motion representation with a reference amplitude vector through Eq. 6. A depiction of the amplitude vector alteration is seen in Fig. 3

**Fig. 3** Amplitude of ‘Cof’ vector changes



$$BH = X_{ra} \times r_1 + p \times r_2; ra = \left\{ \frac{N}{3} \dots .N \right\} \tag{4}$$

$$F = N_1(D) \times \exp\left(2 - t\frac{2}{T}\right) \tag{5}$$

$$Cof_i = \begin{cases} (a + 1) + r_3 \\ a \times N_2(D) \\ r_4(m) \\ N_3(D) \times N_4(D)^2 \times \cos((r_4 \times 2) \times N_3(D)) \end{cases} . \tag{6}$$

Equation 6 defines the “mean count of search agents ( $p$ )” as  $\lceil N/3 \rceil$ , where  $p$  agents are randomly selected from the total population of agents.  $N$  is the total number of iterations; ‘ $t$ ’ is the current iteration; and ‘ $T$ ’ is the total iterations. ‘ $r_1$ ’, ‘ $r_2$ ’, ‘ $r_3$ ’, ‘ $r_4$ ’ are random numbers uniform in (0,1). ‘ $N_1$ ’ is a standard normal random number, while ‘ $N_2$ ’, ‘ $N_3$ ’ and ‘ $N_4$ ’ are normal random numbers of the size and dimensions of the problem. Plus, over time (across iterations), parameter ‘ $a$ ’ is vital to balance exploration and exploitation. It is defined mathematically as Eq. 7

$$a = -1 + t\frac{-1}{T}. \tag{7}$$

### 2.3 Maternity Herds (MaH)

Maternity Herds provide a unique solution that leads to population diversity. Based on Eq. 8, they simulate births and female-led migration. Where ‘ $X_{rand}$ ’ is a gazelle randomly selected from the population. The numbers ‘ $r_{i3}$ ’ and ‘ $r_{i4}$ ’, either 1 or 2, help to direct the movement. Additionally, ‘ $Cof_{i,r}$ ’ is another coefficient that randomizes, which is determined with the help of Eq. 6

$$MH = (BH + Cof_{2,r}) + (r_{i3} \times male_{gazelle} - r_{i4} \times X_{rand}) \times Cof_{3,r}. \tag{8}$$

### 2.4 Bachelor Male Herds (BMH)

This structure depicts individual males competing to challenge winning males and secure their territories, a significant aspect of the exploration phase. This dynamic structure is modeled via Eq. 9, where  $X(t)$  represents the current location of the search agent. Also, ‘ $D$ ’ is a displacement factor, and it is determined using Eq. 10. ‘ $r_6$ ’ shows a random value between 0 and 1

$$BMH = (X(t) - D) + (r_{i5} \times male_{gazelle} - r_{i6} \times BH) \times Cof_r \tag{9}$$

$$D = \left( |X(t)| + |male_{gazelle}| \right) \times (2 \times r_6 - 1). \tag{10}$$

### 2.5 Migration to Search for Food (MSF)

Gazelles migrate often to feed and evade predators while capable of remarkable global exploration. This behavior is expressed in Eq. 11. In this mobility, improved running and jumping height facilitate global exploration. This behavior is strictly used in the search for a global solution

$$MSF = (ub - lb) \times r_7 + lb. \tag{11}$$

The variables ‘ub’ and ‘lb’ represent the lower and upper bounds of the problem space, respectively, while ‘ $r_7$ ’ is a random number between 0 and 1. The TSM, MH, BMH, and MSF are applied to all gazelles to generate the next generation of gazelles in each iteration. At the end of each iteration, gazelles are sorted by fitness; highest quality solution are retained while inferior ones are discarded. Therefore, these four movement strategies allow MGO to dynamically adapt, maintain diverse search capabilities, and promote reliable convergence.

### 2.6 Pseudocode, Flowchart, and Complexity Analysis of the MGO Algorithm

In this section, the pseudocode, shown in Algorithm 1, and the flowchart in Fig. 4 are simulated by MGO with its iterative process of each Leader, Competing, Migration, and Offspring generation. The subsequent computational complexity of this algorithm is detailed as well. The MGO algorithm generally integrates its various mechanisms, to balance local and global search while reducing premature convergence. MGO also falls into the rare MH classification without needing hyperparameter tuning.

Algorithm 1: The pseudocode of the MGO algorithm

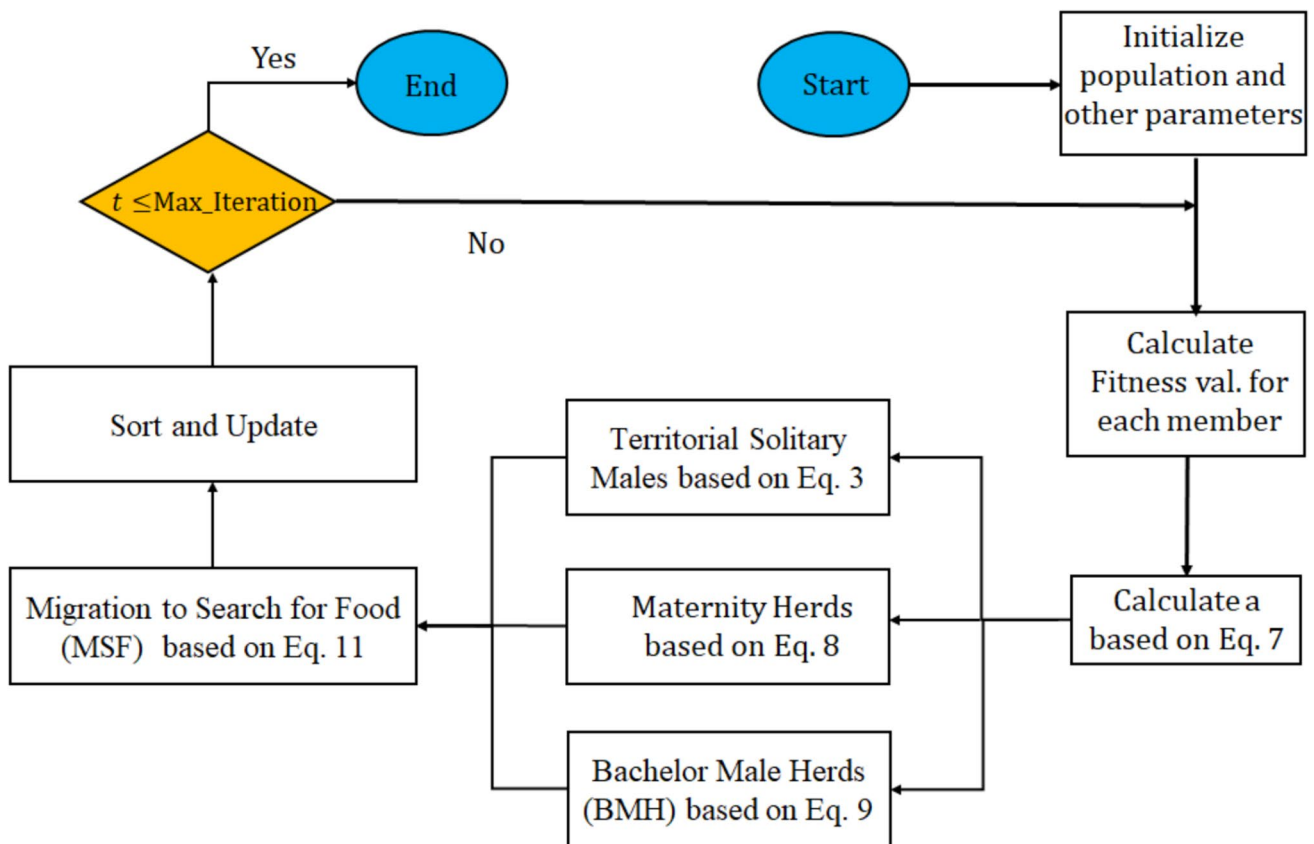


Fig. 4 Flowchart of the MGO algorithm

1. Initialize population (gazelles) randomly in the search space.
2. Evaluate fitness for all gazelles.
3. While (stopping condition not met) do:
  - a. Compute Territorial Solitary Males (TSM) update (Eq. 3).
  - b. Compute Maternity Herd (MH) update (Eq. 8).
  - c. Compute Bachelor Male Herds (BMH) update (Eq. 9).
  - d. Compute Migration to Search for Food (MSF) update (Eq. 11).
  - e. Evaluate new fitness values and update the best solution.
4. Return the best solution found.

The complexity of the MGO is governed by three factors: initialization of the population, fitness calculation, and solution updating. The initial population of gazelles is randomly generated with a complexity of  $O(N)$ . The process, which is required for every search agent, adds a further complexity of  $O(N \times f(P))$ , with  $f(P)$  being the function evaluation time. Maximum computations are done in the solution update phase of the MGO, which includes four movement mechanisms through which each agent updates its position. These mechanisms are applied iteratively to all agents over  $T$  iterations in an  $M$ -dimensional search space, resulting in an overall update complexity of  $O(T \times N \times M)$ . The total computational complexity of MGO can be written as  $O(T \times N \times M)$  or  $O(N \times f(P))$ , where  $f(P)$  represents the number of factors. MGO scales linearly with the population size ( $N$ ) and the dimension of the problem ( $M$ ), indicating that it is efficient for small to medium-sized optimization problems. However, the computations get heavy for high-dimensional problems ( $M \gg 1000$ ). The population should be made adaptive or parallelized for high-dimensional training problems. Also, fitness evaluations and updates in MGO can be parallelized, which allows GPU acceleration, making them useful for HPC applications. MGO is as efficient as traditional MH algorithms while demonstrating greater convergence robustness. This is due to its adaptive movement and hierarchical search mechanisms.

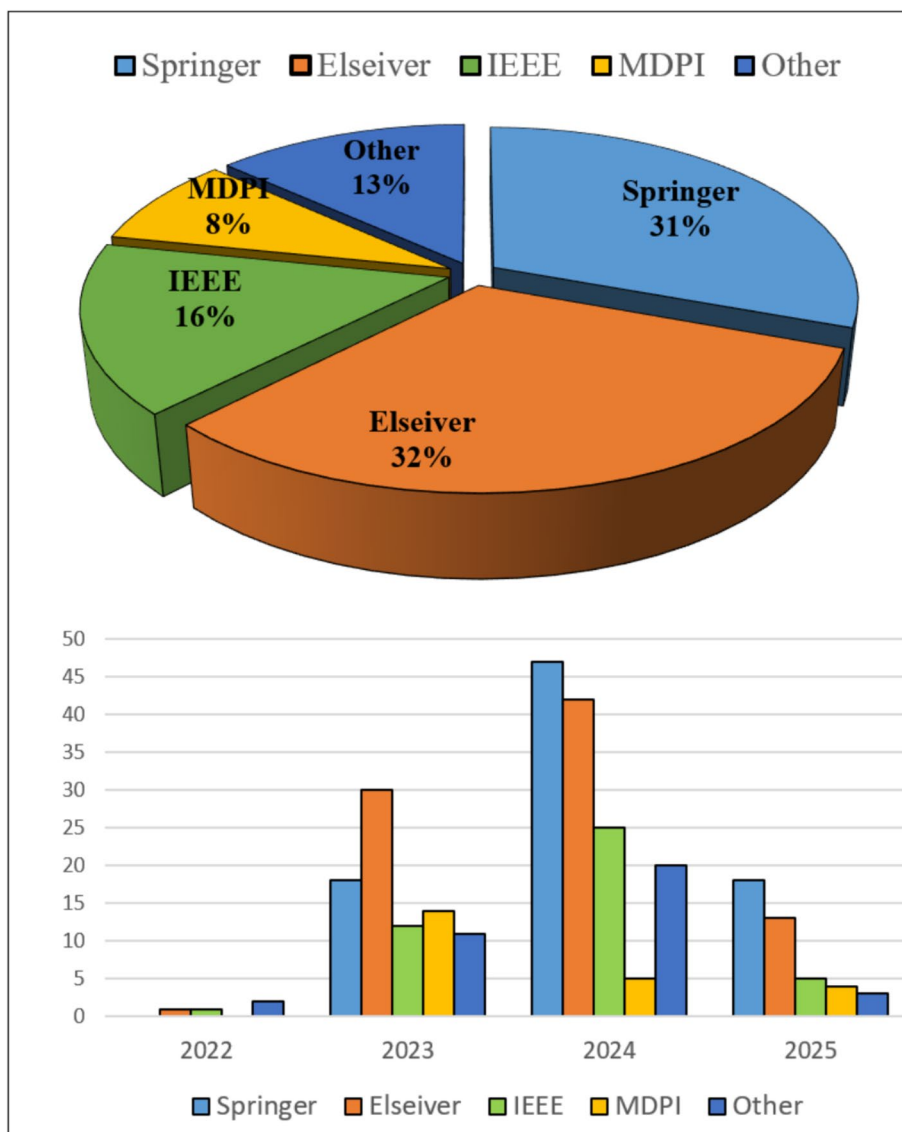
### 3 Statistics of MGO-Based Studies

This section presents a statistical analysis of academic citations to the MGO algorithm. To identify relevant studies, we searched Google Scholar, Web of Science, and Scopus, and used keywords such as "metaheuristic", "optimization algorithm", "nature inspired algorithms", "mountain gazelle optimizer", "MGO", and "performance of metaheuristics". The analysis was based on 271 citations between October 2022 and March 2025, of which 89 (32.8%) were academic studies in which the MGO algorithm was directly used to solve specific problems. The criteria used to select the literature included peer-reviewed studies, articles that introduced new MH algorithms related to MGO or surveyed existing ones, papers that presented an empirical evaluation or benchmark, and articles where the MGO-based algorithm is derived from natural or biological phenomena such as swarm intelligence or evolutionary principles. The exclusion criteria included non-peer-reviewed literature, articles that did not focus on MGO, and articles that lacked precise empirical or theoretical analysis. The quality of each selected study was evaluated according to several critical criteria: relevance, which determines if the paper addresses MH algorithms or their application in optimization problems; methodological rigor, ensuring robust evaluation of the algorithms through suitable benchmarks or real-world applications; novelty and contribution, assessing whether the study presents new algorithms, modifications, or insights that enhance the field; and clarity, evaluating the

paper's writing quality, including clear explanations of the algorithm's mechanics, implementation, and results. The criteria were implemented to guarantee that the chosen research had excellent scientific quality and significantly contributed to the domain of MH optimization.

Academic references to the MGO algorithm have been made through articles and conference proceedings published by various reputable publishers. The references to the MGO algorithm by prestigious publishers, such as Springer, Elsevier, IEEE, and MDPI, are shown in Fig. 5. In 2022, only five academic publications (1.8%) referred to the MGO algorithm. MGO entered the literature as a newly developed algorithm during this period, and the first academic discussions began. In 2023, the use of MGO increased significantly, with 72 publications (26.6%). During this period, Elsevier became the publisher with the most publications. In 2024, the number of MGO-related publications peaked at 135 publications (49.8%), marking the highest number of publications. This year, Springer hosted most of the publications related to this algorithm. In the first quarter of 2025, 59 papers (21.8%) were published. This indicates that the publication trend has continued to increase. When the distribution of academic publications by publishers is examined, it is seen that Elsevier hosts the most publications, with 86 publications (32%). Springer is in second place with 83 publications (31%), while the IEEE publishing house follows with 43 publications (16%). The studies published in MDPI are represented by 23 publications (8%), while

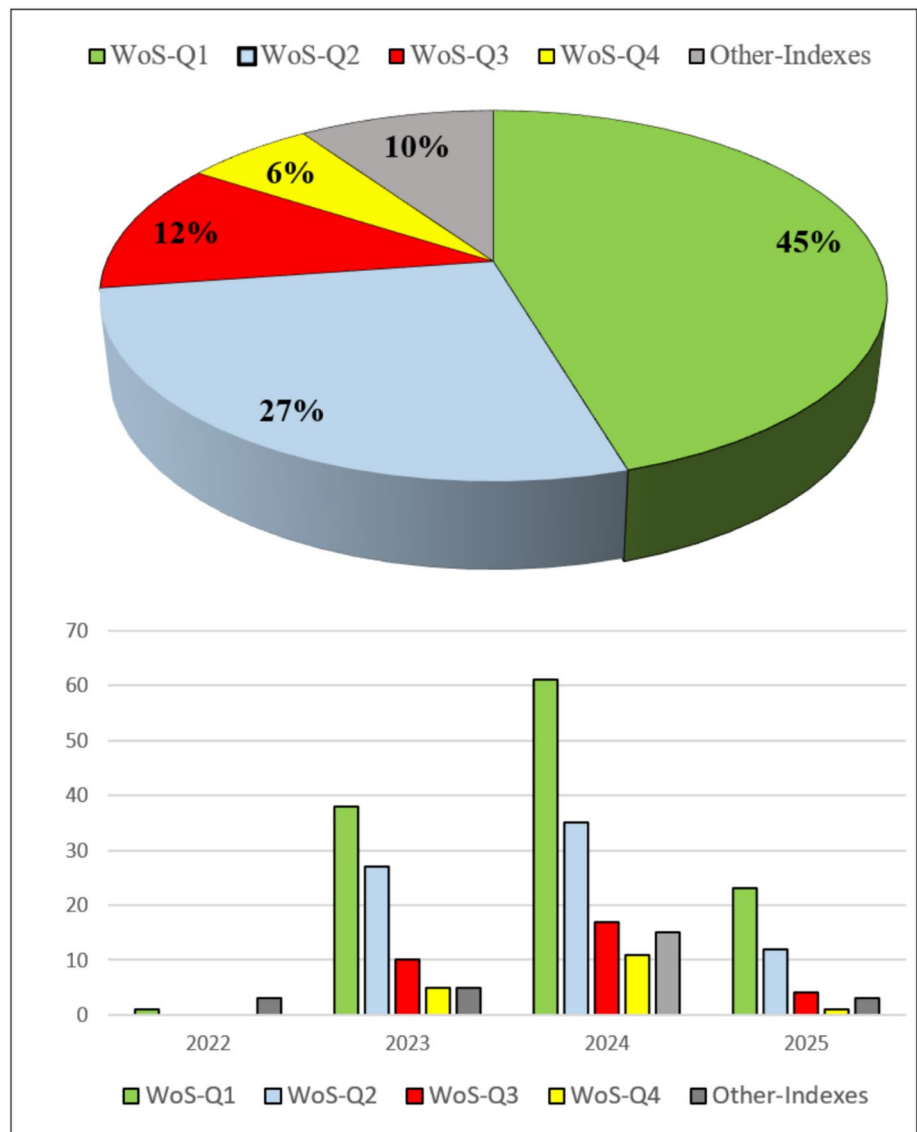
**Fig. 5** The distribution and proportion of MGO-related publications across different publishing platforms



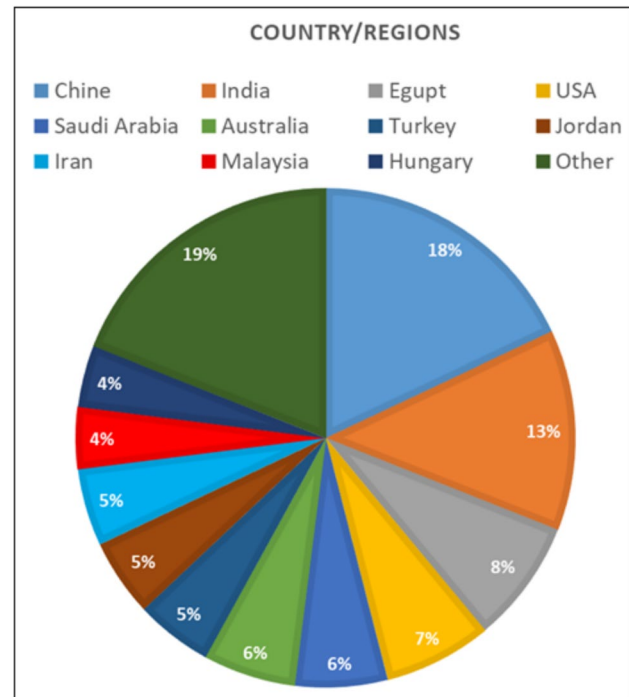
the papers published in other publishers are represented by 36 publications (13%). This distribution shows that the studies on MGO are primarily published in reputable academic publishers and have a broad impact area. Among these studies, 88.8% are published in journals, 8.5% are presented in conference proceedings, and the remaining 2.7% are reviews and book chapters. The academic indexes and areas of use in which the MGO algorithm is published are presented in Fig. 6. According to the Web of Science (WoS) index, the distribution is as follows: The number of articles published in Q1 journals is 123 (45.0%), indicating that MGO is an algorithm accepted in high-level academic publication bodies. Publications at the Q2 level are 74 articles (27.0%). Publications at the Q3 level are represented by 31 articles (12.0%). Publications at the Q4 level are determined as 17 articles (6.0%). Publications in other indexes (such as ESCI and Scopus) are at 26 articles (10.0%).

Moreover, Fig. 7 indicates the distribution of academic citations to the MGO algorithm by researchers of various countries and regions. According to the data, China (18%) is the country that contributes the most. China is followed by India (13%), Egypt (8%), and USA (7%). Saudi Arabia (6%) and Australia (6%) have similar rates. Turkey, Jordan, and Iran contribute 5%. Malaysia and Hungary have the lowest contribution of 4%. The remaining 19% of the contributions come from researchers from another 47 countries. This distribution shows that the MGO algorithm is widely used, especially in Asia and the Middle East. The prominence of countries, such as

**Fig. 6** Indexing details of studies that reference the MGO algorithm



**Fig. 7** The proportion of overall attributed citations to different countries or regions



China and India, supports the high academic interest in optimization and AI-based studies in these countries. While countries, such as the USA and Egypt, also have significant contributions, European and Latin American countries have a lower level of participation in these studies. This suggests that MGO has received more academic acceptance in specific regions and that regional academic trends shape its areas of use.

Based on the analysis of these data, the MGO algorithm has been increasingly adopted in literature and applied in different disciplines since its publication. 45% of the articles published in Q1 indexed journals show that the academic community accepts the algorithm as a reliable and effective method. However, there is a decreasing publication trend as of 2025 (21.8%). This situation shows that the algorithm has matured, and hybrid approaches should be developed with new optimization techniques. In the future, using MGO in new areas such as deep learning, quantum computing and biological system optimizations may expand the algorithm's scope.

#### 4 Classification of the MGO-Based Studies

This section highlights a thorough comparison of studies found in the literature using the MGO Algorithm. The papers are categorized based on their methodology and the rationale for their selection, which focuses on either the direct application of MGO or proposed improvements that aim at enhancing its performance. To organize the analysis logically, four significant classes were used to categorize the reviewed studies: *Adapted*, *Variants*, *Hybrid*, and *Improved* (Fig. 8). While 89 studies out of 271 citations belong to one of these classes, most of the references are merely comparative or background descriptions of MGO. The Adapted category includes studies carrying out the original MGO algorithm unchanged, with only minor adjustments being the fitness function tuned for optimization problems. The Variants category contains literature related to the multi-objective optimizations that amend MGO and extend it into a platform capable of accommodating various designs that require simultaneous optimization of multiple criteria. The Hybrid category involves studies where MGO is fused with other techniques or algorithms, resulting in improved performance. The hybrid procedure is further classified into three subcategories according to the auxiliary method: MH algorithms, Deep Learning (DL) models, and Machine Learning (ML) techniques. The Improved category encompasses

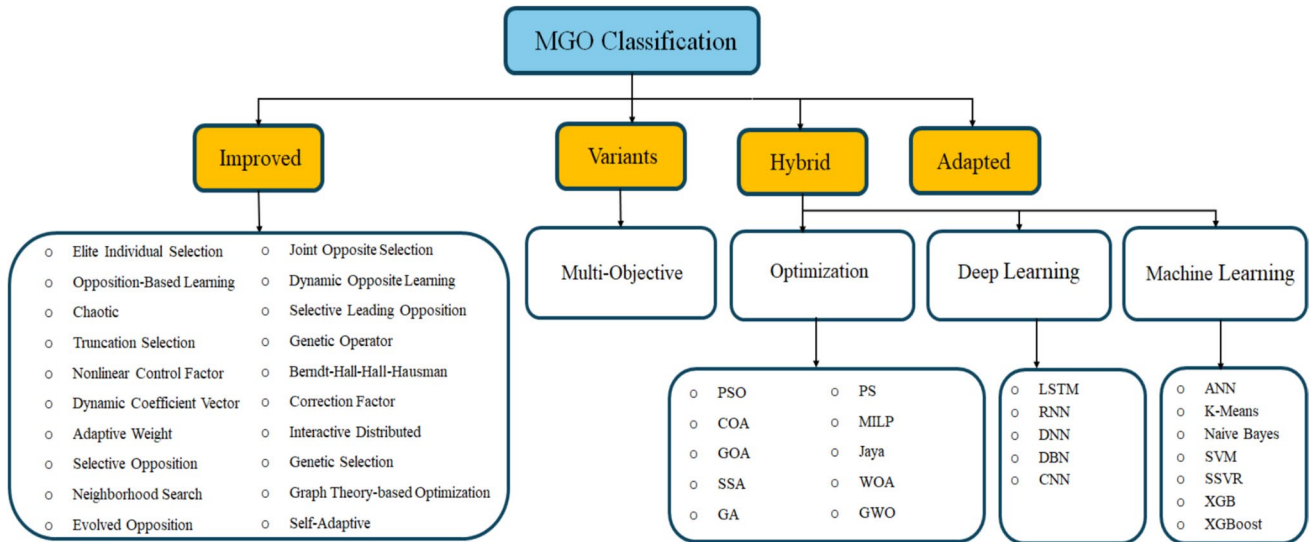


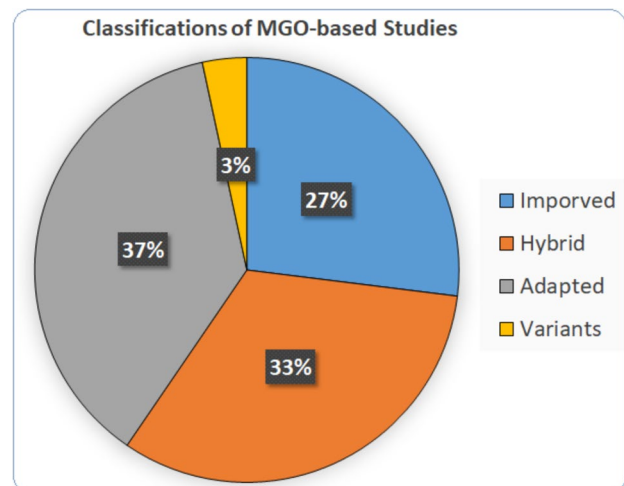
Fig. 8 MGO algorithm’s classification

studies incorporating MGO with several strategies for relieving its limitations or improving its efficiency by domain-specific orientations in its nature for specific fields. A close inquiry into this category demonstrates that the share of studies engaged with introducing 20 distinct enhancement strategies is quite pronounced. The pie chart in Fig. 9 indicates that studies in this category have tackled an impressive assortment of optimization issues through MGOs. Section 5 explains the specific applications targeted by these studies and lists the various problem domains they addressed.

### 4.1 Hybrid Class

This section reviews studies focusing on hybridizing the MGO algorithm with various methods. The relevant research is categorized into three subheadings: ML, DL, and optimization algorithms. The literature contains 29 studies in this category.

Fig. 9 Percentage distribution of classification of MGO-based studies



#### 4.1.1 Machine Learning-Based Studies

Existing studies in this category focus on how the MGO algorithm can be adapted to different domains with machine learning. These range from cybersecurity to financial analysis, air pollution prediction, cooling load estimation, network resource optimization, and engineering design. It has a common feature to do well in optimization problems in tuning the hyperparameters and improving the convergence rate of ML models. Yet, several studies show that the main problem with computational complexity is the lack of focus on computational efficiency analysis, since there is no consistent account of how the complexity of MGO influences the running time. Future research will involve benchmarking MGO with other modern optimization techniques to assess its computational trade-offs.

The study [49] combines MGO with an Artificial Neural Network (ANN) to optimize the design of mechanical parts in many industrial fields, and the algorithm was utilized to optimize the ANN parameters in the automobile, manufacturing, construction, and mechanical engineering fields. In addition to improving the local search, it was then hybridized with the Nelder–Mead algorithm (NM), which, by effectively minimizing design constraints and improving structural efficiency, provides better optimization performance than other MH approaches. Another study [50] used an ANN-MGO hybrid model for groundwater potential assessment in arid regions of East El Oweinat, Egypt, contributing to the pathway toward sustainable development goals. The MGO algorithm was harnessed to optimize the ANN's training process to improve groundwater mapping. The data sample was divided into train and test sets with a ratio of 70:30. A sensitivity analysis was also conducted to check for feature importance. Its achievement of AUC scores of around 90% in places is far beyond traditionally employed predictors of groundwater. It can produce optimum excavation sites and pumping modalities, showing the practical usefulness of water resource management. Moreover, the study [51] optimizes patient trust and decision-making in telemedicine centers using an ANN-MGO framework. The MGO algorithm was applied to improve the performance evaluation of the ANN by selecting optimal demographic characteristics and patient decision-making styles, with sensitivity analysis conducted to validate the framework. The optimized model revealed that married male patients aged 35–50 with a master's degree and flexible decision-making styles exhibited the highest trust levels in telemedicine services. This insight was used to develop targeted strategies to enhance patient satisfaction.

A new controller system, Adaptive Neuro-Fuzzy Inference System (ANFIS)-based Proportional Integral (PI), which is ANFIS incorporating MGO optimization, was introduced by the [52] research team to enhance grid-tied advanced LVRT capabilities for Wind Energy Conversion Systems (WECS). MGO-ANFIS-PI improved voltage stability and power quality performance compared to the standard PI controller and other optimization methods like PSO and GA by testing performed on the hybrid system based on the 9 MW wind power plant and IEEE 39-bus simulations. The research [53] extends an ML-based MGO framework supporting resource allocation optimization and traffic offloading in Fiber-Wireless (Fi-Wi) networks. The MGO algorithm was used for the best router selection and load distributions while optimizing the Optical Network Units (ONUs) to maintain balanced resource allocation. Also, a k-means clustering algorithm [54] was included to help with network planning. The hybrid MGO-GA model enhanced network conditions by about 15% by reducing network congestion and increasing packet delivery ratios, thus exhibiting higher efficiencies over traditional models. The study [55] introduces an MGO-enhanced Naïve Bayes model for cooling load prediction in energy-efficient buildings. The MGO algorithm optimized the hyperparameters of the Naïve Bayes model, minimizing prediction errors in Heating, Ventilation, and Air-Conditioning (HVAC) energy management. The MGO-Naïve Bayes model enhanced cooling load estimation accuracy by 18%, achieving an  $R^2$  value of 0.983 and far exceeding standard regression models.

In the research [56], an MGO-optimized Support Vector Machine (SVM) model is proposed for classifying bankrupt Small and Medium Enterprises (SMEs) as either reorganized or liquidated. The SVM parameters are optimized through the MGO algorithm, which improves the classification accuracy of bankruptcy prediction. The MGO-SVM model achieved 94% accuracy, which is a clear improvement from conventional ensemble learning models, thus firmly establishing the tool as a viable decision-support system for financial institutions. An MGO-based Least-Squares SVM model (LSSVM) to predict PM<sub>2.5</sub> in urban areas was developed in the study

[57]. With the MGO algorithm employed to tune parameters for the LSSVM model, the prediction precision was increased over several cities. A much lower error prediction model was developed than conventional statistical and machine learning models.

The study [58] optimizes shear strength estimation for light and normal-weight concrete using XGBoost with MGO. The MGO algorithm tuned hyperparameters to XGBoost models to build a decision assist for making reliability assessments for reinforced concrete. The XGB-MGO model was able to achieve  $R^2$  values of above 0.995 while outpacing other tree-based models, such as Random Forest and Gradient Boosting. Another study [59] uses XGBoost optimized with MGO to detect cyber threats and enhance the security of the Internet of Things (IoT) in smart cities. MGO finely tuned XGBoost hyperparameters, improving anomaly detection in network traffic data. The MGO-XGBoost model reached an accuracy of 91.13% and a precision score of 95.48%, thereby drastically reducing false positives compared to traditional cybersecurity models. The study [60] develops an MGO-based optimization model to enhance chloride penetration resistance and cost efficiency in High-Performance Concrete (HPC). The MGO algorithm was utilized for hyperparameter tuning in ML models predicting rapid chloride penetrability and cost factors in HPC mixtures. The MGO ensemble model achieved an  $R^2$  value of 0.987 for chloride permeability prediction and 0.993 for cost estimation, surpassing alternative models. Table 1 provides a summary of the research conducted within this category.

#### 4.1.2 Deep Learning-Based Studies

This section includes the analysis of DL-based Hybrid Studies that incorporate MGO into different applications. This analysis stresses its significance in enhancing DL architecture for various applications. The foremost benefits of hybrid approaches with MGO pertain to hyperparametric optimization, feature selection, and convergence of models, leading to its remarkable performance in classifying, regression, and anomaly detection tasks. In the surveyed literature, MGO has significantly outperformed in enhancing different models based on Long Short-Term Memory (LSTM), Recurrent Neural Network (RNN), Deep Neural Network (DNN), and Deep Belief Network (DBN). Some vital observations concerning MGO are that it has been widely adopted in cybersecurity, innovative infrastructure, engineering, and natural language processing. These range from improving detection accuracy with IoT security and fake news detection to electric vehicle battery optimization and structural engineering, showing some of their benefits concerning computational efficiency.

**Table 1** MGO-based hybrid ML studies

Study	Focus on	Role of MGO	Hybrid with
[49]	Mechanical design optimization	To optimize ANN parameters for engineering problems	ANN, and NM Algorithm
[50]	Groundwater potential evaluation	To optimize ANN for groundwater mapping and feature selection	ANN, MODFLOW-USG
[51]	Performance optimization of telemedicine centers	To optimize ANN for patient trust and satisfaction prediction	ANN, Statistical Methods
[52]	Wind energy system optimization	To optimize PI controller parameters in LVRT improvement	ANFIS, PI Controller
[53]	Resource management in fiber-wireless networks	To optimize traffic offloading strategy	K-Means, GA
[55]	Cooling load estimation in buildings	To optimize Naïve Bayes model hyperparameters	Naïve Bayes
[56]	Bankruptcy resolution prediction	To optimize SVM parameters for financial risk analysis	SVM, Ensemble Learning
[57]	Air pollution (PM2.5) prediction	To fine-tune Least-Squares SVM (LSSVM) for air quality forecasting	LSSVM, QRGRU
[58]	Structural integrity assessment (concrete design)	To optimize XGBoost hyperparameters for shear strength estimation	XGBoost
[59]	Smart city cybersecurity	To optimize XGBoost hyperparameters for network anomaly detection	XGBoost, Harris Hawks Optimizer (HHO)
[60]	High-Performance Concrete	Hyperparameter tuning for durability and cost prediction	ML ensemble models

The study [61] merges the MGO with the DBN in IoT environments [62] to boost the IoT's intrusion detection multiple fold. Selecting features is done using the MGO algorithm, thereby enhancing Intrusion Detection Systems (IDS) classification accuracy. In contrast, hyperparameter tuning is done with the Hybrid Dragonfly-WOA (HDFOA-WOA). Overall, a promising 98.9% accuracy of MGO-DBN has been achieved, surpassing conventional IDS models with low false positives and increased detection speed. The study [63] also describes the influence of operating systems on the performance of DL in its vehicle systems. The DL model configurations were optimized using the MGO algorithm to game-stabilize the equilibrium between accuracy, inference time, and resources such as CPU/GPU/memory. Various optimizations provided better computational efficiency to choose the best combination of DL algorithms and operating systems for autonomous driving. Another study [64] integrates MGO with DL to detect fake news in Arabic text, addressing challenges in low-resource languages. The MGO algorithm was said to tune the hyperparameters for a DBN by optimality. Enhanced such that the MGO-DBN model achieved 97.68% accuracy on the COVID-19 Fakes dataset and 95.14% on the Satirical dataset, outperforming the existing fake news detection methods. The study [65] develops an attention-based DL model with MGO to enhance cybersecurity in IoT devices and drones. The MGO algorithm was applied for hyperparameter tuning of an Attention LSTM (ALSTM-NN) model, improving attack detection accuracy. The MGO-ALSTM-NN framework achieved 99.71% accuracy, significantly outperforming standard cybersecurity models.

Another study [66] introduced a hybrid DNN with MGO for the State of Charge (SoC) assessment of Electric Vehicle (EV) Li-ion batteries. The MGO algorithm has been used to optimize weights and biases in DNN, providing better accuracy from the estimation. The MGO-DNN model also reported a Root-Mean-Square Error (RMSE) of just 0.3%; for example, it deeply outperformed other alternative estimation methods like PSO and back propagation-based deep learning methods. The authors in [67] employed the hybrid MGO-long short-term memory (MGO-LSTM) model to forecast pedestrian–vehicle conflicts at uncontrolled and unregulated intersections. In this hybrid approach, the MGO optimization was used to fine-tune the parameters of the LSTM approach utilizing a best-fit training modality, thereby increasing accuracy and improving the model's response time. The MGO-LSTM model, in addition to being the best performer of all models, surpassed performance among other traditional classification models, such as K-Nearest Neighbors (KNN), random forest (RF), and GA-back propagation, which also had difficulty estimating safety intervals accurately. Another study [68] also implemented the MGO in conjunction with LSTM to estimate shear strength in Ultra-High-Performance Concrete (UHPC) beams and applied tuning to consider hyperparameters for potential optimal predictions in shear strength assessments. Overall, they demonstrated the highest prediction outcome in  $R^2 > 0.98$ , thus outperforming all the deep learning optimization efforts, including the direct affiliation with the MGO using DMO, PPSO, ASO, etc. [69] also implemented a recurrent neural network approach, Hybrids Fire Hawk Optimizers to estimate customer turnover in areas of service. Here, they proposed an RNN-FHO, which corresponds with a framework, the Hybrids Fire Hawk Optimizer (HMG-FHO) algorithm, for estimating customer turnover. The model performance and classification accuracy were enhanced using MGO feature selection techniques. The model performed remarkably better, with 93% accuracy, than the traditional turnover prediction models. A summary of the studies conducted in this category is provided in Table 2.

#### 4.1.3 Optimization-Based Studies

This section demonstrates the magnitude of the influence of MGO in solving complex optimization problems from different engineering and computational domains. It utilizes MH algorithms, such as PSO, Crayfish Optimization Algorithm (COA) [70], Salp Swarm Algorithm (SSA) [71], Gazelle optimization algorithm (GOA) [72], Pattern Search (PS) [73], Mixed-Integer Linear Programming (MILP) [74], and JAYA Algorithm to enhance plenty of exploration–exploitation, convergence speed, and increase accuracy. The studies cited are abundant in identifying MGO and integrating it with several algorithms.

The study [75] presented MGO, a Hybrid Qualitative Optimization (HQO) method involving COA and MGO. The decision to apply the MGO algorithm was made to explore a better solution. The HCCMGA hybrid algorithm

**Table 2** MGO-based hybrid DL studies

Study	Focus on	Role of MGO	Hybrid with
[61]	IoT security	Feature selection for IDS enhancement	DBN, Dragonfly-Whale Optimization
[63]	DL performance in autonomous vehicles	Optimize DL model configurations for efficiency	Various DL models
[64]	Fake news detection	Hyperparameter tuning for fake news classification	DBN
[65]	Cybersecurity in IoT-consumer electronics	Optimize ALSTM-NN for attack detection	Attention LSTM, blockchain
[66]	Li-ion battery SoC estimation	Tune DNN weights and biases	DNN
[67]	Pedestrian-vehicle behavior prediction	Optimize LSTM hyperparameters	LSTM
[68]	Shear strength in UHPC beams	Hyperparameter tuning for LSTM predictions	LSTM, GRU
[69]	Customer churn prediction	Feature selection for churn classification	RNN, fire hawk optimization

achieved the best results on 8 of 13 benchmark functions with fast convergence and low standard deviation while outdoing several conventional techniques. Using the GOA and MGO, the process of ascertaining the positioning of the Distributed Generator (DG) in the power networks is optimized in this study [76]. Using MGO, they optimized DG placement to minimize power losses, voltage deviation, and GHG emissions. Active power losses were reduced by 94.42%, which enhanced the technical and non-technical objectives of power planning. The study [77] focuses on optimizing the Photo-Voltaic (PV) model parameter extraction for better energy conversion efficiency. MGO was combined with pattern search (PS) to increase the efficiency of global and local search for parameter extraction of PV models. The error rates in estimating parameters using the MGO-PS hybrid were lower than those of the other algorithms for single-diode and double-diode PV models.

The research work [78] merges PSO with MGO to augment constrained optimization for several engineering applications. MGO enhanced exploration, and PSO facilitated rapid convergence to solve a range of nonlinear, non-convex optimization problems. The MGPSO algorithm performed better than the other MHs and accomplished the best results for 16 out of 23 benchmark functions and the best results for 10 out of 12 IEEE CEC22 benchmark functions. The study [79] proposes a multi-objective optimization model for integrating EVs and renewable energy sources in power systems. MGO was used together with SSA to optimize transmission expansion planning while minimizing cost, CO<sub>2</sub> emissions, and improving voltage stability. The MGO-SSO hybrid reduced computation time by 92%, thus enabling more reliable and cost-effective grid integration for EVs and renewables. Another study [80] optimizes Virtual Inertia Control (VIC) for frequency stability in microgrids integrating Renewable Energy Sources (RESs). The SSA method was used with MGO to tune the VIC parameters and reduce the instability of the power system caused by RES. Compared with conventional tuning methods, the MGO-SSA scheme significantly improves frequency stability in the microgrid.

The study [81] develops intelligent obstacle avoidance and routing for WSNs [82–84]. Combining MGO with SSA allows exploration and exploitation, balancing routing paths and obstacle avoidance. The MGO-SSA hybrid improved routing efficiency by 20.1%, reducing energy consumption and enhancing obstacle avoidance in WSNs. This other paper brings an MGO-JAYA hybrid model for cluster-based routing and Flying Adhoc Networks (FANETs) [85]. MGO was used for dynamic clustering [86]. Simultaneously, JAYA optimized routing decisions, enhancing communication stability in FANETs. The MGO-JAYA hybrid performed much better, enhancing network stability, energy efficiency, and data packet delivery. The article [87] focuses on the water pollution control problem using MGO combined with the Jacobi collocation method. The nonlinear optimization MGO is applied to control problems in models of water pollution transmission. The MGO method has enormously improved control techniques that reduce water pollution. The study [88] aims to optimize BESS placement, sizing, and dispatch in radial distribution networks to enhance voltage stability, minimize system losses, and manage bidirectional power flow. MILP indicates the BESS’s initial placement and sizing, while the MGO confirms the real-time operational feasibility of a hybrid approach. The MGO optimizes the BESS charging and discharging schedules, enhancing grid stability and increasing battery use. The results indicate that, in comparison to existing methods such as GWO (7.414%), WOA (7.329%), and CSA (7.417%), the suggested strategy decreases system

losses by 8.473%. It's a 0.348% increase in the voltage profile is the most substantial compared to GWO, WOA, and CSA. In 47 rounds, MGO attained the optimum fitness value of 47.260, demonstrating superior convergence relative to GWO (60 iterations), WOA (20 iterations), and CSA (79 iterations). The studies that belong to this category are included in Table 3.

Evaluating the studies in this area substantiates MGO's efficacy as a powerful optimization technique. These studies demonstrate that MGO possesses extensive applicability in AI-driven modelling, engineering optimization, and decision-making frameworks. Several challenges remain, especially with computational load, applicability to large-scale real-time systems, and integration with advanced artificial intelligence methodologies. Notwithstanding MGO's considerable success in addressing many issues through its hybrid methodology, obstacles persist. Future research should focus on enhancing scalability, real-time processing, and hybrid integration of MGO with reinforcement learning and quantum computing to fully utilize its potential.

## 4.2 Variants Class

This section examines variants based on MGO. This domain has two subcategories in literature: binary and multi-objective [89, 90]. Research in this area is scarce, with just three recent publications. All these experiments represent multi-objective variants, and the published binary version has not yet been included in the literature. Both studies employed MGO-based multi-objective frameworks to address real-world energy challenges, improving cost efficiency, system stability, and environmental sustainability. A primary finding from this research is that MGO enhances energy efficiency, reduces costs, and strengthens system resilience by implementing intelligent load scheduling and Demand-Side Management (DSM).

The first study [91] examines multi-objective optimization applied to energy communities utilizing DSM strategies to enhance economic and environmental objectives while maximizing the benefit of energy distribution. The multi-objective genetic algorithm was evaluated in a multi-objective optimization setting that optimized energy generation, storage, and distribution solutions across three energy community models and applied fuzzy theory and Pareto optimization to minimize costs and limit greenhouse gas emissions. The DSM strategies enabled self-consumption improvement of 8–17%, while grid purchase consumption declined by 9–17% in energy community configurations. Ultimately, the multi-objective genetic algorithm framework for optimizing energy communities provided approximate reductions in cost and greenhouse gas emissions. The second study [92] describes an Internet of Things-enabled Home Energy Management System (HEMS) that applies multi-objective optimization techniques to home energy consumption and appliance scheduling optimization. The study described Multi-Objective MGO (MMGO), using real-time scheduling optimization of appliance energy use to reduce consumption in peak usage, reduce cost, and lower the Peak-to-Average Ratio (PAR). MMGO reduced electricity use cost

**Table 3** MGO-based hybrid optimization-based algorithms

Study	Focus on	Role of MGO	Hybrid with
[75]	Global optimization	Improve solution exploration	COA algorithm
[76]	Power systems (distributed generators)	Optimize DG placement	GOA algorithm
[77]	Photovoltaic model optimization	Improve parameter extraction	PS algorithm
[78]	Constrained optimization	Enhance exploration for global optimization	PSO algorithm
[79]	EV grid integration	Optimize transmission planning	SSA algorithm
[80]	Microgrid stability	Improve virtual inertia tuning	SSA algorithm
[81]	WSN	Optimize routing and obstacle avoidance	SSA algorithm
[85]	FANET routing	Cluster-based routing optimization	JAYA algorithm
[87]	Water pollution control	Solve nonlinear optimization for pollutant control	Jacobi collocation
[88]	Battery energy storage (BESS) optimization	Optimize BESS sizing, placement, and dispatch for voltage stability and loss minimization	MILP

by 12.14%, with a 52.54% reduction in PAR single homes. In cases where MMGO was tested in clustered cases of 50 homes, higher results were obtained in cost (80.15% reduction in cost), and a 25.07% reduction in PAR for homes in peak usage. The MMGO results were validated using IoT and an innovative plug-in for real-time energy use. The authors reported on achieving additional cost savings (compared to other studies) and a reduction in PAR during real-time smart plug integration experimentation.

The study [93] attempts to optimize the parameters of Superconducting Magnetic Energy Storage (SMES) systems for voltage sag mitigation and cost minimization in distribution networks to maintain grid stability during transient load changes. The multi-objective weighted-sum function enhanced the MGO method to minimize simultaneously the voltage sag and the costs of the SMES unit. MGO was employed to optimize the SMES and controller parameters, including tuning the fuzzy logic-based control for the dynamic voltage control. The Karot distribution network in Egypt was tested for the simultaneous startup of 16 irrigation motors and the response of the SMES system. This study shows a 78% capacity (0.625 MJ to 0.135 MJ) and 64% cost (0.6934M to 0.2483M) reduction of MGO-optimized SMES. During the high-load startup of the irrigation motors, the voltage remained above 0.9 p.u., which means that the network is stable. Also, the MGO converges faster, and the transient stability and performance are better than those of the PSO-based SMES optimization regarding reactive power support and voltage recovery time. Table 4 summarizes the characteristics of the studies in this category.

### 4.3 Improved Class

The 24 studies showed improvements in search efficiency, convergence stability, and adaptability to problem types in engineering, energy systems, healthcare, and large-scale optimization problems. Improvements made to MGO, including chaotic mappings, Opposition-Based Learning (OBL) [94], truncation selection, recursive filtering, genetic operators, and hybrid multi-objective models, have enhanced the exploration–exploitation balance, accuracy, and convergence speed. The use of MGO in various applications, including power distribution, energy systems optimization, PID tuning in Maximum Power Point Tracking (MPPT), and tumor identification, illustrates its ability to adapt through different sciences and engineering. MH hybridization has shown the best performance in areas including hybrid feature selection, bioinformatics, and classification problems. At the same time, enhancements in tuning have improved the performance of solar PV, power systems, and medical applications.

#### 4.3.1 Chaotic-Based Strategies

The single-diode PV model enhances the accuracy of PV model parameter extraction. MGO was enhanced by merging chaotic maps and elite individual selection mechanisms to generate CEMGO [95]. The changes help improve search diversity to ensure the optimizer is not stuck in local optima. CEMGO showed an improvement of 23.07% on the RMSE score of MGO, which shows better convergence speed and parameter estimation accuracy of the PV model. The second research used chaos theory [96] to optimize microgrids' energy management, considering the uncertainties in load demand, wind speed, electricity pricing, etc. A chaotic-based local search operator was added to enhance MGO's search effectiveness and reception agility in microgrid systems.

**Table 4** MGO-based studies in the variants class

Study	Focus on	Role of MGO	Optimization scope
[91]	Energy communities	Optimize energy distribution, demand-side management, and sustainability	Multi-objective cost and emissions minimization
[92]	Home energy management	Optimize household appliance scheduling and real-time load balancing	Multi-objective cost, PAR, and user convenience optimization
[93]	SMES optimization in power systems	Optimize SMES sizing, cost, and voltage regulation	Multi-objective weighted-sum function

This enhancement improves MGO's performance against Real-Time Pricing (RTP) models and multi-objective trade-offs in the DEA systems. The enhanced MGO decreased microgrid operation costs, allowing for efficient load distribution and stability amidst fluctuating pricing models. The study [97] optimizes the structural design parameters of a pressure vessel to achieve minimum weight while satisfying structural constraints. In opening Chaotic Logistic Mapping MGO (C-LMGO), the author introduced a chaos-based initialization method and an adaptive step-size tuning to improve the solution precision, stability, and efficiency of global search. This change significantly decreased the material needed while satisfying the necessary safety constraints, which did better than classical stochastic algorithms in optimizing engineering designs.

A distinct study utilizing chaotic maps [98] seeks to enhance feature selection for high-dimensional medical datasets, improving classification accuracy and efficiency in machine learning models. A novel Chaotic-Spiral Disturbance MGO (CSDMGO) is introduced, incorporating many essential elements to enhance search efficiency. Components comprise a nonlinear control variable to improve global and local search efficacy in conjunction with the iterative chaotic map with infinite collapses (ICMIC) for population initialization, augmenting variety. A spiral perturbation mechanism is employed to improve local search and convergence speed, accompanied by a neighborhood search approach to optimize the most beneficial characteristics dynamically. The Binary CSDMGO version markedly outperformed conventional optimization techniques, including MGO, WOA, PSO, and GWO, exhibiting enhanced feature selection accuracy and decreased feature selection across 16 medical datasets. This technique increased sensitivity in illness classification models by accurately identifying critical biomarkers. The study [99] aims to improve the efficacy of MGO in multimodal and high-dimensional optimization challenges. The OBL-ChaosMGO methodology was developed to enhance population diversity and search dynamics by integrating OBL and Chaotic Mapping. The results of more than 31 benchmark test functions demonstrated that OBL-ChaosMGO outperformed GOA, MGO, and seven more algorithms in terms of convergence time and solution correctness. Based on chaos theory, recent research [100] seeks to improve the efficacy of MGO in addressing high-dimensional, large-scale optimization challenges in computer and engineering domains. Numerous substantial enhancements were included in the Modified MGO (MMGO) architecture. This encompasses Logistic Chaotic Mapping for enhanced population initialization, which aids in circumventing premature convergence, and a truncation selection method to preserve a more diversified search space and avert stagnation in local optima. An improved migration search approach was implemented to accelerate convergence speed. The MMGO framework exhibited enhanced performance, surpassing classical MGO, PSO, and Gravitational Search Algorithm (GSA) over 23 benchmark functions and a practical engineering application. MMGO demonstrated enhanced optimization accuracy in high-dimensional test functions, accelerated convergence speeds with diminished computational expense, and resilient performance in parameter estimation for FM sound wave optimization.

### 4.3.2 Opposite Learning-Based Strategies

The study's objective [101] is to effectively establish the H-infinity and m-synthesis controller settings for Doubly Fed Induction Generators (DFIGs) in wind farms. A Dynamic Opposite Learning-based MGO (DOLMGO) was developed to enhance flexibility in fluctuating wind conditions and optimize controller performance for improved stability. The recent change enhanced performance beyond prior optimization approaches while delivering superior performance to mitigate varying wind speeds and compensating for needs. The work [102] focused on enhancing MGO performance to improve efficacy, avoid local optima, and accelerate convergence in challenging optimization problems. A novel technique, called Evolved OBL (EOBL), was implemented to accomplish this. EOBL enhances OBL to produce advanced solutions derived from the search pattern created by MGO in the preceding optimization, facilitating an improved equilibrium between exploration and exploitation. The outcome of this reformulation is the Evolved Opposition-Based MGO (EOBMGO). The EOBMGO was evaluated using the CEC2005 and CEC2019 performance benchmarks, as well as several engineering issues. The results demonstrated that, despite enhancements in performance, EOBMGO produced competitive results against many

top MH algorithms while requiring less processing resources and achieving more accuracy in multidimensional search environments.

The study's primary goal [103] is to find ways to improve the size and lower the cost of standalone Hybrid Renewable Energy Systems (HRES), which comprise batteries, solar panels, and wind turbines. Constraints like LCOE, optimization of surplus power generation, and the Probability of Loss of Power Supply (LPSP) were included in the EOBMGO model to handle the HRES size problem. The data demonstrated that the updated system preserved excellent energy reliability while lowering annual costs. The results showed improved operational and financial viability compared to optimization techniques like GWO, ARO, BOA [104], and WSO [105]. This work aims to increase the accuracy of feature selection and classification for brain stroke detection [106]. Dynamic Opposite Learning (DO) and Selective Leading Opposition (SLO) were combined to create the Joint Opposite Selection MGO (JOS-MGO), hence improving search diversity and classification accuracy. In brain stroke datasets, HHO, Hunger Games Search (HGS), and WOA algorithms reached a sensitivity of 99.34% and a precision of 99.21%; JOS-MGO obtained a classification accuracy of 95.5%.

### 4.3.3 Other Combined Strategies

The study [107] optimizes the Distributed Generation allocation, capacitor bank placement, and network reconfiguration in Radial Power Distribution Networks (RPDNs). MGO has been modified for better performance by including an Adaptive Genetic Operator (AGOMGO). Using the B3H Method of Trading, the study of MGO with low polarization MGO-based trading on a big scale helps with exploration, exploitation, efficiency, and convergence. Overall Network with Additional DGs and Capacitors Improvement. In a 118-bus system, AGOMGO reduced power loss by 90.77%, while in a 136-bus system, the reduction was 87.54%. The values of voltage profiles and stability indices improved remarkably due to the hybrid model. The study [108] makes parameter extraction of three-diode PV models more accurate. The augmented MGO (AMGOIB3H) method essentially shifts nonlinear simulations toward achieving the most substantial search outcome of the Berndt–Hall–Hall–Hausman (B3H) Method. This change improves the MGO's exploitation phase, ensuring an accurate parameter estimation while minimizing deviations from real-world PV system behavior. The AMGOIB3H technique at every environmental condition gives near-zero estimation errors. This technique is more accurate, reliable, and efficient than traditional PV technique parameter estimation.

The study [109] aims to improve the accuracy of node localization in wireless sensor networks using range-free methods. The Enhanced MGO (EMGO) was used to modify the Distance Vector-Hop (DV-Hop) estimation using a correction factor that improved accuracy in multi-hop wireless sensor network (WSN) environments. The EMGO-DV-Hop technique remarkably improved localization accuracy by 48.69%, significantly more than the current effectiveness of MH-based localization methodologies. A particular study [110] tries to enhance MPPT control of solar PV systems using advanced PID controllers. A variant of Enhanced MGO (EMGO) was proposed to improve the effectiveness of PID parameter tuning. This involves improvements to the TSM and BMH phases of search operators. Findings showed that the proposed method was superior to standard optimizers, including GA and GWO, with less ITSE and fast convergence. This improvement resulted in a higher MPPT efficiency, which enhanced the overall performance of the solar PV system. The paper [111] deals with multi-objective Optimal Power Flow (OPF) challenges in large power networks with FACTS-based reactive power compensation. The Interactive Distributed Strategy (IMGO-IDS) was created to enhance the balancing of exploration and exploitation dynamics to reduce power loss and improve voltage stability and reactive power distribution. The results showed that IMGO-IDS outperformed conventional OPF solvers with better accuracy in the IEEE 118-bus and Algerian 114-bus test cases. The results show the importance and efficiency of the technique in enhancing large-scale power systems. The study [112] aims to strengthen structural designs in pressure vessels, trusses, beams, and cantilever structures. They developed the Improved F-Parameter MGO (IFMGO), which has a self-adaptive exploration–exploitation control factor

for the intensity of the search. The results showed that IFMGO surpassed the standard MGO and PSO by achieving higher optimization accuracy and faster convergence in structural engineering problems.

The goal of the research [113] is to improve the siting of shunt reactive compensators within power distribution systems to lower system losses and enhance voltage profiles. The Modified MGO (MMGO) was obtained through loss sensitivity factor-based search space reduction and modified selection operators for the optimal siting of multiple shunt compensators. The results demonstrated loss reduction and other improvements in voltage stability using MMGO, where the power losses decreased to 34.05% on an IEEE 33-Bus system and 35.45% on an IEEE 69-Bus system. The last paper of this related body of study in [114] emphasized cancer diagnosis and where maximizing was the focus of the research for feature selection and classification in micro-array gene expression datasets. The Recursive MGO (RMGO) was developed using multi-filter selection and the recursive-based filter to ensure high levels of accuracy in the feature selection of a minimal gene subset for tumor types. A practical bioinformatics tool revealed that RWGO reflected a favorable outcome relative to the current genetic-based selection process, hence reduced the gene subset with increased classification accuracy.

The study [115] aims to optimize Distribution Network Reconfiguration (DNR) and DG placement while minimizing the number of infeasible solutions violating radiality constraints. The Adaptive MGO (AMGO) was developed to combine graph theory-based optimization techniques that drop non-radial and infeasible solutions during the optimization. A radiality check method was incorporated to ensure that every network layout adhered to radial constraints, thus enhancing solution feasibility and stability. A hybrid decision-making model that considers technical, economic, and environmental objectives was used to optimize power loss, voltage, cost, and emissions. Through several operational scenarios, they tested their strategy on IEEE 33-bus and 69-bus systems. According to the findings, AMGO substantially reduced active power loss by 82.55% (35.36 kW) in the IEEE 33-bus system and 85.48% (32.57 kW) in the IEEE 69-bus system. There are improvements in voltage stability, with Volt Stability Index (VSI), of 1.9936 p.u for IEEE 33-bus system and 2.3847 p.u for IEEE 69-bus system. Also, the total planning costs were decreased to \$3.456 million and \$2.524 million for IEEE 33-bus and 69-bus, respectively. Carbon emissions were lowered to 1.744 million lb/hr and 2.53 million lb/hr. Compared with classical reconfiguration techniques like GWO, PSO, AMWOA and SSA, AMGO gives better results with higher feasibility and less computation time, improving the network performance.

#### 4.3.4 Deep Learning/Machine Learning-Based Strategies

In this subsection, besides these studies, the MGO algorithm and four studies on DL and ML can be checked for improvement or modification studies. In the first study [116], the authors utilized a hybrid DL model to enhance the accuracy of wind power forecasting while optimizing PID controller parameters for power regulation. Researchers suggested a Self-Adaptive MGO (SA-MGO), incorporating Quasi-OBL (QOBL) to improve the exploration–exploitation balance. This optimization helps with tuned PID design for minimum Mean Square Error (MSE) and Total Harmonic Distortion (THD) in Energy Systems. Moreover, a Modified Siamese Transformer Network (MST-Net) was added to better capture the long-term dependencies of wind power. It was found that the Samosa MGO-PID Controller was more accurate and converged faster than the LSTM, Transformer, and standard MGO-PID tuning approach. The model enhances forecast accuracy by 55% and significantly lowers the forecasting errors. A different study [117] enhances the K-Means clustering performance on numerical, categorical, and mixed datasets. The researchers proposed the Chaotic MGO (CMGO), a modification of MGO that uses a chaotic map in the Territorial Solitary Males (TSM) scheme to enhance global search efficacy. Moreover, the Migration to Search for Food (MSF) strategy was discarded to prevent unnecessary exploitation and create a better exploration balance. The Gower distance measure was fused to mitigate K-Means' categorical and mixed-type data limitations. The study demonstrated that CMGO outperformed MGO and additional 14 modern clustering techniques in over 28 datasets obtained from UCI and OpenML. CMGO claimed the highest ranking for numerical and categorical clustering while securing

third for mixed-type clustering. It was shown to have a lower pairwise distance within its cluster, and the mean F-Measure score was higher than the other approaches. Overall, supportive evidence was brought forward for CMGO's ability to cluster data effectively.

The third article [118] put forth a scheme to improve accuracy for COVID-19 classification, employing a hybrid texture-based (textural) deep learning (DL) and machine learning (ML) methodology within the proposed scheme. An Enhanced Chaotic MGO (EMGO) method was developed to fine-tune SVM hyperparameters to improve the classification scheme further denominated MGO-Enhanced SVM (MGO-ESVM). The scheme consisted of components including Advanced Bilinear CLAHE (ABC) preprocessing to increase contrast for X-ray images and overall feature extraction and Texture Rectified Cross-Attention Transformer (TRCAT) to obtain deep texture features to be combined with hand-crafted texture feature extraction using CNN methods. Moreover, the diverse components allowed the finer tuning toward a singular view of COVID-19 classification using MGO-ESVM, which built off the EMGO's ability to fine-tune and promote stability in classification methods. The authors referenced a 99.34% accuracy for the MGO-ESVM model, which was notably increased compared to traditional approaches, such as CNN, ResNet, and other transformer methods. Concerning accuracy, comparing ensemble approaches with CNN would yield the MGO-ESVM model accuracy outpacing performance by 1% to 2% in COVID-19 diagnosis (95% to 98.82% accuracy) while maintaining classification algorithms within reduced computational complexity. The last study [119] develops an advanced Spatiotemporal Support Vector Regression (SSVR) model that uses multi-source information and optimizes regression parameters for long-term forecasting of railway subgrade settlement. The process was enhanced by introducing the Improved MGO (IMGO). IMGO's main features include cross-collaborating multiple strategies to enhance population diversity, optimizing the dynamic coefficient vector to adjust exploration and exploitation intensity with the iterations, and the memory pool and restart mechanism to hinder premature convergence and stagnation in local optima. The IMGO-STSVR model achieved better performance than the DL-based models for settlement predictions, which indicates the proposed model is more accurate, robust, and adaptable, especially in seasonally frozen grounds. The IMGO-STSVR model is more accurate, robust, and flexible than all conventional models, especially in seasonally frozen ground areas. The IMGO-STSVR model is superior to traditional models, especially on seasonally frozen grounds.  $R^2 = 0.97$  is an extremely high value and a pretty good result. The model is superior to CNN, LSTM, and other SVR models in terms of forecasting accuracy for long-term railway subgrade settlement. To summarize the characteristics of studies in this category, refer to Table 5.

The studies presented and reviewed in this category are generally designed to overcome the shortcomings of the original MGO algorithm. Typically, four limitations limit the performance of the study's results. A primary limitation is that the original MGO seems to converge prematurely and stagnate at local optima. The prior MGO implemented behind optimal results, since there was a lack of diversification in the Search Process to escape local optimum. Multiple improved versions added chaotic maps, OBL, and dynamic coefficient vector updates to fix this issue. The chaotic mechanisms utilized in CMGO and Chaotic-Truncation MGO caused the search process to lose memory, so the search was not repetitive, increasing solution diversity. EOBMGO and JOS-MGO also used OBL strategies to enhance the explorer's exploration ability and broaden the solution space for better global exploration. Dynamically adjusting the coefficient vectors enhances reliability during different iterations, so MGO does not get stuck in one area.

Another key limitation of MGO is the imbalance between exploration (global search) and exploitation (local search). The standard version of MGO did not adjust its search strategy dynamically, leading to either too much exploration (slow convergence) or exploitation (local stagnation). To fix this issue, new and improved versions like AGOMGO and IMGO used hybrid search operators, genetic algorithms, and opposition-based strategies to improve broad search and local search. Truncation selection in Truncation MGO ensures that only the best-performing candidates are retained, and the weaker solutions are discarded dynamically by the optimizer. These changes enhanced MGO's performance in high-dimensional landscapes with improved dynamic convergence and exploration strategies.

**Table 5** MGO-based studies in improved class

Study Focus	Role of MGO	Improved by	Advantages
[95] Photovoltaic Parameter Estimation	Improve PV model accuracy and parameter extraction	Chaotic Maps & Elite Selection (CEMGO)	23.07% improvement in RMSE, better solution robustness
[96] Microgrid Operation	Optimize renewable energy integration and cost efficiency	Chaotic-based local search operators	Reduced electricity expenses under real-time pricing models
[97] Pressure Vessel Design	Optimize structural design parameters	Chaotic Logistic Mapping & Adaptive Step-Size	Achieved superior weight minimization and design stability
[98] Feature Selection for Medical Data	Improve feature selection accuracy and model performance	Chaotic Maps & Spiral Disturbance	Enhanced diversity, better local and global search balance
[99] High-Dimensional Problems	Global search enhancement	OBL & Chaotic Mapping	Faster and more robust convergence
[100] Global Optimization	Solve high-dimensional nonlinear problems	Chaotic-Truncation Selection & Logistic Mapping	Increased convergence speed, better global search capability
[101] Controller Parameter Optimization in Wind Farms	Optimize robust H-infinity and $\mu$ -synthesis controllers	Dynamic Opposite Learning-Based MGO (DOLMGO)	Ensured system stability across varying wind speeds
[102] Hybrid Renewable Energy Systems	Optimize HRES sizing	EOBL with Multi-Objective Constraints	Cost reduction, high energy reliability
[103] Global Optimization	Improve local optima escape	Evolved OBL (EOBL)	Faster convergence, better search diversity
[106] Brain Stroke Classification	Feature selection, ML enhancement	Joint Opposite Selection (JOS-MGO)	95.5% accuracy, superior precision
[107] Power Distribution Networks	Optimize DG allocation, capacitor bank placement, and network reconfiguration	Genetic Operators (AGOMGO)	Improved search efficiency, 90.77% power loss reduction in 118-bus system
[108] Solar Photovoltaic Parameter Estimation	Optimize PV model parameters under real-world conditions	Augmented MGO (AMGOIB3H) with Berndt-Hall-Hausman (B3H) Method	Enhanced convergence and accuracy, near-zero error rates
[109] Localization in WSNs	Improve node localization accuracy	Enhanced MGO with Distance Vector-Hop (DV-Hop) Correction	48.69% accurate improvement, better network scalability
[110] Solar PV MPPT Control	PID tuning for efficiency	Enhanced TSM & BMH Operators	Faster MPPT tracking, reduced ITSE
[111] Large-Scale OPF	Solving power flow problems	Interactive Distributed Strategy (IMGO-IDS)	Higher OPF accuracy, IEEE 118-bus validation
[112] Engineering Design	Structural optimization	Self-Adaptive F-Parameter	Faster convergence, improved accuracy
[113] Radial Power Networks	Loss reduction	Loss Sensitivity & Selective Search	34–35% loss reduction, IEEE 33/69-bus validation
[114] Tumor Identification	Gene selection for ML models	Recursive multi-filter MGO	Minimal gene set, high classification accuracy
[115] Power Grid Optimization	Optimize distribution network reconfiguration and DG placement by reducing infeasible configurations	Graph Theory-Based AMGO with Radiality Constraints	Faster convergence, 82.55% power loss reduction, improved voltage stability, lower emissions
[116] COVID-19 Classification	Optimize SVM hyperparameters for COVID-19 detection	Enhanced Chaotic MGO (EMGO) for feature selection and parameter tuning	99.34% classification accuracy, surpassing CNN and transformer-based models
[117] K-Means Clustering	Optimize K-Means clustering for diverse data types	Chaotic MGO (CMGO) with Gower distance integration	Improved clustering performance, first place in numeric and categorical data clustering
[118] Railway Subgrade Settlement Prediction	Improve predictive modeling for settlement variations	IMGO with multi-strategy collaboration, coefficient vector optimization, and memory pool restart	Achieved $R^2 = 0.97$ , outperforming deep learning models in subgrade forecasting

**Table 5** (continued)

Study	Focus	Role of MGO	Improved by	Advantages
[119]	PID Controller Optimization	Optimize PID tuning in wind power forecasting Improve solution stability and efficiency	Self-Adaptive MGO (SA-MGO) with QOBL Truncation Selection Technique	55% improvement in forecast accuracy, enhanced convergence speed Prevented premature convergence, optimized large-scale problems
[120]	High-Dimensional Engineering Optimization			

The third major limitation was MGO's poor scalability in high-dimensional and large-scale optimization problems. When the complexity of the problem increased, standard MGO lost its efficiency, and the convergence was slow. Numerous enhancements have been made, including recursive filtering, multi-filter selection, and adaptive parameter tuning mechanisms. For instance, RMGO was an important machine learning optimization for tumor characterization, significantly improving feature selection in a large-scale biomedical data set. Likewise, IMGO and SA-MGO added collaboration of multiple strategies and self-adaptive learning to adjust search parameters on the go and keep searching efficiently amid complicated multidimensional spaces. In managing other energy systems, MGO frameworks such as MMGO specifically catered to effective multi-objective tuning and allowed the management of several conflicting objectives.

Finally, MGO has encountered significant hurdles regarding computational expense and convergence velocity in real-time and resource-constrained contexts. The original approach was unsuitable for optimization tasks necessitating swift outcomes, as it relied on exhaustive search, potentially leading to considerable processing periods. SA-MGO, DOLMGO, and IMGO dynamically adjusted control parameters to accelerate convergence while maintaining solution quality through self-adaptive learning techniques. By employing memory pool restart techniques, the optimizers in CMGO and IMGO successfully reinstated high-quality solutions, improving efficiency by circumventing unnecessary re-computation. Moreover, hybrid systems integrating MGO with DL models diminished computing complexity while preserving high predictive accuracy, facilitating expedited decision-making. These systems comprise SA-MGO utilizing Transformer models and MGO-ESVM for classification tasks. These modifications have rendered MGO a robust optimizer for extensive, high-velocity optimization issues.

#### 4.4 Adapted Class

This class examines research in which MGO was directly applied to various optimization problems, with few modifications from its base algorithm. The studies reviewed demonstrate the applicability of MGO to a range of interesting fields, such as power and energy systems and control engineering. In general, MGO was used in the research to assist variable selection and system performance and, in some cases, just to aid scheduling or classification. The 33 studies reviewed indicated a strong application of MGO to engineering, smart grid modeling, and predictive modeling, and it was noted that MGO was still in the mix of viable MH algorithms. The reviewed studies examined the use of MGO to assist in optimization on controllers, implement modified operations in power systems, tune ML models, and improve signal processing capabilities and therefore demonstrated the confirmed evidence of MGO's applicability and performance across a spectrum of fields, industry, science, and technology. Following this section, we present a comprehensive discussion of each of the prior studies referenced and present our detailed Tables 6 and 7 of our summary contributions of MGO across several applications. This section will discuss the studies in two sub-topic categories (i.e., power and energy systems and other related applications).

##### 4.4.1 Power and Energy Systems Applications

The project aims [93] to improve the design and cost of small- and medium-sized enterprises (SMEs) for voltage sag correction in power distribution networks. Furthermore, using multi-objective cost minimization methodologies, the MGO was used concurrently to optimize the size of the SMES and the controller's settings, resulting in improved grid voltage stability and lower power loss. The results imply that because the MGO-optimized SMES system with a capacity of 0.135 MJ and a cost of \$0.2483M reduces capacity by 78% and overall cost by 64%, it outperforms the non-optimized one. This demonstrates its superior performance in improving cost-effectiveness and power quality in future electrical grids. The study [121] seeks to maximize a local energy community's energy schedule by assigning renewables and non-renewables appropriately. Energy demand-response scheduling using MGO, BESS, and EVs was employed to lower total operating costs with EVs. Regarding execution time and efficiency, the data show that MGO outperforms DE, GA, and PSO in optimizing the energy distribution schedule. This helps to improve the sustainability and cost efficiency of local energy community systems. The aim of

**Table 6** MGO-based studies in adapted class (power and energy systems)

Study	Focus	Role of MGO	Category
[93]	Superconducting Magnetic Energy Storage	Optimize SMES sizing and controller parameters for voltage sag mitigation	Power and Energy Systems
[121]	Energy Community Scheduling	Optimize renewable energy distribution and storage in local energy communities	Power and Energy Systems
[122]	Load–Frequency Control in Microgrids	Tune 2-DOF PID controllers for better frequency regulation	Power and Energy Systems
[123]	Load Frequency Control in a Three-Area System	Tune Hybrid Fuzzy-PI and PIDF controllers for improved frequency stability	Power and Energy Systems
[124]	Load Frequency Control with Energy Storage	Optimize PIDF controller parameters for frequency regulation	Power and Energy Systems
[126]	Load Frequency Control in Interconnected Microgrids	Fine-tune 2DOF-PID controller for dynamic load balancing	Power and Energy Systems
[127]	Virtual Inertia Control for Low-Inertia Microgrids	Optimize 3DOF-FOPID virtual inertia controller for stability	Power and Energy Systems
[128]	Optimal Power Flow in Power Systems	Optimize power generation scheduling for cost and loss minimization	Power and Energy Systems
[129]	Hybrid Photovoltaic-Wind Power System Optimization	Improve reliability and redundancy allocation in hybrid energy systems	Power and Energy Systems
[130]	Photovoltaic Cell Parameter Estimation	Optimize parameter estimation for single- and double-diode PV models	Power and Energy Systems
[131]	Virtual Power Plant Scheduling	Optimize scheduling and energy management in multi-area virtual power plants	Power and Energy Systems
[132]	Frequency Stabilization in Hybrid Microgrids	Optimize cascaded I-TDN-PI controllers for frequency response	Power and Energy Systems
[133]	Hybrid Power System Sizing	Optimize renewable energy storage and demand-response integration	Power and Energy Systems
[134]	Load Frequency Control in Two-Area Power Systems	Optimize PID-F controller for frequency regulation in hybrid microgrids	Power and Energy Systems
[135]	Load Frequency Control in Multi-Area Power Systems	Optimize FOIPDF controller for better frequency stability	Power and Energy Systems
[136]	Frequency Regulation in Microgrids	Tune PTID controller for better load disturbance rejection	Power and Energy Systems
[137]	Low-Voltage Ride-Through Capability in Wind Power Stations	Optimize PI controller tuning for reactive power regulation and LVRT enhancement	Power and Energy Systems
[138]	Wind Turbine Power Curve Fitting	Improve power curve fitting accuracy using MGO-based parametric modeling	Power and Energy Systems

the work [122] is to lower frequency deviations caused by changes in RES, thereby enhancing the stability of Load–Frequency Control (LFC) in isolated microgrids. Integration of the MGO with a two-degree-of-freedom (2-DOF) PID controller allowed this to be achieved. Dynamic frequency control setting adjustments by the controller ensure reliable operation in microgrids using diesel, solar, or wind. The MGO-optimized LFC system is a solid choice for renewable-integrated microgrids to maintain frequencies consistent based on the results as it improves reaction time, lowers energy loss, and boosts general system dependability when compared to conventional PI, PID, and 2-DOF PID controllers.

The study's goal [123] is to improve the frequency stability of a three-area non-reheat power system with RESs (wind and solar). Hybrid fuzzy-PI and PIDF controllers were used and tuned with MGO to reduce frequency deviations and enhance settling time in LFC. The study discovered that the fuzzy-PI controller optimized via MGO exhibits greater stability and lesser ITAE than other MH-based tuning methods, i.e., Transit Search Optimizer (TSO) and Pelican Optimization Algorithm (POA). Thus, using MGO proves much more effective for stabilizing frequency in renewable-integrated power systems. In the study [124], we use energy storage systems (ESSs)

**Table 7** MGO-based studies in adapted class (other applications)

Study	Focus	Role of MGO	Application domain
[139]	Antenna Array Fault Correction	Optimize radiation pattern correction and minimize SLL degradation	Telecommunication
[141]	Geometrical Constellation Optimization	Improve QAM modulation performance for enhanced signal-to-noise ratio	Telecommunication
[142]	Energy-Efficient Flow Shop Scheduling	Optimize job scheduling for reduced industrial energy consumption	Manufacturing and Production
[144]	Process Planning and Scheduling	Optimize manufacturing process planning with transportation constraints	Manufacturing and Production
[145]	DC Motor Control	Fine-tune PID parameters for speed regulation and liquid-level control	Control Systems
[146]	MIMO System Control Optimization	Tune the PID controller for stability against external disturbances	Control Systems
[147]	PID Controller Tuning in Renewable Power Systems	Tune PID gains for load frequency control in PV-reheat thermal systems	Control Systems
[148]	Automatic Voltage Regulation Stability	Optimize fractional-order PID double-derivative controller for improved voltage regulation	Control Systems
[149]	Optimal Filter Design for Fault Diagnosis	Improve fault detection accuracy through optimized signal filtering	Signal/Image Processing
[150]	Seismic Noise Attenuation	Optimize empirical wavelet transform for enhanced noise reduction	Signal/Image Processing
[151]	IoT–Fog–Cloud Scheduling	Optimize workload balancing and task scheduling in IoT networks	Smart and Autonomous Systems
[153]	Secure and Energy-Efficient Routing in IoT-WSNs	Optimize trust-based clustering for secure IoT-enabled WSNs	Smart and Autonomous Systems
[156]	V2G-Integrated Photovoltaic Energy Storage	Optimize EV charging/discharging schedules to reduce grid load fluctuations	Smart and Autonomous Systems
[157]	Planetary Gearbox Optimization	Optimize gear train design for minimal volume and high-load capacity	Mechanical Engineering
[160]	Truss Structure Optimization	Optimize structural designs for lightweight and high-strength configurations	Structural Engineering

to strengthen the LFC performance of a three-area thermal power system. To achieve this, PIDF controllers optimized using the MGO were put in place. The focus was on fine-tuning the integral and derivative gains. The performance of the MGO-optimized controllers was tested against Harmony Search Algorithm (HSA)-based controllers [125]. Results show that the MGO-PIDF controller and ESSs performed better than HSA-based controllers in which frequency deviation and noise were lower, showing control performance was high in ESS-integrated power systems. The study's objective [126] is to optimize LFC for an interconnected two-area microgrid considering power generation fluctuations from solar, wind, and diesel sources. This was accomplished by introducing a 2DOF-PID controller optimized using the MGO and fine-tuned to accommodate dynamic load variations and DG inputs. The results indicate that the MGO-optimized 2DOF-PID controller outperformed conventional PID and fractional PID controllers, resulting in significantly lower frequency deviations and faster response times. Consequently, it is a viable solution for improving stability in microgrids with variable energy sources.

Renewable energy sources dominate Inverter-Based Low-Inertia Microgrids (LIMGs), and the study's objective [127] is to improve VIC. A 3-Degree-Of-Freedom Fractional-Order PID (3DOF-FOPID) virtual inertia controller was introduced to replace multi-stage VIC controllers, reducing system complexity and power losses. This controller was optimized using the MGO. The results indicate that the MGO-optimized 3DOF-FOPID controller substantially enhanced frequency response, exhibiting excellent stability and robustness in dynamic renewable energy generation environments. Consequently, it is a promising solution for improving the performance of low inertia microgrids. The study's objective [128] is to enhance the efficiency of active and reactive power flow in

transmission networks by minimizing fuel costs, power losses, and voltage deviations. To accomplish this, an Optimal Power Flow (OPF) strategy based on MGO was devised, which involved the optimization of generator outputs, transformer tap settings, and voltage controls. The results show that the MGO-based OPF strategy outperformed PSO, WOA, and Laplacian Particle Optimization (LAPO) algorithms in improving the efficiency and stability of power transmission networks. Specifically, it reduced fuel costs by 11.407%, power losses by 51.016%, and voltage deviations by 91.501%. The objective of the research [129] is to enhance the reliability of hybrid PV and wind power systems by implementing MH-based redundancy allocation. The MGO implemented the Reliability Redundancy Allocation Problem with Component Mixing (RRAP-CM) to optimize hybrid system configurations. The findings reveal that the MGO-based RRAP-CM strategy significantly improved the energy system's resilience, reducing system failures and enhancing sustainability metrics, demonstrating its effectiveness in optimizing the reliability and performance of renewable energy systems.

The study [130] intends to improve the parameter estimation robustness of single- and double-diode PV models, improving the solar system's performance. An advanced MGO-based optimization framework was applied to estimate the unknown parameters in the PV generation units that refined their I–V curve modeling. The results showed that the approach based on MGO was better than all other optimization techniques like GWO, SSA, DE, etc., as it reduced RMSE values to the smallest of  $2.04 \times 10^{-3}$  (SDM) and  $1.39 \times 10^{-3}$  (DDM), thus determining their superior convergence speed, and ensuring greater accuracy of PV model parameter estimation. Study [131] focuses on enhancing the scheduling of multi-area Virtual Power Plants (VPP) by optimizing the Distributed Energy Resources (DERs) integration in smart grids. To achieve this, an advanced MGO-based scheduling model was implemented that supports load balancing and resource allocation strategies for day-ahead and real-time dispatch. Research shows that MGO significantly enhances scheduling efficiency, decreases emissions and operational costs, and proves superior to traditional optimization methods. This indicates MGO's improved efficiency in VPP optimization, enhancing smart grid management. The study in reference [132] seeks to enhance frequency stability in microgrids with high penetration of Renewable Energy Sources (RES). To do this, they implemented MGO-optimized cascaded I-TDN-PI controllers, which helped improve the frequency response. The research finds the controller based on MGO considerably improved system stability as it significantly reduced frequency deviation and response time and outperformed the conventional LFC controllers. This proved helpful in renewables integration and the Load Frequency Control (LFC) controller's management.

The study [133] focuses on the optimization of standalone hybrid power systems consisting of PV units, wind turbines, battery storage, and diesel generators. Utilizing a demand-response-based MGO sizing model that optimizes cost, power loss, and carbon footprint, the results demonstrate that the use of MGO reduced costs (COE = \$0.2334/kWh) and net present cost (NPC = \$6.83M), achieving enhanced economics compared to the traditional models for sizing hybrid power systems. Consequently, it shows the potential to reduce costs and improve the sustainability of hybrid power systems. The research [134] focuses on optimizing LFC in two-area power systems to maintain grid stability for fluctuating renewable energy capture. Using an MGO-tuned PID-F controller, to optimize frequency regulation response for a hybrid microgrid, the study reports that MGO significantly enhances system stability and response time against other LFC controllers based on MH tuning methodology associated with other hybrid energy systems, thereby suggesting its ability to maintain grid stability in the presence of variable renewable energy capture. The research [135] focuses on LFC within multi-area power systems following thermal, hydro, and gas-based generation and RES. An MGO-tuned Fractional-Order Integrated Proportional Derivative with Filter (FOIPDF) controller was developed to optimize stability and response time by addressing uncertainties, governor deadband effects and Generation Rate Constraints (GRCs). Tuning the controller's parameters was meant to improve frequency deviation under constrained operation. The study reports an approximate reduction of Integral Time Squared Error (ITSE) of approximately 96.63% versus WOA, 83.04% versus AOA, and 41.79% versus GWO, demonstrating that the MGO-tuned FOIPDF controller marginally reduces the frequency deviation, and more importantly, improves the resilience of the system.

The study in [136] discusses maintaining or improving frequency stability in a microgrid with changing load and renewable energy sources. To do this, a Proportional Tilted Integral Derivative (PTID) controller

was fine-tuned using MGO for better disturbance rejection and load-following. Results indicated that the MGO-tuned PTID controller system had better damping and lower frequency oscillations. Therefore, it had better power quality than conventional PID controllers. Another study [137] improves the grid-connected wind power station's Low-Voltage Ride-Through (LVRT) capability to enhance the overall system's stability during the voltage dip. MGO-based PI controller tuning was used to actively and reactively regulate DFIGs to lower voltage dip and system transients. Findings show that MGO sharply reduces overshoot by 76% relative to PSO and enhances settling time by a staggering 99% compared to GA, thus assuring superior LVRT performance and enhanced overall system stability during voltage dips. Besides, the study's goal [138] is to optimize wind turbine power curve fitting for performance evaluation and predictive maintenance. The MGO curve fitting was used to make better forecasts incorporating modified hyperbolic tangent, 7th-degree polynomial, and 6th-degree polynomial functions. According to the findings, the MGO-based modified hyperbolic tangent function has the most accurate curve fitting with the lowest SSE and RMSE values among other parametric models, showing the wind turbine power curve's superior performance.

#### 4.4.2 Telecommunication-Based Applications

The study [139] suggests correcting the radiation pattern of defective Linear Antenna Arrays (LAA) due to the minimization of Side Lobe Level (SLL) degradation while maintaining directivity. MGO Algorithm was employed to achieve this goal by making active the amplitude and phase values of functional elements in real time while assigning zero weights to faulty ones. The algorithm was adapted to re-optimize the distorted radiation pattern based on the MH algorithms. The study reveals that HHO produced the lowest values of SLLs, which were -33.45 dB for two faulty elements and -28.92 dB for four faulty elements, outperforming Ant Lion Optimizer (ALO) [140] and WOA. The findings stress the suitability of HHO in restoring the beam, which can have implications for radar and 5G communication systems. The study [141] seeks to enhance the performance of Quadrature Amplitude Modulation (QAM) through optimal placement of geometrical constellation points to achieve improved signal-to-noise ratio (SNR) gains. To do this, the MGO used for constellation shaping significantly reduces phase noise and transmit failures in optical fiber communication systems. The research shows that MGO enhances the optical SNR (OSNR) in 128-QAM by 4.3 dB, significantly improving transmission distance and system robustness compared to conventional shaping techniques. It shows promising results in improving the efficiency and reliability of high-speed communication systems.

#### 4.4.3 Manufacturing and Production-Based Applications

The study [142] aims to optimize no-wait flow shop scheduling and energy consumption at the industrial production system level. The study adapted MGO to discrete scheduling problems using the Large Rank Value (LRV) principle to adequately handle job sequencing constraints [143]. The results show that MGO performs better than GWO, PSO, GA, FHO, and Cuckoo Search (CS). In multiple test cases, it achieved lower energy consumption and faster convergence time of scheduling. This underlines its efficiency in energy-efficient manufacturing. The correct solution for the transportation of Work-In-Process (WIP) inventory between machine cells when an effective system failure occurs is a significant research gap. Transportation constraint consideration is often neglected in the optimization of process planning and scheduling in Flexible Manufacturing Systems (FMS), as stated in [144]. To solve this problem, a novel MGO-supported MH framework, which assists in the concurrent optimization of Process Planning and Scheduling (PPS), is designed to improve the system's overall performance. The results show that MGO significantly outperformed WOA and PSO for scheduling efficiency in real-life manufacturing case studies.

#### 4.4.4 Control Systems-Based Applications

The research [145] aims to optimize the parameters of the PID controller employed for speed regulation in a DC motor and for liquid-level management in industrial automation systems. MGO was employed to optimize the proportional ( $K_p$ ), integral ( $K_i$ ), and derivative ( $K_d$ ) gains to minimize overshoot, rise time, and settling time about dynamic system response. The optimization demonstrated enhanced performance relative to GWO and PSO. The experimental results indicated that MGO attained a rise time of 0.0478 s, zero overshoot, and a settling time of 0.0841 s for DC motor control. This underscores that the examined MGO influences the development of systems characterized by enhanced stability and responsiveness for practical automation applications. The work [146] seeks to develop a resilient MIMO PID controller that mitigates the impact of external disturbances in MIMO control systems. The MGO was employed in this method to dynamically adjust the PID gains, enhancing response, minimizing overshoot, and reducing transition error. The findings indicated that the MGO-PID controller outperforms the PSO-tuned PID system by reducing the Integral Absolute Error (IAE) and enhancing control stability in simulated industrial applications. MGO-PID is recognized to have superior performance in intricate multidisciplinary control contexts. The research [147] seeks to enhance the stability of LFC in hybrid photovoltaic-reheat thermal power systems. An MGO-PID control was designed, and the PID controller gains were tweaked, resulting in increased damping and reduced frequency overshoot compared to measurements. Furthermore, the findings demonstrated that MGO-PID tube placement produced enhancements compared to traditional LFC techniques. The MGO-PID systems minimized overshoot while enhancing the overall stability and efficiency of the hybrid power system. The study [148] seeks to improve the stability of the Automatic Voltage Regulation (AVR) system, guaranteeing effective voltage management under fluctuating load situations. An MGO-optimized Fractional-Order PID with Double-Derivative (FOPIDD2) controller was built to attain enhanced control precision. The results indicate that the MGO-FOPIDD2 controller surpassed conventional AVR tuning methods, exhibiting superior transient response and voltage stability, augmenting the AVR system's overall efficacy.

#### 4.4.5 Signal/Image Processing-Based Applications

The authors in [149] aimed to optimize filter designs for noise reduction to enhance the accuracy of fault diagnostics in complex mechanical systems. An optimal filter design using MGO was carried out, which featured a new sparsity index based on kurtosis and negentropy and was suitable for vibration signal feature extraction. The findings show that the filter optimized with MGO significantly improved the SNR and fault detection accuracy over traditional wavelet and frequency-based filtering methods, thus demonstrating its effectiveness in enhancing the diagnostic performance of mechanical systems. The following study [150] tries to effectively reduce the random noise of seismic signals with a small signal corruption. An MGO-Optimized Empirical Wavelet Transform (OEWT) was designed for optimal mode selection and noise reduction combined with a New Wavelet Thresholding (NWT) method. The OEWT-NWT technique has shown superior performance to existing wavelet denoising methods in terms of better accuracy of signal preserving capability and NWT technique efficiency of noise suppression. This method performs better in processing seismic data for more reliable signal analysis.

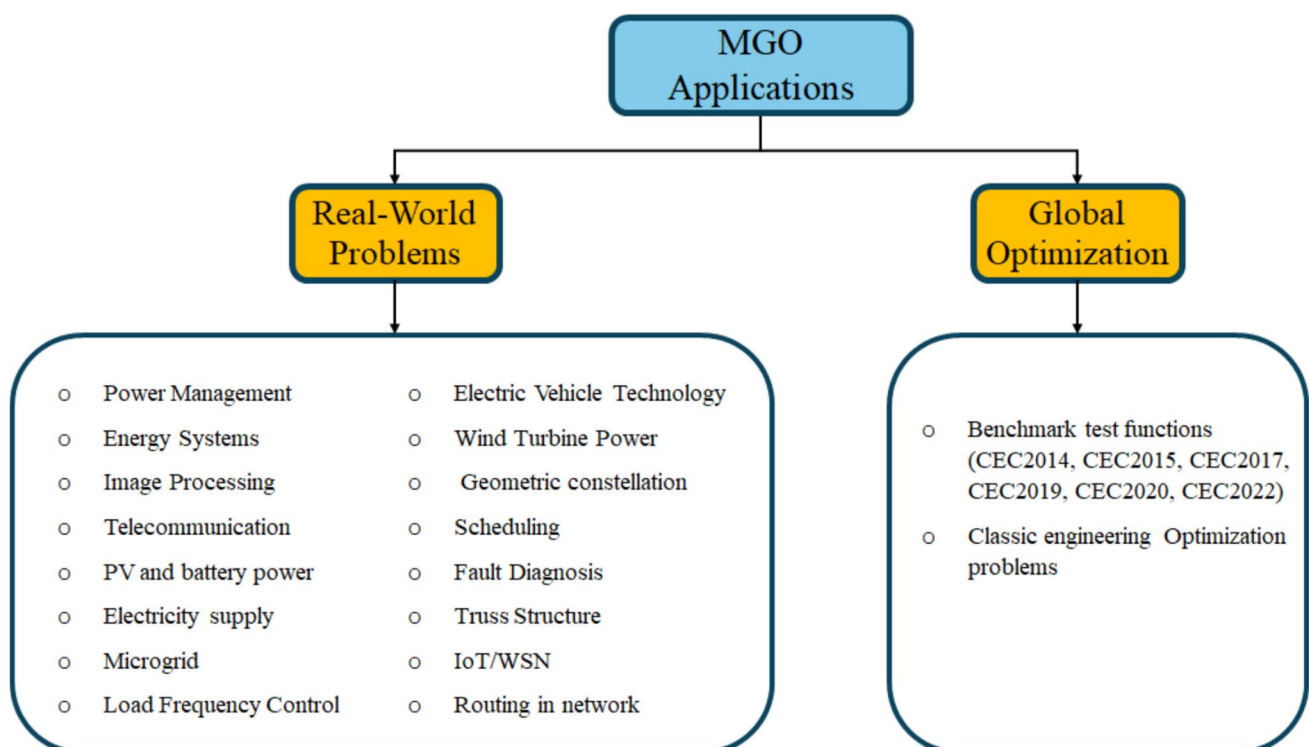
#### 4.4.6 Smart and Autonomous Systems-Based Applications

The purpose of the study [151] was to address the issue of task scheduling in next-generation IoT–Fog–Cloud networks [152]. The MGO was used for dynamic workload balancing and optimal resource allocation between fog and cloud nodes. Findings show that MGO improved scheduling efficiency compared to state-of-the-art task scheduling techniques in IoT networks by significantly reducing latency and energy consumption. Hence, the study proves the efficacy of MGO in enhancing the performance of modern-day distributed networks. The

focus of the investigation [153] is on boosting security and energy efficiency in the IoT-enabled WSNs utilized in smart cities [154]. An MGO-based trust-aware clustering model was developed to optimize secure Cluster Head (CH) selection and energy-efficient data transmission [155]. It has been found that the MGO-based method enhanced the network lifetime by  $1.24\times$  relative to the LEACH-TM,  $6.70\times$  versus the E-LEACH, and considerably boosted trust-based routing efficacy, proving its usefulness in improving the security and energy avoidance of WSNs in smart cities. The purpose of the study [156] was to charge and discharge scheduling of the EV of the V2G (vehicle-to-grid) integrated PV energy storage station to reduce the fluctuation of the grid load and increase the user's revenue. MGO-based energy scheduling was used to reduce the peak-to-valley differences in grid load and increase EV users' discharging income. The findings highlight that the MGO substantially decreased grid peak loads, ensuring the economic viability of both users and grid operators. This method can better trim the grid's peak loads compared to COA and PSO-based scheduling.

#### 4.4.7 Other Engineering Applications

The study [157] specifically targeted the optimization of planetary gearbox designs for volume reduction and increased load capacity due to improved efficiency and durability. To accomplish this goal, the MGO was employed for multi-objective gear train optimization to help facilitate the orientation of gear size, material strength, and weight to achieve the design purpose. The results showed that the MGO was able to obtain optimum volume reduction of gearboxes, proving to be more efficient and faster to converge with more accurate solutions than Hippopotamus Optimization (HO) [158] and Puma Optimizer (PO) [159], demonstrating the efficacy of MGO for gearbox design performance. The research study [160] aimed to optimize the design of truss structures for minimum weight and structural performance. To perform this optimization, MGO was used for structural optimization and was able to navigate high-dimensional non-convex search spaces. The



**Fig. 10** Application domains of MGO-based studies

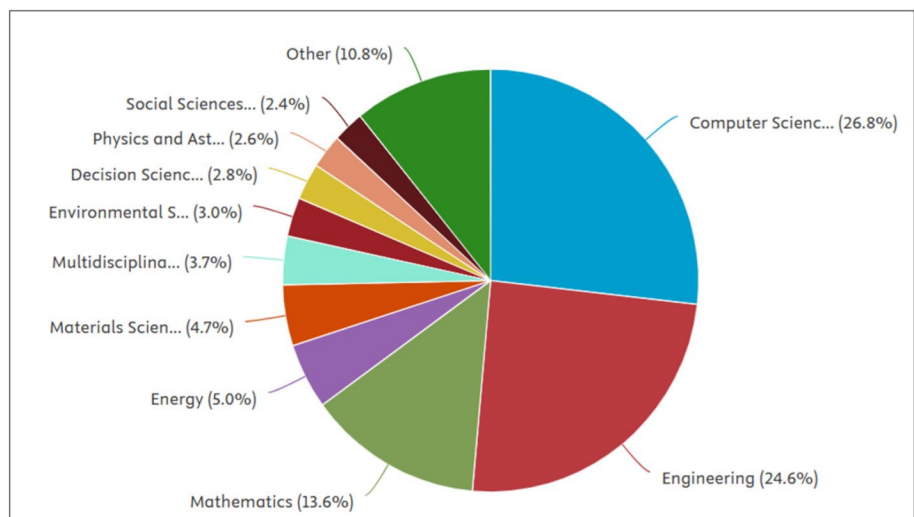
results showed that the MGO outperformed AOA, the Material Generation Algorithm (MGA) [161], and the Crystal Structure Algorithm (CryStAl) [120], which produced truss designs that were lighter and stronger.

### 5 Applications Domain of the MGO-Based Studies

This section summarizes the literature-based uses of MGOs and their classifications. The studies examined primarily focus on applying MGO to handle particular obstacles encountered in the actual world (Fig. 10). Alternatively, the studies are evaluated by employing traditional engineering problems and benchmark test functions that are generally recognized. Even though the following three classes also cover a variety of difficulties, the adapted class is the primary classification for these problems and the application areas that correspond to them.

Furthermore, Fig. 11 visually represents the percentage distribution of applications that use the MGO method. As can be seen, the fields of Computer Science (26.8%) and Engineering (24.6%) constitute almost half of the total publications, indicating that the work is largely concentrated on the axis of technical and applied sciences. This suggests that relevant studies are closely related to topics, such as digitalization, automation, artificial intelligence, and modeling. The field of Mathematics (13.6%), which comes in third place, reveals the concentration of basic theoretical contributions, especially modeling and algorithm development. Applied fields such as Energy (5.0%) and Materials Science (4.7%) also have a significant share, indicating that engineering studies are supported by multidisciplinary approaches. Other disciplines are listed as follows: Multidisciplinary (3.7%), Environmental Sciences (3.0%), Decision Sciences (2.8%), Physics and Astronomy (2.6%), and Social Sciences (2.4%). These rates show that the study has a limited interaction with the social and natural sciences. The Other category has a share of 10.8%; this ratio encompasses a variety of fields that cannot be classified within a specific discipline but contribute significantly. This distribution highlights the interdisciplinary nature of the research and clearly demonstrates the dominant role played by technology-focused fields (particularly computer science, engineering, and mathematics). This supports the study's potential for practical application, as well as its theoretical foundation. This distribution is particularly expected in studies focusing on topics such as data analytics, modeling, and system optimization.

**Fig. 11** Percentage distribution of optimization problems based on the MGO algorithm



**Table 8** Sample benchmark test functions

Benchmark function	Formula	Dim	Range	$f_{\min}$	Type
F1 Sphere	$f_1(x) = \sum_{i=1}^n x_i^2$	30	[-100, 100]	0	Unimodal
F2 Schwefel 2.22	$f_2(x) = \sum_{i=1}^n  x_i  + \prod_{i=1}^n  x_i $	30	[-10, 10]	0	Unimodal
F3 Schwefel 1.2	$f_3(x) = \sum_{i=0}^{n-1} \left\{ \sum_{j=0}^{j<i} x_j \right\}^2$	30	[-100, 100]	0	Unimodal
F4 Schwefel 2.21	$f_4(x) = \max_i \{  x_i , 1 \leq i \leq n \}$	30	[-100, 100]	0	Unimodal
F5 Generalized Rosenbrock	$f_5(x) = \sum_{i=1}^{n-1} [100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2]$	30	[-30, 30]	0	Unimodal
F6 STEP	$f_6(x) = \sum_{i=1}^n ([x_i + 0.5])^2$	30	[-100, 100]	0	Unimodal
F7 Quartic	$f_7(x) = \sum_{i=1}^n ix_i^4 + \text{random}[0, 1)$	30	[-1.28, 1.28]	0	Unimodal
F8 Generalized Schwefel	$f_8(x) = \sum_{i=1}^n -xi \sin(\sqrt{ x_i })$	30	[-500, 500]	-418.9829*5	Multimodal

## 6 Behavior Analysis of MGO Algorithm

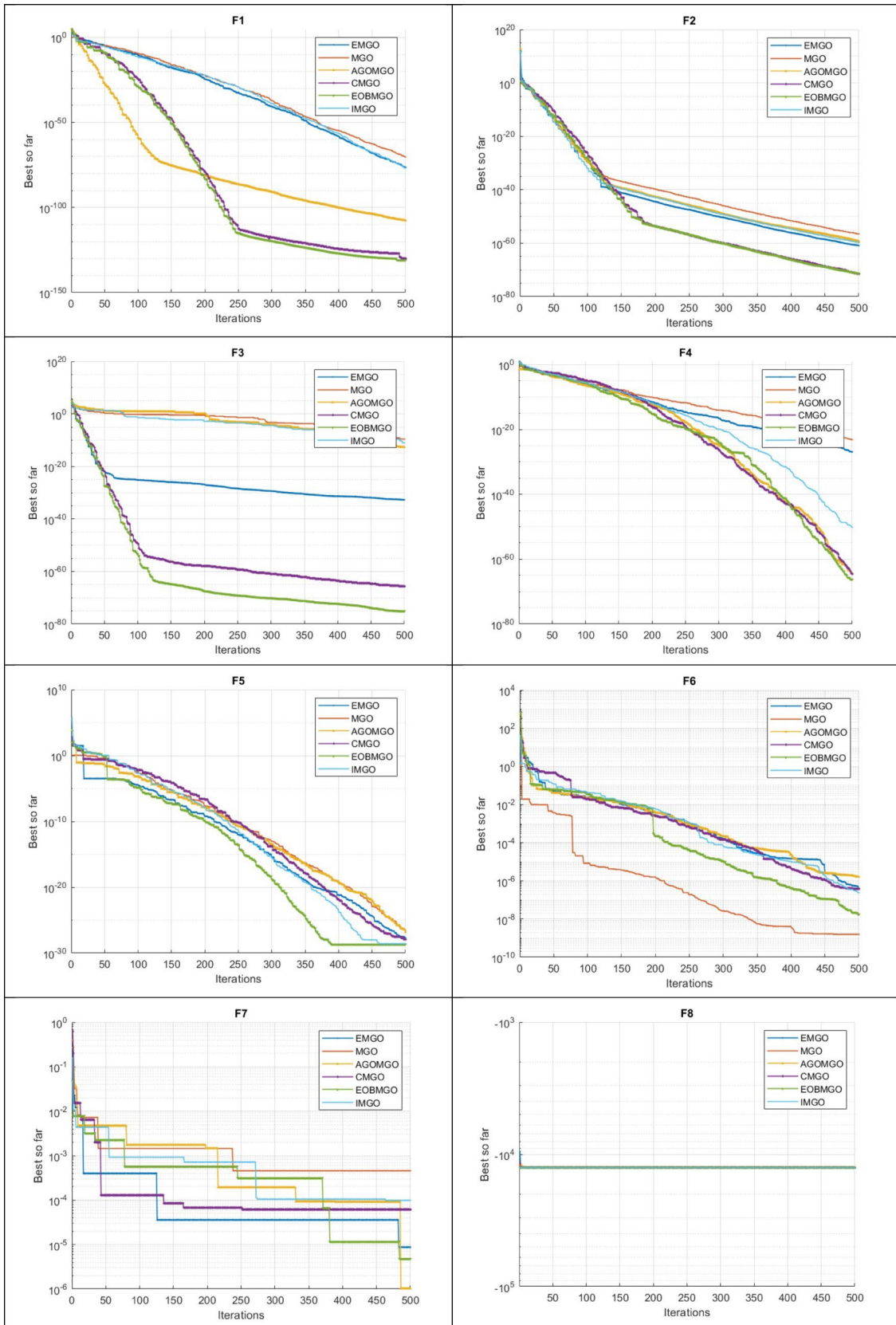
This section presents the results of the evaluation of MGO's efficiency and performance on eight benchmark test functions from the CEC category (see Table 8), which represent a case in numerical analysis. These are well-known functions that are used in the literature by many researchers [162]. In this regard, a comparison is made of six MGO-based algorithms (MGO [29], IMGO [98], EOBMGO [103], AGOMGO [107], EMGO [109], and CMGO [120]). The hyperparameters and initial conditions of all algorithms are assumed to be the same. All simulations were implemented in MATLAB on a computer with a Core i7-11800U 2.3 GHz CPU and 16 GB RAM. The population size, maximum number of iterations, and number of independent runs were fixed at 30, 500, and 10, respectively, for each algorithm during the analysis.

The analysis findings are presented in Table 9. The eight objective functions (F1–F8) for the six variations of MGO demonstrate various performance trends. EOBMGO proved to be the most efficient algorithm, continuously surpassing others in the majority of functions, especially excelling in F1 and F6. Although EOBMGO exhibited superior performance across several objective functions, it also revealed considerable variability in specific functions, such as F4, where its elevated standard deviation signified instability in its optimization process. CMGO, positioned second, exhibited robust performance across various functions, particularly excelling in F4 and F7; however, it encountered difficulties in F1 and F2, where its values were markedly higher than those of EOBMGO. IMGO and AGOMGO were positioned third, exhibiting erratic performance. Although IMGO demonstrated superior optimization outcomes in F5, F6, and F7, it faltered in F3, F4, and F2, hence constraining its total ranking. Likewise, AGOMGO exhibited subpar performances across various functions, particularly F3, F2, and F1, rendering it the least dependable choice overall. MGO exhibited its prowess in F1, achieving optimal performance; nonetheless, it received the lowest overall ranking due to inadequate outcomes in other functions, particularly F6, F3, and F7. MGO had notably poor performance in the extremely sensitive goal functions, specifically F2, F4, and F8. In conclusion, EOBMGO emerges as the best balanced and dependable algorithm among the many functions, whereas MGO and AGOMGO encountered difficulties in properly optimizing several functions. The ranking reveals that EOBMGO is the top performer overall, succeeded by CMGO, whereas IMGO and AGOMGO exhibit subpar performance in numerous essential domains.

**Table 9** Simulation result for some variants of the MGO algorithm

Func	MGO		IMGO		AGOMGO		CMGO		EOBMGO		EMGO	
	Avg	Std	Avg	Std	Avg	Std	Avg	Std	Avg	Std	Avg	Std
F1	4.48E-70	2.45E-69	3.58E-124	2.37E-124	1.17E-103	1.73E-91	<b>1.17E-130</b>	<b>6.41E-130</b>	<b>1.17E-130</b>	<b>6.41E-130</b>	3.43E-103	1.73E-91
F2	1.06E-41	4.69E-41	1.36E-43	1.71E-42	1.64E-53	1.14E-52	<b>1.48E-71</b>	<b>8.08E-71</b>	1.37E-63	1.71E-58	1.64E-53	1.14E-52
F3	1.23E-07	5.14E-07	7.29E-08	6.94E-08	7.31E-08	4.01E-13	2.51E-66	1.37E-55	<b>7.29E-72</b>	<b>7.91E-63</b>	6.34E-32	1.51E-31
F4	4.22E-24	5.32E-02	3.88E-44	1.63E-43	3.21E-64	4.87E-63	3.99E-64	1.41E-63	1.41E-63	<b>1.40E-64</b>	2.27E-24	1.41E-23
F5	2.55E-27	1.37E-19	<b>1.01E-28</b>	<b>4.01E-25</b>	2.54E-27	1.01E-71	1.39E-28	3.01E-20	<b>1.01E-28</b>	<b>4.01E-25</b>	2.02E-28	2.04E-20
F6	<b>2.71E-08</b>	<b>9.84E-08</b>	5.34E-05	4.89E-05	1.23E-07	1.63E-06	5.34E-05	4.89E-05	5.34E-05	4.89E-05	1.23E-05	1.63E-06
F7	4.01E-04	3.08E-04	4.03E-05	3.79E-05	<b>8.88E-06</b>	<b>4.15E-05</b>	4.03E-05	3.79E-05	<b>8.88E-06</b>	<b>4.15E-05</b>	<b>8.88E-06</b>	<b>4.150E-05</b>
F8	<b>-1.26E+04</b>	<b>2.47E-08</b>	<b>-1.26E+04</b>	<b>1.14E-03</b>	<b>-1.26E+04</b>	<b>1.14E-03</b>	<b>-1.26E+04</b>	<b>1.14E-03</b>	<b>-1.26E+04</b>	<b>1.14E-03</b>	<b>-1.26E+04</b>	<b>2.25E-07</b>
Rank	5		3	3	3	2	2	1	1	1	5	5

The optimal values are indicated in bold for clarity



**Fig. 12** Convergence curve behavior of various variants of the MGO algorithm

In Fig. 12, we present the convergence behavior of the various MGO variants over eight benchmark functions (F1–F8). For F1, both CMGO and EOBMGO converge with the lowest error and the steepest decline in error, while AGOMGO lags. For F2, CMGO and EOBMGO display the best performance, continuously decreasing error values over time, whereas EMGO and MGO show significantly slower convergence. Similarly, for F3, once more, we see CMGO and EOBMGO leading the models with a steep, consistent decline in error, while EMGO showed little-to-no decrease in error. F4 may have been a challenge for all the MGO variants but still provided more optimal convergence rates for CMGO and EOBMGO. For F5, all the algorithms had similar downward trends, but the performance of IMGGO and EOBMGO resulted in lower error rates, indicating better long-term performance over time. For F6, the original MGO algorithm experienced a sharp decline in the early iterations and quickly reached a plateau. EOBMGO started slightly higher (in terms of error) but improved steadily and consistently, finishing higher than the other variants. However, the best result in this function belongs to the standard (original) MGO algorithm. The results for F7 produced more fluctuation but still show that AGOMGO, EOBMGO, and CMGO reached lower final error values, with MGO reaching a lower final average with improvements. Finally, for F8, almost all the algorithms exhibited similar convergence behavior. Overall, EOBMGO and CMGO consistently outperform in convergence behavior, indicating differences in exploitation versus exploration behaviors. While AGOMGO initially shows some promise, it fails to maintain the same performance level across benchmark functions. A similar observation applies to the IMGGO variant. EMGO generally outperforms the baseline in convergence behavior, only outperforming the standard MGO. Consequently, we see the importance of using more hybrid enhancements; outperforming the baseline MGO is a strong argument for enhancement functions.

The computing cost and complexity of the MGO and its variations should be taken into account in addition to the noted algorithmic restrictions. MGO is a metaheuristic approach that repeatedly evaluates fitness functions across several agents and iterations. This has a direct impact on runtime, particularly in high-dimensional situations. When  $T$  is the number of iterations,  $N$  is the population size, and  $D$  is the number of decision variables, the temporal complexity of the original MGO is  $O(T \times N \times D)$ . Most enhanced versions (such as EOBMGO, CMGO, and AGOMGO) introduce additional mechanisms (e.g., chaos maps, opposition-based learning, and genetic operators), which increase the computational overhead due to extra matrix operations or population adjustments per iteration. While these modifications improve convergence and accuracy, they also raise the algorithm's time and space complexity, particularly in real-time or resource-constrained applications. For instance, variants incorporating adaptive scaling, elite selection, or parallel search operators may push complexity toward  $O(T \times N \times D^2)$  in the worst case. Moreover, as benchmark dimensions (e.g.,  $D = 1000+$ ) increase, memory consumption also becomes a concern. Therefore, future research should concentrate on optimizing these improvements for computational scalability and efficiency, primarily through parallel computing (e.g., GPU-based acceleration) or sparse solutions encoding in large-scale settings, even though hybrid and improved MGOs offer notable performance gains.

## 7 Discussion and Challenges

The MGO has proven to be an effective MH algorithm for solving a broad range of global optimization problems inspired by mountain gazelles' social structure and territorial behavior. This survey analyzed MGO's application across multiple domains, including engineering, energy systems, machine learning, and biomedical applications, revealing its evolving role in the optimization community. By examining the studies categorized as Adapted, Variants, Hybrid, and Improved, we highlighted MGO's unique advantages and challenges, providing a comprehensive perspective on its capabilities and limitations. In addition, certain limitations and strengths of the MGO algorithm need to be discussed. In this regard, a summary is presented in Table 8.

### 7.1 Strengths of MGO

A significant advantage of MGO is its equitable exploration and exploitation mechanism, enabling it to traverse extensive and intricate solution spaces effectively. Motivated by the movement patterns of territorial gazelles,

the exploration phase guarantees that the algorithm avoids premature convergence to poor solutions and persists in global searching. The exploitation phase refines the solutions and focuses on promising regions in the solution space, thus ensuring fast convergence whenever required. MGO's parameter-free advantage, which enables a more straightforward application over a broader range of problems, is another key benefit. MGO does not depend on any user-defined parameter for the optimization process, which differentiates it from many other MH algorithms, and so on, that require extensive parameter tuning. It is easier to put into real-world use because it does not need an expert in that area's algorithms to adjust. MGO has also been found to be robust in multi-objective optimization, enabling its application in energy systems, machine learning, control systems, and biomedical optimization. One of the key reasons behind the widespread usage of this algorithm is its ability to handle complex and multidimensional search spaces while ensuring solution diversity and high quality. The performance of MGO has also been enhanced by hybridization with other MH algorithms, machine learning models, and deep learning frameworks. Some studies in various areas, such as innovative grid management, microgrid optimization, and predictive modeling, have shown that hybridized MGO models can offer more dynamic and adaptive solutions for time-sensitive, large-scale issues, particularly in real-time optimization contexts. Hybrid models, which integrate the global search capabilities of MGO with the local refining of alternative algorithms, frequently surpass conventional approaches, delivering enhanced convergence rates and superior accuracy.

## 7.2 Challenges and Limitations

Despite its many strengths, MGO faces challenges and limitations that must be resolved in future research. Premature convergence, especially in high-dimensional or multimodal optimization problems, is arguably the most significant issue experienced. The problem occurs due to being stuck in local optima and not exploring the other areas of the search space. Although adaptations like chaotic maps and hybridization Strategies improve exploration, MGO can converge more slowly than other algorithms, such as PSO or GWO, especially on simple optimization problems. This limitation indicates that MGO needs further improvements in its exploration phase, especially for complex issues that require a more exhaustive search range. Another limitation of MGO is its computational complexity, particularly in high-dimensional search spaces. As MGO executes many search operations (migration, territorial defense, and herd behavior) to get diverse solutions, its computational cost increases with problem complexity and several dimensions. This could produce inefficiencies regarding real-time optimization tasks, especially in large-scale applications. Even though attempts at parallelization or distributed computing may help with this issue, most of these adaptations are not seen in the literature.

Another considerable challenge for MGO is the lack of robustness in optimization contexts that are highly nonlinear, constrained, or noisy. In difficult situations, even if MGO is capable of finding the global optimum, it is possible that MGO would not be able to find the optimum simply because the optimum cannot be identified or found when the problem is constrained (e.g., some constraints complicate the problem), noisier, or due to other complexities. As mentioned, the hybridization of MGO with reinforcement learning has been studied in hybridized designs to improve MGO. On the other hand, researchers have implemented additional algorithms that are based on or use some deep learning models to enhance the learning process of MGO in uncertain environments. The potential advantages of MGO hybridized with reinforcement learning or deep learning could certainly improve MGO's ability to learn from previously randomly selected optimization steps and adapt to compound problems and their changes. In conclusion, even though MGO has solved and provided adequate solutions for numerous multi-objective optimization problems in varying applications, a few additional challenges still rely on relatively quick convergence, computational efficiency (in variable-length runs), computational scalability, and robustness in dynamic and permanent high-dimensional spaces. Therefore, future studies should address the potential to improve the exploration step in MGO to develop and advance the computational design of MGO to solve real-time optimization problems and enhance the computational scalability of MGO.

In general, while overall the results of reviews related to MGO-based studies are optimistic, we find that critical assessments ultimately uncover variations and inconsistencies of procedure within literature. For instance, it was

**Table 10** A concise overview of the MGO algorithm, highlighting its advantages, limitations, and future directions

Advantages	Shortcomings	Future insights
MGO has a well-balanced exploration and exploitation mechanism, enabling effective search across vast solution spaces	Premature convergence can still occur in certain problem types, especially in high-dimensional spaces	Explore hybrid versions of MGO, combining it with reinforcement learning or quantum computing to enhance scalability and adaptivity
It is parameter-free, eliminating the need for extensive parameter tuning	Computational complexity can increase significantly with high-dimensional problems or complex hybrid strategies	Improve MGO's scalability for large-scale optimization tasks and real-time applications, especially in dynamic environments
MGO has shown superior performance in multi-objective optimization, with applications in engineering, energy, and AI-driven models	Convergence speed can be slower compared to other MHs in some simple problems	Development of parallel or distributed versions of MGO to improve computational efficiency and speed
It performs well in dynamic environments by balancing diversity and convergence	Lack of robustness in highly nonlinear and multimodal problems that require intensive exploration	Enhancing MGO's robustness and adaptability to nonlinear, multimodal, and time-sensitive problems
MGO has demonstrated excellent flexibility, adapting to various domains, including power systems, control engineering, and biomedical applications	Diversity in population can be low, leading to convergence on suboptimal solutions	Further integration with machine learning models for better real-time decision-making and optimization
MGO is known for its simplicity and ease of adaptation in various domains without complex modifications	The algorithm may struggle with large solution spaces that require complex optimization beyond its current capabilities	Investigating advanced hybrid algorithms combining MGO with AI-driven methods, including neural networks, deep learning, and evolutionary algorithms
MGO's adaptability to various problem types makes it a versatile solution in real-world applications	The algorithm may have difficulty finding global optima in cases with high-dimensional, noisy, or constraint-heavy optimization problems	Exploration of hybrid MGO models for complex multidisciplinary problems, such as AI, IoT, and quantum systems, to enhance its problem-solving abilities

shown across various studies that enhancement models based on MGO consistently outperformed baseline models in the majority of standard benchmark functions. Still, due to differences in operating conditions, characteristics of actual functions, or stopping criteria, not all studies showed the same outcomes, at least in an applied study context. This is problematic because not all studies report the same evaluation measures (some report accuracy and convergence speed, while others report robustness or computational efficiency), and so, direct comparisons are limited. Furthermore, in many research designs, there has been a lack of statistical significance-testing and cross-validation, which compromises the generalizability of results. Inconsistencies illustrate the need for standardized benchmarks, agreed-upon documentation methods, and experimental trials carried out with sound statistical reasoning to allow evaluations of MGO and its variants to be re-evaluated with both transparency and reproducibility in mind. Table 10 provides a summarized depiction of the MGO algorithm, outlining its strengths, weaknesses, and potential future enhancements.

In the discussion section, the features of MGO itself, as well as comparisons with some of the existing well-known MH algorithms on different parameters and metrics, are presented in Table 11. In this sample, in terms of convergence speed, MGO exhibits a medium convergence rate, making it effective for many optimization tasks, though not as fast as some other algorithms like ARO and MFO, which demonstrate fast convergence. Algorithms like PSO, PO, and SCSO have a convergence speed ranging from medium to fast, allowing them to reach solutions relatively quickly, especially in complex problems. On the other hand, GA tends to have a slower convergence rate compared to most other algorithms, which can make it less efficient in some scenarios. When it comes to accuracy, MGO stands out with high accuracy, making it a suitable choice for solving a wide range of optimization problems. PSO, PO, ARO, and MFO also provide high accuracy, particularly in multi-objective and high-dimensional problems. SCSO offers medium-to-high accuracy, while SCA and ACO typically yield medium accuracy. DE delivers high accuracy, but GA, though it can achieve medium-to-high accuracy, often requires more careful parameter tuning to reach its optimal performance. Regarding parameter sensitivity, MGO is particularly beneficial as it is parameter-free, making it less sensitive to parameter settings compared to other algorithms. In contrast, PSO, PO, SCSO, and ARO have a medium level of parameter sensitivity, meaning that they still require some parameter tuning to optimize their performance but are not as sensitive as GA and DE, which are highly parameter dependent. SCA, ACO, HS, BFO, and MFO also exhibit varying levels of sensitivity to parameter adjustments, with MFO being relatively less sensitive. Finally, in terms of susceptibility to local optima, MGO, ARO, and MFO are less prone to getting stuck in local optima, allowing them to explore the solution space more effectively. On the other hand, SCA, DE, GA, and ACO tend to be more susceptible to local optima, especially in complex or high-dimensional problem spaces.

**Table 11** Comparison of MGO with other optimization algorithms

Algorithm	Convergence speed	Accuracy	Parameter sensitivity	Susceptibility to local optima
MGO	Medium	High	Low (parameter-free)	Low
PSO	Medium to fast	High	Medium	Medium
PO	Medium	High	Medium	Medium
SCSO	Medium to fast	Medium to high	Medium to high	Medium
ARO	Fast	Medium to high	Medium	Medium–low
SCA	Medium	Medium to high	Medium	High
ACO	Medium	Medium	Medium to high	Medium
DE	Medium	High	High	High
GA	Slow to medium	Medium to high	High	High
HS	Medium	Medium to high	Medium	Medium
BFO	Medium to fast	Medium to high	Medium	Medium
MFO	Fast	High	Medium	Medium–low

## 8 Conclusion and Future Work

The MGO algorithm is a robust nature-inspired MH algorithm that solves complex optimization problems by imitating mountain gazelles' social and territorial behavior. The primary strength of the MGO is the balance struck between exploration and exploitation through dynamic gazelle movement and hierarchy adaptability. Because of its capabilities, MGO can effectively explore huge solution spaces, which makes it appropriate for a range of real-world optimization issues, including machine learning, energy systems, and engineering design. Despite being a strong optimization method, MGO faces difficulties in significant dimensional problems, including premature convergence, computational complexity, scalability limitations, etc. This paper reviewed in detail the 89 MGO-related studies from different perspectives. We have filled the literature gap by systematically classifying and reviewing MGO-based studies, showing how the algorithm has evolved and what the future holds. This study presents an overview of the MGO algorithm and its future evolution, providing a concise overview of key open problems and directions many researchers of the MGO algorithm still must tackle. This review categorizes studies into four groups: adapted, variants, hybrid, and improved. Most of the studies have adopted the original MGO to solve optimization problems from various scientific domains, including parameter tuning, hyperparameter optimization, etc. These studies comprise the adapted category (37%). This category includes those studies that modified the MGO for multi-objective problems. One-third of the studies, or 33%, fall into the hybrid category that investigated MGO with other MH algorithms, ML, and DL. Improving the performance of MGO, especially concerning faster convergence, solution accuracy, and population diversity, is the aim of the studies classified under the 'improved' category; these studies make up 27% of the total. Although MGO is successful, its performance is still limited by the problems of maintaining the diversity of solutions and fast convergence on large-scale and high-dimensional problems. Various techniques would address the limitations of MGO in the future. Making MGO more adaptable to dynamic, real-time optimization environments will lead to opportunities for its application in areas such as autonomous systems, smart cities, and predictive modeling. In summary, MGO has demonstrated great flexibility, efficiency, and it is a powerful optimization tool. However, there is plenty of room for improvement, particularly in scalability, computing efficiency, and real-time applications. This overall review of MGO gives the principles it uses, its earlier applications, and those possible in the future. Though the past and present show good use of MGO, the future also seems bright. Continual hybridization and adaptation to the demands of complex real-world problems will determine the future of MGO. There are many challenges that MGO faces, some of which have been identified for enhancement and advancement. Key areas for improvement and future research include the following:

- Hybridization with Deep Reinforcement Learning [163]: Future research should explore hybridizing MGO with reinforcement learning, which can improve the algorithm's learning capability and performance in dynamic, real-time systems, such as robotics or adaptive control systems.
- Quantum Computing Integration: Incorporating quantum computational theory into MGO could significantly enhance its computational speed and exploration abilities, especially for large-scale optimization problems. This integration may also help solve MGO's scalability limitations in complex, real-time applications.
- Parallelization and Distributed Computing: Research into parallelization and distributed computing techniques for MGO could improve its performance, making it more suitable for extensive applications like smart cities, autonomous systems, and IoT networks that require rapid decision-making under changing conditions.
- Deep Learning and AI-Driven Optimization [164]: Investigating the application of MGO in deep learning, feature selection, and AI-driven optimization could lead to a more dynamic and flexible methodology, which would be particularly useful for solving complex challenges in these rapidly advancing fields.
- Enhancing Population Diversity in High-Dimensional Problems [165]: To sustain global search efficacy, future work should focus on maintaining diversity within the MGO population, especially in high-dimensional optimization problems. This could involve developing strategies to preserve diversity throughout the optimization process to avoid premature convergence.

- **Theoretical Analysis:** In the context of proposing new variants or hybrid mechanisms for MGO, it is essential to consider the lack of theoretical support for MHs.

This review not only provides an organized overview of MGO's evolution but also presents critical insights into its strengths, limitations, and future directions. We anticipate that ongoing advancements in hybrid MGO models and their integration with emerging technologies will significantly expand MGO's applicability in tackling some of the most pressing optimization challenges.

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## Declarations

**Conflict of interest** The authors declare no competing interests.

**Consent to publish** All the authors agreed to publish the manuscript.

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