Marine Predator Algorithm and Related Variants: A Systematic Review

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***Abstract*—The Marine Predators Algorithm (MPA) is classified under swarm intelligence methods based on its type of inspiration. It is a population-based metaheuristic optimization algorithm inspired by the general foraging behavior exhibited in the form of Levy and Brownian motion in ocean predators supported by the policy of optimum success rate found in the biological relationship between prey and predators. The algorithm is easy to implement and robust in searching, yielding better solutions to many real-world problems. It is attracting huge and growing interest. This paper provides a systematic review of the research progress and applications of the MPA by analyzing more than 100 articles sourced from Scopus and Web of Science databases using the PRISMA approach. The study expounded the classical MPA's workflow. It also unveiled a steady upward trend in the use of the algorithm. The research presented different improvements and variants of MPA including parameter-tuning, enhancement of the balance between exploration and exploitation, hybridization of MPA with other techniques to harness the strengths of each of the algorithms towards complementing the weaknesses of the other, and more recently proposed advances. It further underscores the application of MPA in various areas such as Engineering, Computer Science, Mathematics, and Energy. Findings reveal several search strategies implemented to improve the algorithm's performance. In conclusion, although MPA has been widely accepted, other areas remain yet to be applied, and some improvements are yet to be covered. These have been presented as recommendations for future research direction.**

Keywords*—Exploitation-exploration; marine predator algorithm; metaheuristic algorithms; metaheuristic-hybridization; meta-heuristics; optimization; predator prey systems

I. Introduction

There is a proliferation of optimization methods for finding optimum solutions to engineering, scientific, real-world, and social problems [1, 2]. This is necessitated by the corresponding increase in complex optimization problems that require solutions. These methods can broadly be classified into deterministic and stochastic methods (Fig. 1). The deterministic methods can be further classified into gradient-based and non-gradient-based methods. For instance, mathematical linear and non-linear programming methods are all gradient-based since they rely on gradient computation to locate global solutions. Conversely, non-gradient-based deterministic methods use direct algorithms, conditions, and static, and dynamic data structures instead of gradients to compute the global optimum solution [3–6].

One prevailing limitation of mathematical programming methods includes greater chances of local optima stagnation while searching in non-linear space. As such, researchers have used different initial designs, hybridization, and modifications to overcome the drawbacks. This, however, makes the solution problem specific. Non-gradient deterministic methods possess weaknesses including difficult implementation and require a deep knowledge of mathematics before application.

One of the ways by which researchers address the drawbacks of the deterministic methods is by exploring alternatives from the stochastic approaches. The popular stochastic method in use is metaheuristics [1, 7] which uses random variables and operators to perform a global search while trying to avoid being trapped in local optima. Metaheuristic algorithms are now being applied in several research fields such as business management, medical imaging, environmental studies, engineering design, mathematics, robotics, image segmentation, etc., changing the trends and the look and feel of the research world. These methods are simple and easy to understand and implement. However, they do not guarantee a global solution despite possessing outstanding qualities such as being gradient-free, problem-independent, adaptable, and near-global solutions over other optimization methods.

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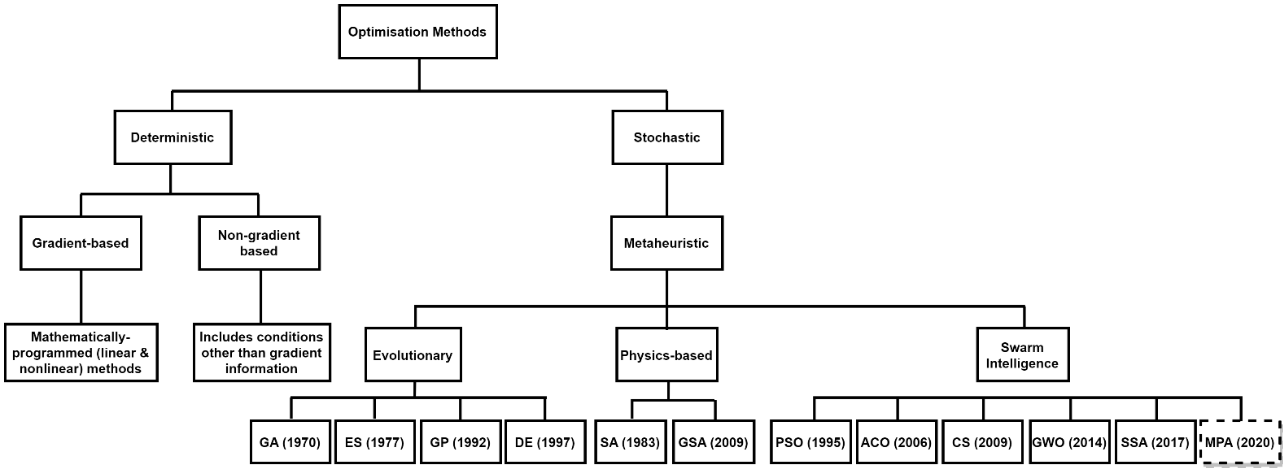

Fig. 1. Category of optimization algorithms featuring metaheuristics.

Metaheuristic methods can be grouped into three groups based on their type of inspiration (Fig. 1). These are evolutionary algorithms, physics-based, and swarm intelligence methods.

Evolutionary algorithms are the oldest form of metaheuristics, grouped based on biological interaction within the space of nature. In this group, the earliest method proposed in the 1970s was the Genetic Algorithm (GA) [8]. GA is hinged on two biological concepts: mutation and cross-over, used in domain search and improvement of initialized random populations. Other popular algorithms proposed by this group about the same time include Evolution Strategy (ES) in 1977 [9], Genetic Programming (GP) in 1992 [10], Differential Evolution (DE) in 1997 [11], etc.

The second group of metaheuristic methods classified in this study is physics-based. In this group, inspiration is drawn from various laws of physical nature. The search for optimal solutions is strictly based on the laws of physics. Inspired by the laws of thermodynamics, the oldest popular method first proposed under this group is Simulated Annealing (SA) in 1983 [12]. A Gravitational Search Algorithm (GSA) was later proposed in 2009 [13] which is based on Newton's law of masses gravity and interaction as a way of position update to search for the optimum solution. Swarm intelligence is the third group of these metaheuristic approaches in this study. In this group, the algorithms imitate a set of behaviors found in flocks, swarms, schools, and herds of several natural creatures. The first method proposed in this group was Particle Swarm Optimization (PSO) in 1995 [14]. PSO is an optimization algorithm inspired by the behavior of schools of birds or fish. Subsequent algorithms proposed in this group include Ant Colony Optimization (ACO) in 2006 [15], Cuckoo Search (CS) in 2009 [16], Grey Wolf Optimizer in 2014 [17, 18], Salp Swarm Algorithm (SSA) in 2017 [19], and Marine Predator Algorithm (MPA) in 2020 [1] to mention a few.

The Marine Predators Algorithm (MPA) is a population-based metaheuristic optimization algorithm inspired by the general foraging behavior exhibited in the form of Levy and Brownian motion in ocean predators supported by the policy of optimum success rate found in the biological relationship between prey and predators [1]. MPA is characterized by being simple in implementation and robust in solution search yielding better solutions to many real-world problems [20]. It is swarm-based, a relatively new algorithm introduced in 2020 by Faramarzi and his team, and it is attracting huge and growing interest. The algorithm was originally proposed for use in engineering and mathematical problems. However, due to its high performance and search success, it has gained wide acceptance, and it has been applied in several domains. It uses two motions: Levy flight and Brownian motions to perform a search for local or global solutions. The strategies employed by MPA for use in different situations as originally proposed by [1] are:

- When the search encounters sparsely populated prey, MPA applies the Levy flight grazing strategy and later changes to Brownian motion when a crowded population of prey is detected.
- In addition to the swift fluctuation of the hunting strategy, the predators transform their actions towards finding locations with more crowded prey.
- The predators are too smart in retention of visited locations, keeping the memory to provide information that could help other predators when needed.
- Being easy to implement, possessing fewer parameters, and yielding good results, MPA has taken over the metaheuristic space as seen in the literature.

The MPA, introduced in 2020 and utilized across various domains, faces challenges associated with exploration-exploitation imbalance common among intelligent algorithms [21–23]. In addition, weaknesses such as poor solution quality, easily trapped in local optima, and slow convergence speed have been noticed. Consequently, many researchers have proposed various improvements and variants of the algorithm through parameter tuning, hybridization, and enhancements (modifications). Among these include a hybridization of Improved MPA and PSO known as IMPAPSO [24], enhanced MPA (EMPA)[25], four new variants of MPA: (i) multi-objective MPA (MMPA) (ii) modified MMPA (M-MMPA) (iii) Gaussian-based mutation M-MMPA (M-MMPA-GM), and (iv) Nelder-Mead simplex technique into M-MMPA (M-MMPA-NMM)[2], Three-scale image decomposition (TSD), Kirsch compass operator (FR-KCO), and MPA (TSD-FR-KCO-MPA) [26], Local Escaping Operator MPA (LEO-MPA) [20], opposition based learning MPA and grey wolf optimization (MPAOBL-GWO) [27], Tuned-MPA [28], a hybrid method that combines MPA with Fuzzy Proportional-Integral-Derivative with Filter (FPIDF) (MPA-FPIDF) [29], Boost MPA (BMPA)[30], combining the MPA with CNN (IMPA-CNN)[31], a modified version of MPA known as MMPA[32], MPALS and HMPA [33], modified type of MPA (MMPA)[34], hybrid MPA-Support Vector Machine (MPA-SVM) [35], MPA to optimize a trained ANN (MPA-ANN) [36], an improved MPA and ResNet50 (IMPA-ResNet50) [37], MPA and Proportional-Integral-Derivative-Acceleration (PIDA) (MPA-PIDA)[38], advanced MPA (AMPA) [39], MPA and multi-verse optimization algorithm (MPA-MVO)[40], Learning-Automata (LA)-based Jellyfish search MPA (LA-JS-MPA) [41], fractional-order comprehensive learning MPA (FOCLMPA) [42], Fusion Multi-Strategy Marine Predator Algorithm (FMMPA) [43], reinforcement learning (RL) and MPA (Deep-MPA)[44], MPA and naked mole-rat algorithm (NMRA)(MpNMRA) [45], Dynamic Foraging Strategy MPA (DFSMPA) [46], MPA with mechanism for teaching and learning (MTLMPA) [47], diversity-aware MPA (DAMPA) [48], MPA, modified conformable fractional-order accumulation operation (MCFAO) [49], two variants: BBD-based MPA, and CCD-based MPA [50], an enhanced version of the MPA (EMPA)[51], an enhanced multi-strategy MPA - Variational Mode Decomposition (MPA-VMD) [52], Tuned-MPA proportional–integral–derivative proportional derivative (PID-PD) controller [53], Open Circuit Voltage MPA (OCV-MPA) [54], Marine Predator Algorithm and Hide Object Game Optimization (MPA-HOGO) [55], multi-stage improvement of the MPA (MSMPA)[56], etc. This study presents an extensive review of MPA and its variants based on improvements. It analyzes its strengths and improvements and provides future research directions. The major contributions of this study can be summarized as follows:

- A detailed and clear explanation of the workflow of the classical MPA including a flowchart and pseudocode is provided, see Section II.
- A steady upward trend in MPA has been revealed based on some qualitative statistics of the articles published over the years, see Section III.
- The review highlights MPA's uniqueness based on the predator's ability to execute various movements corresponding to the prey's behavior.
- Several variants of the MPA have been presented which are made up of various search improvement strategies, see Section VI.

The rest of this paper is organized as follows: Section II presents the standard MPA with its source of inspiration, major components, and flowchart steps. Section III presents the materials and method used in this research, where the PRISMA approach is highlighted. Section IV discusses proposed variants of MPA for performance improvement. Section V showcases the application of MPA in different areas. Furthermore, Section VI gives supporting discussions. Section VII presents future research directions. Finally, Section VIII presents the conclusion of the entire research work.

II. Standard MPA

The MPA is a population-based metaheuristic optimization algorithm inspired by the general foraging behavior exhibited in the form of Levy and Brownian motion in ocean predators supported by the policy of optimum success rate found in the biological relationship between prey and predators [1]. The algorithm was objectively proposed for use in engineering and mathematical problems.

It is a popular fact that the entire search strength of every metaheuristic algorithm is measured in three characteristics: exploration, exploitation, and the ability to escape local minimum/optima [57]. Exploitation serves as the main ability of the algorithm to search for every nearby detail while exploration ensures that the algorithm completes its search of the entire search space. The MPA uses two motions, Levy flight, and Brownian motions to search for local or global solutions. Because Levy flight is associated with mostly short steps, it is well suited to local search or exploitation. However, the Brownian motion on the other hand is associated with larger step sizes and hence it is suitable for global search or exploration. Either of these two motions alone cannot be sufficient in performing a search, and therefore the two are combined to improve the searchability of MPA. The algorithm is unique and widely acceptable compared to other metaheuristic algorithms due to its search strategies and memory recall as proposed by [1].

Based on its similarities to other metaheuristic algorithms, the MPA begins by defining an initial uniform population distribution of solutions in the search space based on trial using Eq. (1).

$$\mathrm{X_0}=\mathrm{X_{min}}+\mathrm{rand}(\mathrm{X_{max}}-\mathrm{X_{min}}) \tag{1}$$

Here, $\mathrm{X_{min}}$ and $\mathrm{X_{max}}$ are referred to as the lower and upper bound variables, respectively, while $rand$ is the uniform random vector of a range 0 to 1.

Next, a matrix of top predators also called Elite is created based on the generated distribution in Eq. (1). Additionally, top predators according to the survival of the fittest theory are more gifted at foraging. Therefore, a matrix of top predators is constructed that serves as a tentative solution known as Elite. This matrix's array supervises the search for locating prey relative to its available information or address as given in Eq. (2).

$$\mathrm{Elite}=\begin{bmatrix} X^I_{1,1} & X^I_{1,2} & \cdots & X^I_{1,d} \\ X^I_{2,1} & X^I_{2,2} & \cdots & X^I_{2,d} \\ \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots \\ X^I_{n,1} & X^I_{n,2} & \cdots & X^I_{n,d} \end{bmatrix}_{n\times d} \tag{2}$$

Here, $\overrightarrow{X^I}$ denotes a vector of the top predator that is duplicated *'n'* times to form the Elite matrix, *'n'* is known as the number of search agents, and *'d'* represents the dimensions. Every predator is a search agent and a potential prey as they both search for food. When each iteration is completed, the Elite is updated where better predators replace top predators.

Furthermore, a second matrix of the same size as the Elite matrix known as Prey is formed and its predators' addresses are updated according to the Elite's as depicted in Eq. (3), where $X_{i,j}$ denotes the *jth* dimension of *ith* prey. MPA depends on these two matrices throughout its iterations.

$$\text{Prey} = \begin{bmatrix} X_{1,1} & X_{1,2} & \cdots & X_{1,d} \\ X_{2,1} & X_{2,2} & \cdots & X_{2,d} \\ \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots \\ X_{n,1} & X_{n,2} & \cdots & X_{n,d} \end{bmatrix}_{n\times d} \qquad (3)$$

A. The Core of the MPA Optimization Process and Modeling

Based on the proposed model by [1], the optimization workflow of the MPA goes through three conditions while imitating the entire life of predators and prey. These three phases are split across three levels of velocity scenarios experienced by these aquatic creatures:

Condition 1: "When the speed of the predator gets faster than that of the prey" (high-velocity ratio).

Condition 2: "When the speed of the predator becomes almost equal to that of the prey" (unit velocity ratio).

Condition 3: "When the speed of the predator becomes slower than that of the prey" (low velocity ratio).

When condition 1 holds, this implies that the velocity ratio is high ($V \geq 10$), and consequently, the algorithm applies the best strategy for the predator which is to stand still without any movement. This approach [1] is expressed and modeled mathematically by Eq. (4).

From Eq. (4), $\overrightarrow{Prey}_l = (\overrightarrow{Prey}_l + P.\vec{R} \otimes \overrightarrow{stepsize}_l)$ where $\vec{R}_B$ is a vector containing the Brownian motion's normal distribution of random numbers.

$$\text{While Iter} < \frac{1}{3}\ \text{Max\_Iter then,}$$

$$\overrightarrow{\text{stepsize}}_l = \vec{R}_B \otimes (\overrightarrow{\text{Elite}}_l - \vec{R}_B \otimes \overrightarrow{\text{Prey}}_l),\ l = 1, \ldots, n \qquad (4)$$

The operator ⊗ is an element-wise product. Computing the product of $\vec{R}_B$ by prey simulates the prey's movement. The symbol *P=0.5* is a constant control parameter that minimizes/maximizes predator or prey's step sizes, while *R* denotes a vector of uniform random numbers in the range [0, 1]. The first condition's scenario occurs at one-third of the entire iterations where the step size is high due to the high velocity of movement toward achieving high exploration. The variable *Iter* represents the current iteration while *Max_Iter* stands for the maximum iteration.

Next, when condition 2 occurs, that is, the predator and prey are moving at almost the same velocity (unit velocity ratio i.e., $V \approx 1$), depicting a scenario where both are searching for their food, the algorithm tries to detect the type of motion used by each. At this point, if the prey is moving in Levy motion, the predator's best approach becomes switching to Brownian motion. The situation happens in the middle of the optimization process when exploration attempts to switch to exploitation. Thus, both behaviors would matter, and half of the population would be assigned to exploration while the other half would be assigned to exploitation. Assuming the prey and predator are moving in Levy and Brownian motions, respectively, this can be represented or modeled mathematically by Eq. (5 and 6):

$$While\ ^1/_3 < Max\_Iter < ^2/_3\ Max\_Iter, \text{ then}$$

Considering the first half of the population,

$$\overrightarrow{\text{stepsize}}_l = \vec{R}_L \otimes (\overrightarrow{\text{Elite}}_l - \vec{R}_L \otimes \overrightarrow{\text{Prey}}_l),\ l=1, \ldots, \frac{n}{2}$$

$$\overrightarrow{\text{Prey}}_l = \overrightarrow{\text{Prey}}_l + P.\vec{R} \otimes \overrightarrow{\text{stepsize}}_l \qquad (5)$$

From Eq. (5), $\vec{R}_L$ is a vector containing the Levy motion's distribution of random numbers. The vector $\vec{R}_L$ and *Prey* are multiplied to simulate the Levy-wise movement of the *Prey*. The step size is added to the location of the *Prey* to complete this simulation.

On the other hand, the assumption for the second half of the population is thus:

$$\overrightarrow{\text{stepsize}}_l = \vec{R}_B \otimes (\vec{R}_B \otimes \overrightarrow{\text{Elite}}_l - \overrightarrow{\text{Prey}}_l),\ l=\frac{n}{2}, \ldots, n$$

$$\overrightarrow{\text{Prey}}_l = \overrightarrow{\text{Elite}}_l + P.CF \otimes \overrightarrow{\text{stepsize}}_l \qquad (6)$$

Where $CF=(1-\frac{Iter}{Max\_Iter})^{(2\frac{Iter}{Max\_Iter})}$ represents an adaptive parameter that regulates the step size of a predator's movement. The vector $\vec{R}_B$ is multiplied with the *Elite* to mimic the movement of the predator Brownian-wise and update the prey's location based on the predator's Brownian-wise movement.

Condition 3 occurs when the velocity of the predator becomes slower than that of the prey (low-velocity ratio, usually *V = 0.1*). This scenario usually occurs at the final phase of the optimization workflow, and it commonly targets high exploitation performance. The best option for the predator at this point is Levy's motion. This scenario is modeled mathematically by Eq. (7):

$$\text{While Iter} > \frac{2}{3}\ \text{Max\_Iter}$$

$$\overrightarrow{\text{stepsize}}_l = \vec{R}_L \otimes (\vec{R}_L \otimes \overrightarrow{\text{Elite}}_l - \overrightarrow{\text{Prey}}_l) \qquad l=1, \ldots, n$$

$$\overrightarrow{\text{Prey}}_l = \overrightarrow{\text{Elite}}_l + P.CF \otimes \overrightarrow{\text{stepsize}}_l \qquad (7)$$

where the vector $\vec{R}_L$ is multiplied with the *Elite* to simulate the predator's movement in Levy form and adding the step-size to the location of the *Elite* to mimic the predator's movement aids in updating the location of the prey. The algorithm is presented thus (Algorithm 1):

Algorithm 1: Standard MPA Pseudocode

Step 1: **Initializing Phase**

Initialize the parameters of the algorithm (Population size, dimensions, maximum Iterations)

Uniformly distribute the initial solution using ***Equation 1***.

Step 2: **Evaluation Phase**

while (the termination condition does not satisfy)

  Evaluate the fitness of the solutions

  Step 3: **Construction Phase**

Construct the **Elite matrix** using ***Equation 2***

Construct the **Prey matrix** using ***Equation 3***

  Step 4: **Optimisation Phase**

    Stage 1: **High Velocity Ratio**

    if ($Iter < \frac{1}{3} Max_{Iter}$) $then$

      Update Prey using ***Equation 4***

    Stage 2: **Unit Velocity Ratio**

      Else if ($\frac{1}{3} Max\_Iter < Iter < \frac{2}{3} Max\_Iter$) $then$

    Considering the first half of the population ($l = 1, \ldots, \frac{n}{2}$)

      Update Prey using ***Equation 5***

    For the second half of the population ($l = \frac{n}{2}, \ldots, n$)

      Update Prey using ***Equation 6***

    Stage 3: **Low Velocity Ratio**

      Else if ($Iter > \frac{2}{3} Max\_Iter$) then,

        Update Prey using ***Equation 7***

      end ***if***

    end ***if***

  end ***if***

  Step 5**: Update Phase**

  Update the **Elite matrix** and save it in memory.

  Apply the FADs effect, then update using ***Equation 8***

  Further, **Update the Elite matrix** and update the memory.

end ***while***

Overall, the steps proposed by [1] imitate the movement of predators and prey when seeking food in aquatic habitats. Their work assumes that there is an equal percentage of Levy and Brownian motion over the lifetime of a predator.

Because Fish Aggregating Devices (FADs) influence the time taken by predators at a particular place and point in time, e.g., sharks spend 80% of the time around them and 20% at other places, the attraction by FADs is creating a local optimum and their jump to search other places is seen as avoidance of being trapped. The effect of FADs is therefore modelled mathematically as follows:

$$\overrightarrow{\mathrm{Prey}_l} = \begin{cases} \overrightarrow{\mathrm{Prey}_l} + \mathrm{CF}\left[\vec{\mathrm{X}}_{\min} + \vec{\mathrm{R}} \otimes \left(\vec{\mathrm{X}}_{\max} - \vec{\mathrm{X}}_{\min}\right)\right] \otimes \vec{\mathrm{U}} & \text{if } r \le \mathrm{FADs} \\ \overrightarrow{\mathrm{Prey}_l} + [\mathrm{FADs}(1-r)+r]\left(\overrightarrow{\mathrm{Prey}_{r1}} - \overrightarrow{\mathrm{Prey}_{r2}}\right) & \text{if } r > \mathrm{FADs} \end{cases} \quad (8)$$

From Eq. (8), FADs are assigned the value 0.2 (i.e., FADs = 0.2) which is defined as the probability of its effect in the optimization process, and $\vec{U}$ denotes a binary vector that contains arrays inclusive of zero and one. The array is formed by first generating random numbers in [0, 1] and thereafter, transforming it such that the array becomes zero if it is less than 0.2 and one otherwise. The parameter r represents a uniform number in [0,1]. $\vec{X}_{max}$ and $\vec{X}_{min}$ are vectors that contain upper and lower limits respectively of the dimensions. The subscripts r1 and r2 represent the prey's matrix indexes [1].

The MPA as depicted in ‘Algorithm 1’ and Fig. 2, has good provision for memory tracking and recalling. This helps the predator remember foraging success from the places it has visited. The flow requires updating the prey, applying the FADs effect, and evaluating the matrix for possible fitness updates for the Elite. At each stage of the iteration, the fitness value is compared with that of the previous iteration, and the best overwrites the current solution. This continually refines the quality of the solution as each iteration elapses.

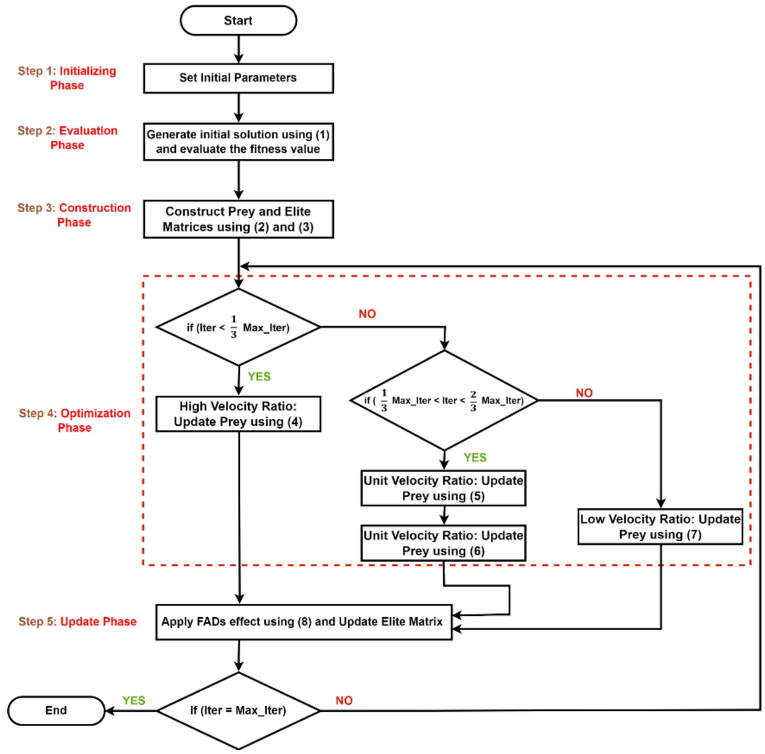

Fig. 2. MPA flowchart.

III. Materials and Method

This study applies the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) approach [58] in searching, collecting, synthesizing, and analyzing a systematic literature review (SLR) of the original MPA, proposing related modifications, and variants according to some selected articles. The study uses two databases: Scopus and Web of Science, and an additional database: Google Scholar (for verification purposes only).

First, to validate the proposed topic, a search for the terms "Marine Predator Algorithm and Related Variants: A Systematic Review" was carried out which gave no single result from the Scopus database. A similar search was also conducted with the same search string in the Web of Science database, and it also did not produce a result. Furthermore, a search for the exact match of the same title on Google Scholar yielded no results.

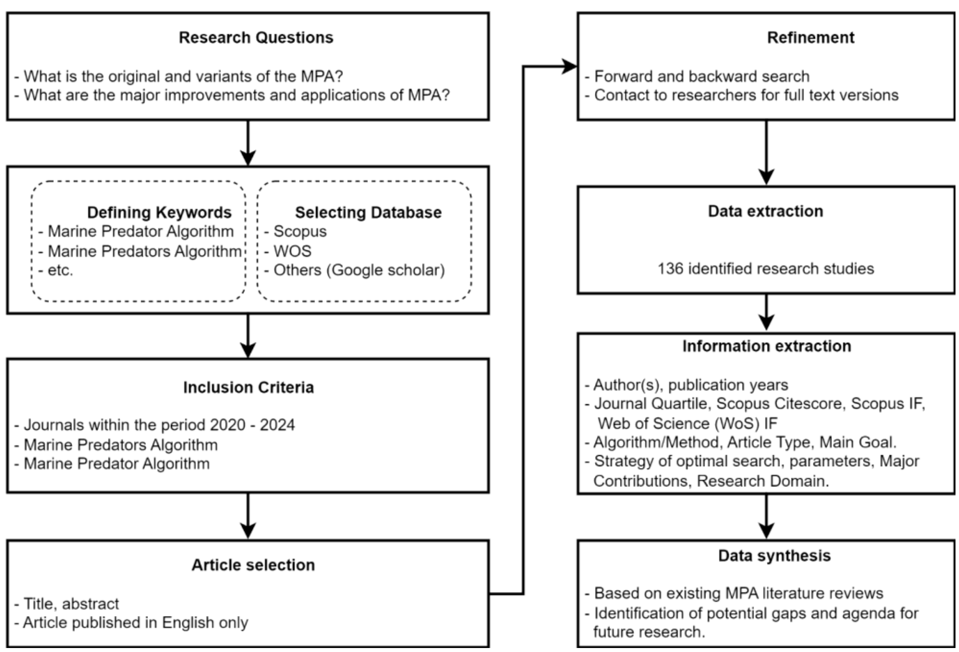

Fig. 3. The complete SLR process.

In Fig. 3, the complete SLR process is presented beginning with the formation of the research questions until the final data synthesis. It is important to note that the extraction of information from the articles was limited to the name of the author(s), publication years, journal quartile, Scopus CiteScore, Scopus IF according to Journal Indexed by Thomson Reuters (Clarivate Analytics), Web of Science IF, the algorithm or method used by the author(s), the article type (i.e., experimental result or review), main goal of the research, strategy for optimal search, parameters, major contributions, and the research domain.

Secondly, a careful search string was constructed to obtain relevant information and related articles (Fig. 4). An advanced search of the Scopus database using the constructed search string yielded 140 documents and a similar search conducted on the Web of Science database gave 143 papers as of 1st August 2024. The two search results were combined, and duplicate records were removed, reducing the document size to 170. A title-abstract screening was conducted where 11 articles were further excluded based on relevance and 1 other article was excluded, being written in Chinese language. Furthermore, 22 articles were excluded due to lack of full access. Overall, 136 articles were used in the entire synthesis of this review process.

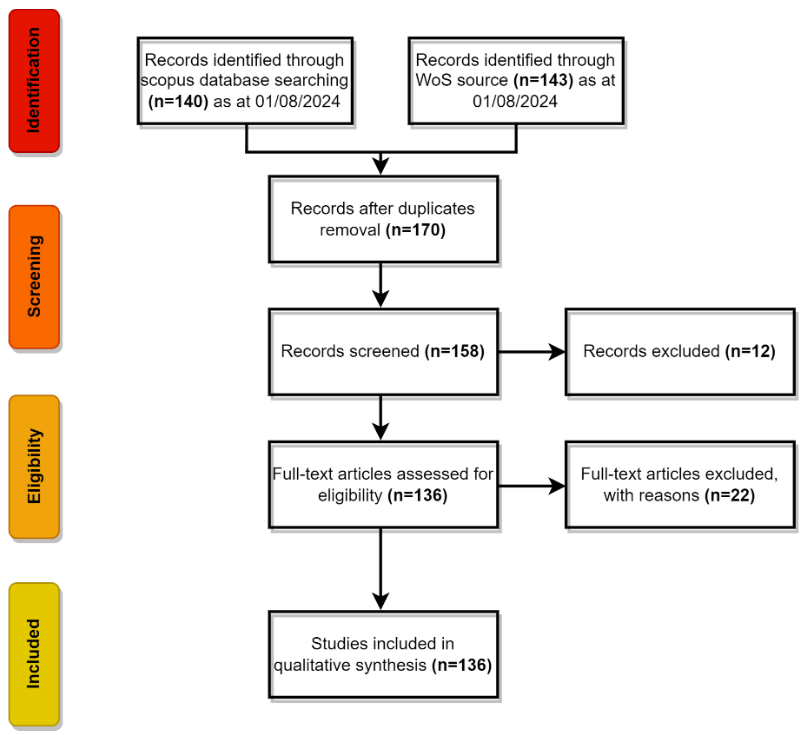

Fig. 4. Articles search and screening process.

The pie chart in Fig. 5 presents the diagrammatic distribution of retrieved MPA-related articles according to subject areas based on Scopus data. The top five subject areas are Engineering, Computer Science, Mathematics, Energy, and Material Science, with 28.2%, 26.0%, 10.9%, 7.1%, and 5.8%, respectively.

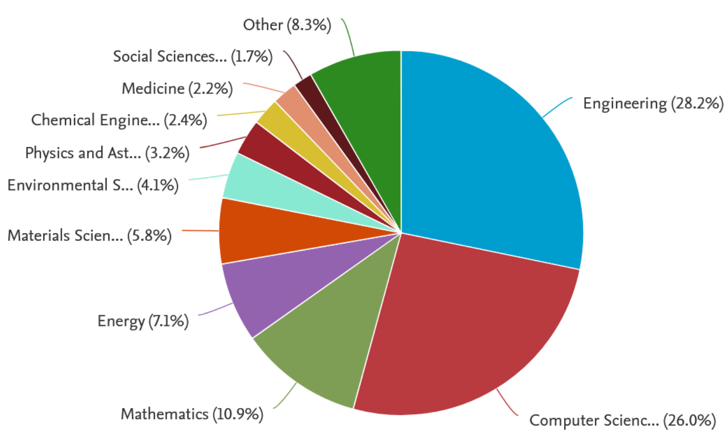

Fig. 5. MPA-related articles according to subject areas (Source: Scopus).

The research trend of the application of MPA for solving various problems is depicted based on the number of research articles that are published per year (Fig. 6,). The record shows a steady upward trend in the number of articles published over the years, reflecting a strong growth in the algorithm's usage. Beginning with 12 journal articles in 2020, the number progressively increased to 168 by 2023, showcasing a 93% rise over the observed period. As of the search date, the record of published articles in 2024 was 148 while still counting. More publications are underway as the year progresses. This significant growth highlights the major rapid application of the algorithm, indicating positive acceptance and potential usage for further development and innovation.

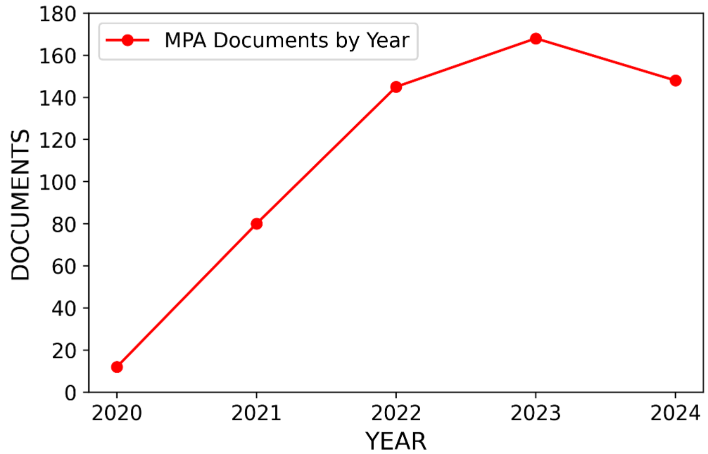

Fig. 6. MPA-related publications by year (Source: Scopus).

MPA stands out from other algorithms due to the predator's ability to execute various movements based on prey behavior. The predator can opt for Levy motion or Brownian motion based on the best encounter strategy, ensuring a dynamic connection between predator and prey. Specifically, the predator employs the Levy strategy when prey density is low and switches to Brownian motion when prey density is high.

As a metaheuristic algorithm, MPA is expected to meet some requirements of the major characteristics that measure its ability to solve optimization problems which include the ability to handle exploration, exploitation, local optimums, and convergence rate [41]. Each metaheuristic method differs in the way it does this based on the nature of the problem under consideration.

Three control parameters determine the sensitivity of MPA. The first is fish aggregating devices (FADs), which control the effect of FADs alongside their influence on the optimization flow. Secondly, P minimizes/maximizes predator's or prey's step sizes. Adjusting the step sizes in MPA helps to regulate its exploration and exploitation. The third parameter is the control factor (CF), which is an adaptive parameter that regulates the step size of a predator's movement. In study [1], it was found that the parameter 'P' became more sensitive than FADs to optimizing some unimodal functions. However, in multimodal functions, FADs gave higher performance. In some instances, the parameters presented no sensitivity.

IV. Proposed Variants of MPA for Performance Improvement

A. Parameter-tuned MPA

One of the earliest approaches adopted by researchers towards improving the performance of MPA was the application of parameter tuning. It is a general approach used in optimization and machine learning modeling to obtain optimum parameter values. The process requires tweaking some set of parameters used in controlling the behavior of the model/algorithm that are also adjustable to obtain an improved model with optimal performance.

In the original MPA, all population position updates are influenced by a constant value, denoted as P. As per the described position updating equations of MPA, there is a risk of premature convergence during the optimization iteration, limiting the exploration of the entire search space. Additionally, the alternation between Brownian and Lévy motions in the optimization process may lead to significant steps, causing the optimal solution to be crossed. Instead, dynamic updates of population positions could be achieved by incorporating other approaches such as the sine and cosine functions to improve the MPA's performance [32].

Some researchers such as [28] tried to improve the performance of MPA through a tuning process. Their study looked at the three most sensitive aspects of performance control of MPA which included the way the iterations are distributed across the iterations' phases, the size of the population in the second phase, and the effect of FADs. The experiment first tested different values of the iterations on each phase of the algorithm's optimization process e.g., allocating one-third of the iterations to each phase and later changing it produced little improvement in the results. The tests reveal that the least cost of optimal power flow (OPF) optimization in IEEE 48-Bus using MPA can be obtained in the first phase of the algorithm at three-fifths, phase two at one-fifth, and phase three at one-fifth of the iterations, respectively.

Concerning population size, the tasks of exploration and exploitation in MPA ideally require splitting the entire population size into two halves. However, it is important to note that some optimizations' minimum can be achieved when the population is divided into two-thirds and one-third for the prey and predators, respectively [28]. While maintaining the classical fact that FAD or eddy current effect in MPA is meant to keep the iteration from being trapped at the local minimum, however, the mathematical representation shows that FADs are also local minima. Therefore, a search could be conducted to obtain the optimal value of FADs as in [28], starting with an initial value of 0.2 until better performance was obtained at FAD = 0.3. This shows that tuning the value of FAD in the IEEE 48-Bus system could yield better performance. After tuning and obtaining the optimal parameter values for the iterations' distribution, population size, and FADs for the MPA, an experiment was set up in two folds: holistic and inter-bounded OPF and ultimately comparing the performance of the tuned-MPA with GA. Overall findings showed that the tuned MPA outperformed GA in convergence, accuracy, and computational requirements. Furthermore, the holistic fold produces better solutions and requires higher computational power. While the inter-bounded OPF generates faster results and is less computationally intensive.

Another similar MPA parameter-tuning case is found in [53], which in a bid to obtain the optimum load frequency control (LFC) settings to create a balance between power generation and demand, proposed a novel PD-P-PID cascade controller for LFC applications, utilizing the MPA for optimal parameter tuning. Tested on various power systems, including single and multi-area setups, the MPA-tuned PID-PD controllers exhibited superior performance compared to existing literature. The controller's robustness was evaluated on various power systems, and its parameters were optimized using MPA, demonstrating superior performance in terms of settling time and oscillations in frequency and tie-line power deviation compared to existing works. Their findings underscore the effectiveness of the MPA-tuned PD-P-PID controller in LFC applications. Table I provides more related works on MPA hyperparameter tuning where various degrees of success were achieved using parameter tuning.

TABLE I. RELATED WORKS ON MPA HYPERPARAMETER-TUNING

Ref.	J. Quart.	Scopus CiteScore (2022)	Scopus IF	WOS IF	Algorithm	Article Type	Strategies for optimal search	Major Contributions	Research Domain
[28]	Q1	9.0	4.342	3.9	Tuned-MPA	Experiment/Result	Parameter tuning	Tuning was done to obtain the optimal parameter values for the iteration distribution, population size, and FADs for the MPA.	Optimal power flow
[26]	Q1	8.2	5.861	3.88	TSD-FR-KCO-MPA	Experiment/Result	Levy and Brownian	MPA was used to obtain optimum parameters	Medical image fusion
[40]	Q4	2.0	1.771	0.5	MPA, MVO	Experiment/Result	Levy and Brownian	MPA is used to solve the final optimization problem	Electric vehicles
[59]	Q3	3.0	3.536	2.0	MPA	Experiment/Result	barrier parameters' influence	Incorporating barrier parameters influence, MPA is compared with GWO, and EO for effectiveness	Transformer oil breakdown
[60]	Q2	5.6	5.127	6.87	MPA	Experiment/Result	Levy and Brownian motion	MPA was used to obtain optimum parameters	Wind renewable energy
[61]	Q1	3.5	2.4	2.4	MPA	Experiment/Result	MPA is combined with the principle of key-term separation	MPA is combined with the principle of key-term separation	Mathematical computation
[62]	Q1	10.0	5.599	5.606	MPA	Experiment/Result	Levy and Brownian motion	compares several metaheuristic optimization algorithms that are used as frameworks for optimization	Selective harmonic elimination
[7]	Q1	14.1	9.177	9.7	MPA	Review			Microgrid, feature selection, etc.
[63]	Q2	4.7	3.271	2.9	MPA	Experiment/Result	Seven robust battery models were proposed for Lithium-ion batteries.	MPA is used as an optimizer of the objective function for the proposed seven models.	Li-ion batteries
[53]	Q2	7.7	4.203	4.1	Tuned-MPA PID-PD	Experiment/Result	Tuning	the performance of the Load Frequency Controller (LFC) was greatly improved by using tuned-MPA.	load frequency controller design

B. Improvements in MPA Exploitation-exploration Balance

The balance between exploration and exploitation is crucial in metaheuristic algorithms for effective optimization. The MPA addresses this balance by dynamically adjusting the exploration rate during optimization iterations. This adjustment facilitates a combination of exploration and exploitation, strategically applied at the start and end of the optimization process. MPA utilizes a control factor (CF) as an adaptive parameter to regulate step size for predator movement, contributing to the algorithm's effectiveness in navigating the search space. Because of the spread of iterations that are partitioned into stages, the search agents in MPA do not have sufficient trials for the search and discovery of spaces and the exploitation of optimal solutions [42].

Some researchers criticized the exploitation and exploration searchability of the classical MPA proposed by study [1]. The study in [45] opined that the step sizes that are randomly generated by the Levy distribution are large and best suited for exploration. This happens in some instances, probably occasioned by sudden jumps from smaller step sizes to larger ones during the search transition from exploitation to exploration [1]. They further stated that many modifications would be required to improve its exploitation ability. While possessing a convergence factor advantage, the larger steps generated by the Levy motion could jump the global minimum. As such, many of them focused on how to improve this aspect of the algorithm.

One possible solution found in the literature in this aspect is in the work done by [24], which proposed a hybridization of Improved MPA and PSO known as IMPAPSO algorithm for the optimization of the non-linear optimal reactive power dispatch (ORPD) problem. To improve MPA's exploration stage, they replaced the Brownian motion's random walk of the search agents with a high-tailed Weibull distribution. Secondly, the exploitation stage of classical MPA which is in phase 3 was also modified to use either PSO or MPA based on probability, to improve the convergence of the algorithm. The proposed IMPAPSO was evaluated using various test suites including IEEE 30, IEEE 57, and IEEE 118 bus systems. The strength of the proposed algorithm was examined in a rigorous comparison with other methods. Overall, the proposed IMPAPSO yielded an outstandingly high speed of convergence, outperforming its counterparts. The power loss was minimized to 96%, 10%, and 9% in IEEE 30, IEEE 57, and IEEE 118 bus systems, respectively.

Another example is found in study [2], which applies a strategy known as the dominance strategy based on exploration-exploitation (DSEE) to improve search exploitation-exploration. First, the classical MPA was modified to produce a multi-objective MPA (MMPA). Secondly, a strategic technique called dominance strategy based on exploration-exploitation (DSEE) was applied to count the returned dominant solutions in every returned solution, from which exploitation is carried out during the exploitation phase. This version was called M-MMPA. Thirdly, the Gaussian-based approach was incorporated into MPA to produce M-MMPA-GM which is a version that delves deeper into the present to discover better non-dominated solutions. This helps to discover better solutions by taking some distance from the present solution. The fourth version was incorporated with Nelder Mead simplex at the beginning of the optimization phase to build a front that helps MPA realize better solutions within the optimization flow.

Additionally, a multi-stage improvement of the MPA (MSMPA) was proposed by study [56]. MSMPA maintains the multi-stage search advantage and incorporates a linear flight strategy in the middle stage to enhance predator interaction, especially for those further from the historical optimum, promoting exploration. In the middle and late stages, the search mechanism of PSO is integrated to boost exploitation capabilities, reducing stochasticity and effectively constraining predators from jumping out of the optimal region. Additionally, a self-adjusting weight was employed to regulate convergence speed, achieving a balanced exploration-exploitation capability. The algorithm was tested on various CEC2017 benchmark test functions and three multidimensional nonlinear structure design optimization problems, which demonstrated superior convergence speed and accuracy compared to other recent algorithms.

Furthermore, the study in [45] applied the exploitation ability of NMRA to MPA in a bid to address its poor search exploitation. The authors proposed the hybridization of MPA and a naked mole-rat algorithm (NMRA) named MpNMRA – a self-adaptive algorithm. While retaining all the main parameters of both approaches, the basic part of MPA was attached to the worker stage of NMRA to improve search exploitation and exploration. The MpNMRA converges faster than other algorithms in comparison. The study in [55] applied HOGO to modify the search transition in MPA to gradually shift from exploration to exploitation as iterations progress, utilizing the global most appropriate solution at each iteration.

Other studies that worked on improving the exploitation-exploration of MPA are highlighted in Table II. These include [20] which incorporated local escaping operator (LEO) into classical MPA to tackle poor exploitation and exploration; [27] applied opposition based learning (OBL) strategy with Grey Wolf Optimizer (GWO) into MPA to overcome weaknesses; [43] incorporated MPA with spiral complex path search strategy based on Archimedes' spiral curve for perturbation, expanding the global exploration range and strengthening the algorithm's overall search capabilities; [44] integrated reinforcement learning (RL) into MPA to improve its global searchability; [39] combined chaotic sequence parameter and adaptive mechanism for velocity update to better MPA's exploitation and exploration search; [34] adopted comprehensive learning (CL) approach that improves search and transitioning within exploration and exploitation on MPA; [51] applied ranking-based mutation operator to identify the best search agent, enhancing exploitation capabilities and preventing premature convergence; [46] used dynamic foraging strategy (DFS) to tackle sudden transition between the Levy Flight and Brownian Motion; and [47] incorporated teaching mechanism into MPA's first phase to promote its global search ability. Table II summarizes the major improvements in MPA exploitation and exploration with various major contributions.

TABLE II. IMPROVEMENTS IN MPA EXPLOITATION-EXPLORATION

Ref.	J. Quart.	Scopus CiteScore (2022)	Scopus IF	WOS IF	Algorithm	Article Type	Strategies for optimal search	Major Contributions	Research Domain
[24]	Q3	5.5	3.542	3.2	IMPAPSO	Experiment/Result	high-tailed Weibull distribution and PSO	Exploration is improved by replacing the Brownian motion's random walk of the search agents with a high-tailed Weibull distribution. The exploitation stage in phase 3 is also modified to use PSO or MPA based on probability.	Optimal reactive power dispatch
[64]	Q1	19.1	11.057	10.4	EMPA	Experiment/Result	Differential Evolution (DE) operator	DE operator is integrated into the exploration face of the standard MPA to escape local solution	PV Modelling
[2]	Q1	9.0	4.342	3.367	MMPA M-MMPA M-MMPA-GM M-MMPA-GM-NMM	Experiment/Result	multi-objective, dominance strategy based on exploration-exploitation (DSEE), Gaussian-based approach, and Nelder Mead simplex	MMPA adopts classical MPA's search for MOPs, multi-objective modified MPA (M-MMPA) is a modification of the classical MPA to use DSEE strategy search phase for exploration and exploitation, Gaussian-based mutation (GM) was integrated into M-MMPA to have a new model M-MMPA-GM, and Nelder-Mead simple method (NMM) was integrated to M-MMPA-GM to create a front for it to get to a better solution while maintaining the minimum possible time (NMM-M-MMPA-GM).	Engineering design
[26]	Q1	8.2	5.861	3.88	TSD-FR-KCO-MPA	Experiment/Result	Levy and Brownian motion	MPA is combined with two other methods to address some drawbacks faced in medical image fusion that includes loss of edges due to ineffective high-frequency part of the fusion's rules, and low-contrast in fused images	Medical image fusion
[20]	Q1	12.3	8.664	8.038	LEO-MPA	Experiment/Result	Local Escaping Operator (LEO)	LEO is incorporated into classical MPA to tackle poor exploitation and exploration	Engineering design
[27]	Q1	12.6	9.602	8.5	MPAOBL-GWO	Experiment/Result	OBL and GWO	OBL strategy with Grey Wolf Optimizer (GWO) is integrated into MPA to overcome weaknesses.	PV System
[43]	Q2	4.5	3.143	2.7	FMMPA	Experiment/Result	Fusion multi-strategy	MPA is incorporated with a spiral complex path search strategy based on Archimedes' spiral curve for perturbation, expanding the global exploration range and strengthening the algorithm's overall search capabilities	Robot path planning
[44]	Q1	12.3	8.635	8.0	Deep-MPA	Experiment/Result	reinforcement learning (RL)	RL is integrated with MPA to improve its global searchability.	Renewable energy system design
[39]	Q2	6.8	4.352	3.9	AMPA	Experiment/Result	chaotic sequence parameter and adaptive mechanism for velocity update	AMPA combines chaotic sequence parameters and adaptive mechanisms for velocity update to better MPA's exploitation and exploration search	Antenna Signals
[34]	Q1	11.9	7.811	5.431	MMPA	Experiment/Result	Comprehensive Learning (CL) approach	CL approach that improves search and transitioning within exploration and exploitation is used on MPA	Economic emission dispatch.
[51]	Q2	4.7	3.308	3.5	EMPA	Experiment/Result	ranking-based mutation operator	the ranking-based mutation operator is used to identify the best search agent, enhancing exploitation capabilities and preventing premature convergence.	ANN classification
[45]	Q1	12.6	9.602	8.5	MpNMRA	Experiment/Result		the basic part of MPA is attached to the worker stage of NMRA	Engineering Design
[46]	Q1	12.3	8.635	8.0	DFSMPA	Experiment/Result	Dynamic Foraging Strategy (DFS)	DFS is used to tackle sudden transitions between the Levy Flight and Brownian Motion	Real-world engineering
[47]	Q3	3.9	2.393	2.6	MTLMPA	Experiment/Result	Mechanism for Teaching & Learning	teaching mechanism is incorporated into MPA's first phase to promote its global search ability	Engineering Design

C. Hybridization of MPA with other Techniques

Hybridization is the combination of two or more techniques to solve problems. The primary purpose of doing this is to harness the strengths of each approach and use them to complement the weaknesses of the other. Literature has shown that by combining MPA with other algorithms, there could be high-performance improvements. For instance, [45] combined MPA with NMRA with the sole aim of addressing the limitations of MPA (i.e., poor exploitation) and NMRA (i.e., narrow exploration) while leveraging the strengths of the two. MPA suffers from poor exploitation while NMRA suffers from weak exploration, and they both get into local optimum stagnation due to early or untimely convergence. Therefore, the strengths of MPA (i.e., good exploration) and NMRA (i.e., good exploitation) were used to address their weaknesses and to improve the entire performance. Overall, the authors reported a significant performance improvement. The proposed hybridization (MpNMRA) was found to be more suitable for lower dimensional problems, even though it also provides satisfactory performance in high dimensional cases.

Another example is found in study [29], which proposed a hybrid method known as MPA-FPIDF, a combination of MPA and Fuzzy Proportional-Integral-Derivative with Filter (FPIDF) to optimize Fuzzy PIDF-LFC to enhance the performance of a hybrid microgrid system, incorporating PV and wind energy sources along with real irradiance and wind speed data, as well as energy storage devices. The MPA was used to optimize the input scaling factors, output gains, and membership function boundaries of the proposed FPIDF controller. The performance of MPA-FPIDF controller is compared with the conventional MPA-PIDF controller and other controllers reported in the literature for the same case study, including PSO-PIDF, COR-PIDF, and COR-FPIDF controllers. In addition, various scenarios are implemented to assess the robustness and sensitivity of the proposed controller to step load perturbations, variations in system parameters, and uncertainties associated with renewable energy sources such as wind speed fluctuations and solar irradiance variations.

In study [44], a hybrid method that combines reinforcement learning (RL) and MPA known as Deep-MPA was proposed to minimize the cost of the microgrid power system. RL was integrated with MPA to improve global searchability. The proposed Deep-MPA design was validated against various algorithms, demonstrating a 6% reduction in energy costs.

Furthermore, the study in [52] proposed an enhanced multi-strategy MPA-Variational Mode Decomposition (MPA-VMD) method for pipeline leakage detection. This was meant to address the limitations of MPA by focusing on improving convergence speed and avoiding local optima. The enhanced MPA was used to find critical parameters in variational mode decomposition (VMD), and dynamic entropy was employed to select effective modes. The algorithm incorporates strategies like a good point set at the initial population stage to enhance search accuracy. It introduces a nonlinear convergence factor and Cauchy distribution during the search process to optimize the predator step size for better global search capabilities. The method effectively escapes local optima, leading to improved convergence speed.

The studied literature reported diverse hybridizations of MPA with other techniques, yielding various performance improvements (Table III). These include [24] which combined high-tailed Weibull distribution's improved MPA and PSO; [27] which integrated MPA, OBL, and GWO; [29] where MPA was integrated with Proportional-Integral-Derivative-Acceleration (PIDA); [35] coupled MPA and SVM where MPA was used to optimize SVM classifier's hyper-parameters for FS and classification; [36] which hybridized MPA and ANN, where MPA was used to optimize a trained ANN along with its fitness function; [37] which proposed IMPA-ResNet50, an improved version of MPA (IMPA) that was improved using OBL and TL, and ResNet50; [31] combined IMPA and CNN – a modified MPA algorithm for CNN hyperparameter selection, enhancing output performance for classification; [52] combined MPA with variational mode decomposition (MPA-VMD); [54] hybridized Open Circuit Voltage (OCV) reconfiguration model and MPA; [55] integrates MPA with HOGO; [45] integrated MPA with NMRA called MpNMRA, etc. Table III summarizes the major hybridizations of MPA with other techniques.

TABLE III. HYBRIDIZATION OF MPA WITH OTHER TECHNIQUES

Ref.	J. Quart.	Scopus CiteScore (2022)	Scopus IF	WOS IF	Algorithm	Article Type	Strategies for optimal search	Major Contributions	Research Domain
[24]	Q3	5.5	3.542	3.2	IMPAPSO	Experiment/Result	high-tailed Weibull distribution and PSO	Exploration is improved by replacing the Brownian motion's random walk of the search agents with a high-tailed Weibull distribution. The exploitation stage in phase 3 is also modified to use PSO or MPA based on probability.	Optimal reactive power dispatch
[27]	Q1	12.6	9.602	8.5	MPAOBL-GWO	Experiment/Result	OBL and GWO	OBL strategy with Grey Wolf Optimizer (GWO) is integrated into MPA to overcome weaknesses.	PV System
[29]	Q2	9.0	4.342	3.9	MPA-FPIDF	Experiment/Result	Fuzzy Proportional-Integral-Derivative with Filter (FPIDF)	MPA is combined with FPIDF to optimize Fuzzy PIDF Load Frequency Controller (PIDF-LFC) to enhance the performance of a hybrid microgrid system	Microgrid system
[38]	Q1	9.1	6.765	6.8	MPA-PIDA	Experiment/Result	Levy and Brownian motion	MPA is used to optimize the gains of the PIDA controller.	Power modulation
[35]	Q1	11.9	7.415	5.772	MPA-SVM	Experiment/Result	Levy and Brownian motion	MPA was used to optimize the SVM classifier's hyper-parameters for FS and classification.	ligament deficiency detection
[36]	Q2	3.2	2.59	NA	MPA-ANN	Experiment/Result	Levy and Brownian motion	MPA is used to optimize a trained ANN along with its fitness function.	Transistor's design
[37]	Q1	10.0	5.599	5.606	IMPA-ResNet50	Experiment/Result	Transfer Learning and Opposition-Based Learning	OBL is used to improve MPA and TL is used to improve IMPA-ResNet50	Breast cancer diagnosis

Ref.	J. Quart.	Scopus CiteScore (2022)	Scopus IF	WOS IF	Algorithm	Article Type	Strategies for optimal search	Major Contributions	Research Domain
[31]	Q1	12.6	9.602	8.5	IMPA-CNN	Experiment/Result	automating the tuning of hyperparameters in CNN	using a modified MPA algorithm for CNN hyperparameter selection, enhancing output performance for classification.	arrhythmia classification
[49]	Q1	11.9	7.811	5.431	MCFAO	Experiment/Result	time-delay polynomials are applied to improve the model's performance in prediction	MPA is used to optimize the model's hyperparameters	Time series prediction
[50]	Q3	5.0	2.606	2.363	BBD-based MPA CCD-based MPA	Experiment/Result	Incorporates two Response Surface Methodologies (RSMs): Box Behnken Design (BBD) and Central Composite Design (CCD)	MPA is used for biological decolorization process parameter optimization on BBD and CCD.	Biological Processes
[52]	Q2	4.8	2.795	4.1	MPA-VMD	Experiment/Result	Good point set in the initial population stage	improvements involves initializing a good point set and enhancing convergence factor (CF) and Cauchy distribution.	Pipeline leakage detection
[54]	Q2	5.4	5.784	4.0	OCV-MPA	Experiment/Result	Open Circuit Voltage (OCV) reconfiguration model and MPA	OCV model is used to measure the internal aging mechanism as influenced by the external factors of the lithium battery capacity decay, while MPA is used to detect the aging mode associate parameters.	Battery aging mechanism
[55]	Q3	2.0	1.347	0.6	MPA-HOGO	Experiment/Result	Hide Object Game Optimization (HOGO)	HOGO modifies the search transition in MPA to gradually shift from exploration to exploitation as iterations progress, utilizing the global best solution at each iteration.	Engineering design
[45]	Q1	12.6	9.602	8.5	MpNMRA	Experiment/Result		the basic part of MPA is attached to the worker stage of NMRA	Engineering Design

D. Proposed MPA Variants

Another way researchers address the limitations found in classical MPA is by modifying one or more aspects of the algorithm to create variants. An example is in study [46], which proposed a soft dynamic transformation to tackle the MPA's tendency to be trapped in local optima during transitioning from Levy Flight to Brownian motion when optimizing real-world problems. The proposed Dynamic Foraging Strategy MPA (DFSMPA) replicates the traditional MPA, imitating the step size taken to grab prey. It then applies the dynamic foraging strategy (DFS) to reach deeper search locations for a complete global, faster, and more efficient search. This could help prevent being trapped. Instead of the usual three phases that are used in classical MPA to mimic the behavior of predator and prey, the DFSMPA uses the continuous model to convert the various phases. In the two phases of exploration and extraction, the continuous model alternates between the search agents.

In addition, the study in [25] developed an enhanced MPA (EMPA) to identify hidden parameters in various PV and static PV models. In their work, the differential evolution (DE) operator was integrated into the exploration face of the standard MPA to escape local solutions for stability and performance reliability in handling nonlinear optimization cases of modeling PV. The strengths of the proposed enhancement are: (i) maintaining various new solutions in the search and optimizing unexpected convergence. (ii) avoiding being trapped by leaders and the population. (iii) using diverse search mechanisms that combine populations to create a balance between exploration and exploitation. (iv) dynamically changing the solutions by the algorithm to ensure effectiveness and efficiency. (v) dynamic adjustment of the optimization problem and concurrently covering various multi-dimensional areas of the search space.

Furthermore, the study in [51] proposed an enhanced variant of the MPA, called the EMPA, designed for training Feedforward Neural Networks (FNNs). EMPA was intended to minimize classification, prediction, and approximation errors by adjusting connection weights and deviation values. It incorporates a ranking-based mutation operator to identify the strongest search agent, enhancing exploitation capabilities and preventing premature convergence. EMPA combines exploration and exploitation, providing stability and flexibility in achieving optimal solutions. Experimental results on seventeen datasets show that EMPA exhibits faster convergence, higher calculation accuracy, increased classification rates, and strong stability and robustness, improving its productivity and reliability in training FNNs.

Other modifications proposed are presented in Table IV. They include the use of mechanism for teaching and learning to balance search exploitation and exploration [47]; combining chaotic sequence parameter and adaptive mechanism for velocity update to better MPA's exploitation and exploration search [39]; modifying the classical MPA to produce a multi-objective MPA (MMPA), applying a strategic technique called dominance strategy based on exploration-exploitation (DSEE) to count the returned dominant solutions in every returned solution from which exploitation is carried out during the exploitation phase, incorporating Gaussian-based approach into MPA to produce M-MMPA-GM, and incorporating Nelder

Mead simplex at the beginning of the optimization process, building a front that helps MPA realise better solutions within the optimization flow [2]; using a local escaping operator (LEO) to improve MPA's searchability [20]; applying adaptive weights and OBL to enhance the performance of MPA [30]; combining chaotic sequence parameter and adaptive mechanism for velocity update to better MPA's exploitation and exploration search [39]; the use of CL approach to improve the search and transitioning within exploration and exploitation in MPA [34]; using linearly increased worst solutions (LIS) improvement strategy to address computational cost and accuracy issues associated with existing segmentation techniques, MPALS (MPA + LIS) and RUS are combined into a version called HMPA to serve as a solution to ISP [33]; incorporating logistic opposition-based learning (LOBL) into MPA to enhance the generation of various precise solutions with multiple population [32].; integrating MPA with CL approach and memory aspect of fractional calculus [42]; LA is used to enhance the artificial Jellyfish search algorithm (JS) and MPA, reducing computational complexity while preserving their strengths [41]; MPA is integrated with spiral complex path search strategy based on Archimedes' spiral curve for perturbation, expanding the global exploration range and strengthening the algorithm's overall search capabilities [43]; it was also incorporated with pulse width modulation control boost converter to accurately track the MPP of a solar PV panel [65]; RL was integrated in MPA to improve its global searchability [44]; MPA was enhanced by incorporating a linear flight strategy in the middle stage to enhance predator interaction [56]; ranking-based mutation operator was used to identify the best search agent, to accelerate exploitation capabilities and preventing premature convergence in MPA [51]; DFS was used to tackle sudden transition between the Levy Flight and Brownian Motion [46]; teaching mechanism was also incorporated into MPA's first phase to promote its global search ability [47]; group-ranking of the predator populations, thorough learning approach implemented at stage 2 of MPA, and variable step-sizes control approach was applied [48]; etc.

TABLE IV. PROPOSED MPA MODIFICATIONS

Ref.	J. Quart.	Scopus CiteScore (2022)	Scopus IF	WOS IF	Algorithm	Article Type	Strategies for optimal search	Major Contributions	Research Domain
[64]	Q1	19.1	11.057	10.4	EMPA	Experiment/Result	Differential Evolution (DE) operator	DE operator is integrated into the exploration face of the standard MPA to escape local solution	PV Modelling
[2]	Q1	9.0	4.342	3.367	MMPA M-MMPA M-MMPA-GM M-MMPA-GM-NMM	Experiment/Result	multi-objective, dominance strategy based on exploration-exploitation (DSEE), Gaussian-based approach, and Nelder Mead simplex	MMPA adopts classical MPA's search for MOPs, multi-objective modified MPA (M-MMPA) is a modification of the classical MPA to use DSEE strategy search phase for exploration and exploitation, Gaussian-based mutation (GM) was integrated into M-MMPA to have a new model M-MMPA-GM, and Nelder-Mead simple method (NMM) was integrated to M-MMPA-GM to create a front for it to get to a better solution while maintaining the minimum possible time (NMM-M-MMPA-GM).	Engineering design
[20]	Q1	12.3	8.664	8.038	LEO-MPA	Experiment/Result	Local Escaping Operator (LEO)	LEO is incorporated into classical MPA to tackle poor exploitation and exploration	Engineering design
[30]	Q1	14.3	9.028	8.7	BMPA	Experiment/Result	adaptive weights and OBL	optimization capabilities of the MPA were enhanced with adaptive weights and OBL, resulting in a Pareto front.	Image segmentation
[39]	Q2	6.8	4.352	3.9	AMPA	Experiment/Result	chaotic sequence parameter and adaptive mechanism for velocity update	AMPA combines chaotic sequence parameters and adaptive mechanisms for velocity update to better MPA's exploitation and exploration search	Antenna Signals
[34]	Q1	11.9	7.811	5.431	MMPA	Experiment/Result	Comprehensive Learning (CL) approach	CL approach that improves search and transitioning within exploration and exploitation is used on MPA	Economic emission dispatch.
[33	Q1	23.0	11.674	8.139	MPALS HMPA	Experiment/Result	MPALS = MPA + LIS (linearly increased worst solutions improvement strategy.) HMPA = MPALS + ranking-based updating strategy (RUS)	LIS is used to address computational cost and accuracy issues associated with existing segmentation techniques. MPALS and RUS are integrated into a version called HMPA to serve as a solution to ISP.	Image Segmentation
[32]	Q1	13.4	8.364	8.7	MMPA	Experiment/Result	Incorporates logistic opposition-based learning (LOBL)	LOBL technique is incorporated to enhance the generation of various precise solutions with multiple populations.	Engineering design

Ref.	J. Quart.	Scopus CiteScore (2022)	Scopus IF	WOS IF	Algorithm	Article Type	Strategies for optimal search	Major Contributions	Research Domain
[42]	Q1	12.3	8.664	8.8	FOCLMPA	Experiment/Result	comprehensive learning (CL) approach	integrates MPA with the CL approach and memory aspect of fractional calculus.	Knowledge-based systems
[41]	Q1	12.3	8.664	8.8	LA-JS-MPA	Experiment/Result	Learning-Automata (LA)	LA is used to enhance the artificial Jellyfish search algorithm (JS) and MPA, reducing computational complexity while preserving their strengths.	Data clustering
[403	Q2	4.5	3.143	2.7	FMMPA	Experiment/Result	Fusion multi-strategy	MPA is incorporated with a spiral complex path search strategy based on Archimedes' spiral curve for perturbation, expanding the global exploration range and strengthening the algorithm's overall search capabilities	Robot path planning
[65]	Q3	5.5	3.542	3.2	MPA	Experiment/Result	Pulse width modulation control boost converter	MPA is incorporated with a pulse width modulation control boost converter to accurately track the MPP of a solar PV panel.	Solar PV systems
[44]	Q1	12.3	8.635	8.0	Deep-MPA	Experiment/Result	reinforcement learning (RL)	RL is integrated with MPA to improve its global searchability.	Renewable energy system design
[56]	Q3	3.5	2.071	2.4	MSMPA	Experiment/Result	linear flight strategy	MPA is enhanced by incorporating a linear flight strategy in the middle stage to enhance predator interaction	Engineering design
[51]	Q2	4.7	3.308	3.5	EMPA	Experiment/Result	ranking-based mutation operator	the ranking-based mutation operator is used to identify the best search agent, enhancing exploitation capabilities and preventing premature convergence.	ANN classification
[46]	Q1	12.3	8.635	8.0	DFSMPA	Experiment/Result	Dynamic Foraging Strategy (DFS)	DFS is used to tackle sudden transitions between the Levy Flight and Brownian Motion	Real-world engineering
[47]	Q3	3.9	2.393	2.6	MTLMPA	Experiment/Result	Mechanism for Teaching & Learning	teaching mechanism is incorporated into MPA's first phase to promote its global search ability	Engineering Design
[48]	Q2	4.7	2.941	2.524	DAMPA	Experiment/Result	group-ranking of the predator populations	group-ranking of the predator populations, thorough learning approach implemented at stage 2 of MPA, and variable step-sizes control approach	Task scheduling in Cloud Computing

E. Recent Proposed Improvements in MPA

Recently, more articles have been published with many improvements still underway. Some of these proposals include a hybrid MPA and Particle Swarm Optimization (MPA-PSO), combining the global and local search abilities of PSO with the MPA [66], Multi-Population-based MPA (MultiPopMPA) which uses global, balanced, and local search strategies simultaneously throughout the search process [67], and a multi-strategy MPA, Regularized ELM, and CFA, integrating multiple algorithms [68]. Furthermore, an improved MPA (IMPA) with Deep Gated Recurrent Unit (DGRU), a hybrid model combining IMPA and DGRU for better accuracy and generalization in profit prediction [69], and an improved MPA (IMPA), using adaptive weight adjustment and dynamic social learning mechanisms [70] have been proposed. A summary of the recent literature is presented in Table V.

TABLE V. RECENT PROPOSED MPA IMPROVEMENTS

Ref.	J. Quart.	Scopus CiteScore (2023)	Scopus IF	Proposed Algorithm	Article Type	Main Goal	Strategies of Optimal Search	Major Contribution	Research Domain
[66]	Q3	4.1	1.3	Hybrid MPA and Particle Swarm Optimization (MPA-PSO)	Experiment	To develop an optimal resource allocation strategy for vehicular edge computing networks	Combining the global and local search abilities of PSO with the MPA	Improved performance in resource allocation by leveraging the strengths of both MPA and PSO	Vehicular Edge Computing (VEC)
[67]	Q2	8.1	3.1	Multi-Population-based MPA (MultiPopMPA)	Experiment	To improve the search capabilities of the MPA by using a multi-population and multi-search strategy.	The algorithm uses global, balanced, and local search strategies simultaneously throughout the search process.	The proposed MultiPopMPA outperforms other metaheuristic algorithms in terms of precision, sensitivity, and F1-score metrics	AI, specifically in training ANN for classification tasks.
[68]	Q3	2.3	0.278	Multi-Strategy MPA, Regularized ELM, and CFA	Experiment	Accurate prediction of passenger flow to	Combining multiple algorithms to handle complexity and	High prediction accuracy and strong convergence performance with only 30	Passenger Flow Prediction.

Ref.	J. Quart.	Scopus CiteScore (2023)	Scopus IF	Proposed Algorithm	Article Type	Main Goal	Strategies of Optimal Search	Major Contribution	Research Domain
						help local authorities with resource regulation.	uncertainty in passenger flow prediction.	iterations needed to reach the optimal solution	
[71]	Q2	6.2	3.5	Quantum Theory-based MPA (QTbMPA)	Original Research	To develop an automated deep learning model for classifying brain tumors from MRI images	Bayesian optimization for hyperparameters and QTbMPA for feature selection.	Improved accuracy and sensitivity in brain tumor classification using a hybrid deep learning framework.	Medical image analysis
[72]	Q1	9.7	3.6	Chaotic-based MPA (CMPA)	Experiment	Improve the search performance of the MPA for feature selection in schizophrenia classification using EEG signals.	Combining MPA with chaotic maps (logistic, tent, henon, sine, and tinkerbell maps).	The proposed SCMPA significantly outperforms other MPA variants in feature selection and classification accuracy.	Schizophrenia classification using EEG signals and metaheuristic algorithms.
[73]	Q1	7.5	3.8	Enhanced Gorilla Troops Optimizer (EGTO), with MPA	Experiment	To enhance the performance of the Gorilla Troops Optimizer (GTO) by integrating high and low-velocity ratios inspired by the MPA.	Balancing exploration and exploitation phases using high and low-velocity ratios	EGTO achieves superior performance in global optimization and engineering design problems compared to other algorithms.	Optimization and Engineering Design.
[74]	Q1	9.6	3.662	Modified MPA - convolutional neural networks (DCNNs).	Original Research	To develop an optimal structured DCNN for automatic COVID-19 diagnosis using chest CT scans.	Utilizes a novel encoding scheme based on IP addresses, an Enfeebled layer for variable-length DCNN, and divides large datasets into smaller chunks for random evaluation.	The proposed DCNN-IPMPA model outperforms other benchmarks with high accuracy and competitive processing time.	Deep Learning and Medical Imaging.
[69]	Q1	9.6	5.0	Improved MPA (IMPA) with Deep Gated Recurrent Unit (DGRU).	Experiment	Improve profit prediction in financial accounting information systems	Dynamic flight behavior between Levy and Gaussian to enhance MPA's performance	Hybrid model combining IMPA and DGRU for better accuracy and generalization in profit prediction.	Financial accounting information systems and profit prediction.
[75]	Q2	11.4	4.5	Recursive Spider Wasp Optimizer MPA (RSWO-MPA)	Experiment	To improve gene selection methods for cancer classification using microarray data.	Combines ReliefF filter method with RSWO-MPA for efficient gene selection.	Achieves higher accuracy, selects fewer features, and exhibits more stability compared to other algorithms.	AI and Bioinformatics
[70]	Q1	7.5	3.8	Improved MPA (IMPA).	Experiment	To enhance the MPA by addressing its limitations such as local optima traps, insufficient diversity, and premature convergence.	Adaptive weight adjustment and dynamic social learning mechanisms.	IMPA significantly improves optimization performance in engineering design problems by balancing exploration and exploitation.	Optimization algorithms in engineering design
[76]	Q1	9.6	5.0	Adaptive MPA (AMPA).	Experiment	Optimize the steam gasification process for converting palm oil waste into environmentally friendly energy	Incorporation of AMPA into the SVM framework to enhance prediction precision and efficiency	Development of an intelligent optimization framework surpassing conventional machine learning techniques.	Renewable energy and intelligent systems.
[77]	Q2	5.3	2.5	MPA combined with a BP Neural Network.	Experiment	Inversion of the permeability coefficient of a high core wall dam	Lévy and Brownian movements.	Comparison of three methods for seepage parameters inversion and demonstrating the advantage of the MPA.	Hydrology and Hydraulic Engineering.
[78]	Q2	3.5	3.4	MPA for optimized tuning of PI controllers	Experiment	Enhance the low-voltage ride-through (LVRT) capability of grid-connected photovoltaic (PV) systems	MPA, Grey Wolf Optimization (GWO), and Particle Swarm Optimization (PSO).	MPA provides better results with higher convergence rates and improved system performance.	Electrical Engineering and Renewable Energy.
[79]	Q3	2.2	1.5	Improved MPA	Experiment	To optimize process parameters in multi-process manufacturing to	Utilizes reverse learning strategies and mixed control parameters to	Proposes a multi-process parameter optimization method using an improved MPA,	Mechanical Engineering and Manufacturing.

Ref.	J. Quart.	Scopus CiteScore (2023)	Scop us IF	Proposed Algorithm	Article Type	Main Goal	Strategies of Optimal Search	Major Contribution	Research Domain
						improve product quality	enhance optimization capability	addressing the severe coupling of multiple processes.	
[80]	Q3	4.1		MPA Aquila Optimizer (MAO)	Experiment	To present a hybrid method combining MPA and AO for droop control in DC microgrids	Combining the strengths of MPA and AO to enhance exploration and exploitation.	Superior convergence ability and promising performance in droop control.	Electrical Engineering
[81]	Q3	2.4	1.2	MPA for robot path planning	Experiment	To design an optimal path for a robot to navigate from its starting point to its goal while avoiding obstacles	Heuristic search-based methods, potential field-based methods, sampling-based methods, hybrid methods, and evolutionary methods	The proposed method uses the Marine Predator Algorithm, which shows good performance in different situations.	Robot path planning and autonomous driving.
[82]	Q2	3.6	1.6	MPA- P-P-FOPID controller.	Experiment	To design a cascade P-P-FOPID controller optimized by the MPA for improving load frequency control in electric power systems.	The MPA is employed for its parameter-less, derivative-free, user-friendly, flexible, and simple nature.	The proposed controller demonstrated superior performance in reducing integral time absolute error (ITAE), settling time, and frequency and tie-line power deviations compared to other recent approaches. It also showed robustness against parametric uncertainties.	Electric power systems
[83]	Q1	19.9	6.2	improved binary MPA	Experiment	To develop an efficient offloading method that reduces energy consumption and meets time constraints in edge computing environments	The binary MPA is used for its effectiveness in solving optimization problems under constraints	The proposed method effectively meets deadlines while reducing energy consumption, even with an increasing number of users.	Edge computing.
[84]	Q2	4.3	2.7	Enhanced MPA (EMPA) - SVM	Experiment	To improve the accuracy and efficiency of IGBT switching power loss estimation using an optimized SVM model.	The EMPA is employed for its effectiveness in parameter optimization, leveraging its ability to handle complex, multi-dimensional search spaces.	The integration of EMPA with SVM results in a model that significantly enhances the accuracy and efficiency of power loss estimation in IGBT, outperforming traditional methods.	power electronics
[85]	Q1	11.2	6.2	MPA	Analytical	To identify and analyze the structural biases in the MPA using the BIAS Toolbox and Generalized Signature Test (GST).	The study employs the BIAS Toolbox and GST to detect and evaluate the structural biases within the MPA, revealing how these biases affect the algorithm's performance.	The article highlights significant structural biases in the MPA, which cause the population to revisit specific regions of the search space, leading to increased computational costs and slower convergence.	optimization algorithms
[86]	Q1	11.5	7.5	Improved Weighted MPA (WMPA)	Experiment	To enhance the accuracy and efficiency of SOM estimation by selecting the most relevant hyperspectral features using the improved WMPA.	The WMPA is optimized to improve feature selection by leveraging its ability to handle complex, multi-dimensional search spaces effectively.	The improved WMPA demonstrates higher accuracy and stability in predicting SOM content compared to traditional methods, providing a robust and efficient approach for SOM estimation.	agricultural and environmental monitoring
[87]	Q1	7.7	4.8	Enhanced Hybrid Aquila Optimizer with MPA (EHAOMPA)	Experiment	To enhance the performance of the Aquila Optimizer in solving combinatorial optimization problems by integrating it with the MPA.	The hybrid algorithm leverages the exploration capabilities of MPA and the exploitation strengths of AO to effectively navigate the search space and find optimal solutions.	The EHAOMPA demonstrates superior performance in various benchmark problems compared to traditional AO and other optimization algorithms, showing promise in solving industrial-constrained design problems and optimizing hyperparameters for	combinatorial optimization.

Ref.	J. Quart.	Scopus CiteScore (2023)	Scop us IF	Proposed Algorithm	Article Type	Main Goal	Strategies of Optimal Search	Major Contribution	Research Domain
								COVID-19 CT-image detection.	
[88]	Q1	14.8	7.2	improved MPA combined with Extreme Gradient Boosting (XGBoost)	Experiment	To enhance the accuracy and efficiency of shipment status time predictions using a hybrid approach that combines MPA and XGBoost.	The improved MPA incorporates opposition-based learning, chaos maps, and self-adaptive population strategies to optimize the parameters of the XGBoost model.	The hybrid model demonstrates superior performance in predicting shipment status times compared to traditional methods, providing a robust and efficient solution for logistics and supply chain management.	logistics and supply chain management
[89]	Q2	4.3	2.4	improved MPA (multi-objective optimization).	Experiment	To enhance the resilience of power grid infrastructure by optimizing core backbone grid planning using a multi-objective 0–1 planning problem.	The improved MPA incorporates file management and an enhanced top predator selection mechanism to effectively explore the Pareto frontier for optimal solutions.	The algorithm successfully forms core backbone grids for the IEEE 39-node and IEEE 300-node systems, ensuring economic feasibility and optimal network connectivity while balancing active and reactive power demands.	power systems
[90]	Q2	4.3	2.7	MPA optimized random forest (RF) algorithm with laser-induced fluorescence (LIF) technology	Experiment	To develop a more efficient and accurate method for diagnosing transformer faults, overcoming the limitations of traditional methods.	The study employs principal component analysis (PCA) and kernel principal component analysis (KPCA) for dimensionality reduction, followed by the MPA-RF model for optimal fault diagnosis.	The research demonstrates that the MSC-KPCA-MPA-RF model achieves the best results, with a fitting coefficient of 0.9963 and a mean square error of 0.0047	power systems and electrical engineering
[91]	Q1	9.5	2.6	MPA optimized pavement maintenance and rehabilitation (M&R) scheduling	Experiment	To develop a sustainable M&R scheduling optimization model that considers highway agency costs, environmental impacts, and social effects.	The MPA is used to handle the computational complexities of optimizing M&R scheduling for large-scale networks	The sustainable model reduces CO2 emissions by 6.5% and improves equity and safety indices by 40.7% and 2.5%, respectively, compared to conventional methods	pavement management systems and sustainable infrastructure engineering.
[92]	Q1	12.6	7.2	Clustering Wavelet Opposition-based MPA (CWOMPA) enhanced-MPA	Experiment	To improve optimization performance and feature selection in high-dimensional datasets, particularly in medical diagnosis.	CWOMPA incorporates fuzzy clustering, wavelet basis function, and adaptive opposition-based learning to enhance population diversity and prevent premature convergence	Demonstrates CWOMPA's superior performance in optimization and feature selection across various benchmark functions and medical datasets	Meta-heuristic optimization algorithms and feature selection in medical datasets.
[93]	Q1	5.7	2.6	Hybrid MPA-PSO to tackle the Energy Scheduling Problem (ESP).	Experiment	To optimize electricity bills, energy consumption, and user comfort by finding the best schedule for smart appliances	The proposed method enhances the searching capabilities of MPA using PSO components to improve schedules with poor fitness values	The research demonstrates the efficiency and high performance of the hybrid method in optimizing ESP objectives compared to other methods	Internet of Things (IoT) and smart grid technology
[94]	Q4	1.3	1.74	Modified MPA (MMPA) for automated atrial fibrillation detection using ECG signals.	Experiment	To develop a method for automatically detecting atrial fibrillation using transient single lead ECG readings	The algorithm utilizes Heart Rate Variability (HRV) and frequency analysis for feature extraction, followed by classification using SVM	The study's innovative contribution is the application of the MMPA for identifying atrial fibrillation in brief ECG data, achieving a maximum accuracy of 99.8%.	Biomedical Engineering and AI.
[95]	Q1	6.5	4.1	bidirectional gated recurrent unit (BiGRU) optimized MPA	Experiment	To analyze the influence of scraper geometry and roughness on the coating process using advanced predictive and simulation models.	The MPA-BiGRU pseudo-lattice Boltzmann (pseudo-LB) method is employed to simulate the coating flow without specific rheological equations.	The study finds that rectangle geometry is suitable for high coating speeds, while trapezium geometry is better for low speeds. Scraper roughness significantly affects the process with rectangle geometry.	materials science and engineering

Ref.	J. Quart.	Scopus CiteScore (2023)	Scop us IF	Proposed Algorithm	Article Type	Main Goal	Strategies of Optimal Search	Major Contribution	Research Domain
[96]	Q2	4.6	2.7	Improved MPA (IMPA)	Experiment	To optimize water resource allocation in Huaying City by balancing social, economic, and ecological benefits	The IMPA employs chaotic initialization for population diversity, golden sine algorithm for balanced exploration and exploitation, and quadratic interpolation for enhanced search accuracy.	The study demonstrates that IMPA outperforms other algorithms in terms of stability and accuracy for water resource optimization, providing a new approach for sustainable water management.	water resource management and optimization algorithms.
[97]	Q2	10.2	4.7	MPA	Comparative	To minimize the deficit of agricultural water supply by optimizing reservoir operations under baseline and climate change conditions.	The MPA uses random walk strategies (Brownian and Levy motions) and elite matrices to enhance exploration and exploitation phases.	Demonstrates that MPA outperforms GA in terms of reliability, resiliency, and vulnerability in reservoir operations.	Water Resource Management and Optimization Algorithms.
[98]	Q2	3.4	1.7	PRMPA-Spectral-SMOTE with improved MPA (IMPA).	Experiment	To enhance the classification performance of biomedical data, which is often high-dimensional and imbalanced	The algorithm uses minimal-redundancy maximal-relevance (mRMR) for feature selection, Spectral-SMOTE for data resampling, and an improved MPA for optimizing key parameters.	The method significantly improves the classification accuracy of biomedical data, outperforming other data resampling methods	biomedical data
[99]	Q1	9.8	3.4	Uniform MPA (UMPA), combines uniform design with the MPA	Experiment	To accurately and efficiently detect neural unit modules in brain networks, which can aid in disease detection and targeted therapy	UMPA leverages uniform design to ensure evenly distributed solutions and MPA for optimization, incorporating Lévy flight and Brownian movement strategies.	Integration of uniform design with MPA, resulting in improved performance in identifying neural unit modules compared to other methods.	brain network analysis
[100]	Q1	9.7	3.6	Reinforcement Learning MPA (RLMPA) to enhance global optimization.	Experiment	Improve Optimization-Address weak convergence, limited balance capacity, and optimization limitations in MPA by introducing RLMPA.	**Three Location Update Strategies:** Ranking paired mutually beneficial learning; Gaussian random walk learning; and Modified somersault foraging.	Enhanced Performance: RLMPA shows superior performance in global optimization, search efficiency, and convergence speed compared to 10 competitive algorithms.	engineering design

V. Applications of MPA in Various Domains

The MPA has found wide acceptance across many research domains. Focusing on areas with the widest coverage and most recent development, Engineering (28.2%), Computer Science (26.0%), Mathematics (10.9%), and Energy (7.1%) of the applications, the following summaries are presented.

A. Engineering

The highest of MPA's applications based on Table V are in real-world engineering designs [1]. In this domain, MPA has been used to solve real-world problems such as pressure vessel design, tension/compression spring design, and welded beam design [1], estimating the parameter of frequency-modulated sound wave (FM), speed spectrum radar Polly phase code design (SSRPP), and Lennard-Jones (LJ) potential problem [45]. These problems are constrained engineering benchmarks and were made with associated practical engineering examples. With the help of the death penalty approach, the constrained problems were converted to unconstrained ones. Another real-world problem solved includes demand-controlled ventilation of the operating fan schedule, where a 2-zone (entry and exit) retail store stocked with a supply and exhaust fan for ventilation was examined. The main objective was to "reduce the fan's energy consumption using demand-controlled ventilation subject to airflow and the amount of carbon dioxide (CO_2)".

B. Computer Science

In this area, MPA has been used to develop an efficient offloading method that reduces energy consumption and meets time constraints in edge computing environments [83] and to develop an optimal resource allocation strategy for vehicular edge computing networks [66]. It has also been used to design an optimal structured deep convolutional neural network (DCNN) [74], in training ANN for classification tasks [67], incorporation into the SVM framework to enhance prediction precision and efficiency [76] and was combined with a BP Neural Network [77] for improved performance. Furthermore, on the Internet of Things (IoT) and smart grid technology, MPA was used to optimize electricity bills, energy consumption, and user comfort by finding the best schedule for smart appliances [93].

C. Mathematics

The proposed variant of MPA such as DFSMPA was also applied to three sets of standard mathematical test functions and one set of real-world engineering optimization problems including (i) Classical functions such as unimodal, multimodal, and fixed multimodal functions. (ii) Contemporary numerical optimizations CEC-BC-2017 comprises 30 composition and hybrid functions. (iii) CEC06-2019 (100-Digits challenge). and (iv) Ten CEC-2020 problems applicable to real engineering optimization [46].

D. Energy

MPA has been applied in power systems and electrical engineering to develop a more efficient and accurate method for diagnosing transformer faults, overcoming the limitations of traditional methods [90], and enhancing the resilience of power grid infrastructure by optimizing core backbone grid planning using a multi-objective 0–1 planning problem [89]. In addition, a cascade P-P-FOPID controller optimized by MPA for improving load frequency control in electric power systems was also designed [82]. Furthermore, MPA and AO have been combined for drop control in DC microgrids [80]. In electrical engineering and renewable energy, MPA has been applied to enhance the low-voltage ride-through (LVRT) capability of grid-connected photovoltaic (PV) systems [78] and to optimize the steam gasification process for converting palm oil waste into environmentally friendly energy [76]. MPA has been used in power electronics to improve the accuracy and efficiency of IGBT switching power loss estimation [84].

Comprehensively, the research application domain and tasks include real-world and engineering design [2, 20, 32, 45–47, 55, 58, 70, 73, 77, 79, 85, 91, 95, 100–108], microgrid feature selection [7], antenna signals [39], selective harmonic elimination [62], power modulation [38], ligament deficiency detection [35], transistor's design [36], breast cancer diagnosis [37], task scheduling in cloud computing [48], time series prediction [49], medical image fusion and analysis [26, 71, 72, 74, 92], economic emission dispatch [34], wind renewable energy [60], mathematical computation [61, 87], image segmentation [30, 33, 109, 110], PV System and modelling [27, 64, 65, 111], Optimal power flow [28], Biological Processes [50], Microgrid system [29], optimal reactive power dispatch [24], ANN training and classification [51, 67], pipeline leakage detection [52], arrhythmia classification [31], load frequency controller design [53], knowledge-based systems [42], data clustering [41], robot path planning [43, 81], battery aging mechanism [54], li-ion batteries [63], transformer oil breakdown [59], renewable energy system design [44], dynamic clustering simulation [112], marine stabilized platforms [113], joint regularization semi-supervised ELM [114], oil layer prediction [115], EEG/ERP signal [116], urban green space type [117], SVM optimization [118], solar-powered BLDC motor design [119], network reconfiguration and distributed generator allocation [121], wind and solar energy [122], DNA storage [123], white blood cell classification [124], wireless sensor network coverage [125], hybrid heartbeats [126], distribution system [127], task scheduling in cloud computing [128], shrimp freshness detection and classification [129], evolutionary computations [130], energy management system [131], hybrid active power filter [132], gene selection in cancer microarray classification [133], supercapacitor modelling [134], COVID-19 detection modelling [135], wind power forecasting [136], thermal error modelling of electrical spindle [137], electrical power system & renewable energy [76, 78, 80, 82, 84, 89, 90, 138], DC motors [139], feature selection in metabolomics [140], optimal power flow [141], fuel cell steady-state modelling [142], structural damage detection [143], production planning [144], wind energy systems [145], AI and Bioinformatics [75, 94, 98, 99], Vehicular Edge Computing (VEC)[66, 83], passenger flow prediction [68], Internet of Things (IoT) and smart grid technology [93, 120], financial accounting information systems [69], agricultural and environmental monitoring [86], logistics and supply chain management [88], and water resource management and optimization algorithms [96, 97].

VI. Discussion

Although the classic MPA proposed by study [1] was for a single objective and possessed some shortcomings, multi-objective variants were later proposed and other subsequent improvements were made [133], [146–148]. It is worth noting that most of the improvements in the literature were based on enhancing MPA's initial population, exploitation, exploration, and convergence.

Firstly, opposition-based learning (OBL), a novel technique introduced by Tizhoosh, has been widely adopted by numerous researchers to improve the initial population quality of metaheuristic algorithms. The OBL has been used to produce a more widely distributed initial population for MPA.

Furthermore, many scholars applied varying OBL approaches to tackle MPA's limitations. These include integrating the OBL strategy with GWO into MPA [27], OBL and TL were also used to improve MPA and IMPA-ResNet50 using a modified MPA algorithm for CNN hyperparameter selection to improve output performance for classification [31], enhancing the optimization capabilities of MPA with adaptive weights and OBL [30], and logistic OBL (LOBL) technique was incorporated in study [32] to enhance the generation of various precise solutions with multiple populations. In study [106], quasi-learning (Q-learning) was introduced to help MPA fully utilize the information generated by previous iterations and subsequent ones, QOBL was introduced to support an increase in population diversity, reducing the risk of convergence to inferior local optima. In addition, the quasi-opposition learning and spiral search strategies were incorporated into QRSS-MPA to improve it [123].

Additional strategies adopted in the literature to control MPA's exploration-exploitation search include chaotic maps' exploitation capabilities alone. Several chaotic maps can be implemented to improve the exploration-exploitation process [108]. The chaotic map can be applied to balance the trade-off between the exploration and exploitation phases. The self-adaptive population method automatically adjusts the population size for each iteration. It helps to increase the convergence speed [101, 108]. In study [107], chaotic maps, opposition-based learning strategy (OBLS), and teaching-learning-based optimization (TLBO) with strong exploitation operators were combined. MPA was first modified to have MMPA that leverages chaotic maps and OBLS in the initialization stage to generate high-quality individuals. Parameter-free teaching-learning-based optimization method with a strong exploitation operator was incorporated into MPA (MMPA-TLBO), which effectively trades off between the exploitation and exploration process. Furthermore, [114] applied a multi-strategy approach involving three strategies to improve the performance of MPA. It included a chaotic opposition learning strategy to generate a high-quality initial population, adaptive inertia weights, adaptive step control factors to improve exploration, utilization, and convergence speed, and a neighborhood-dimensional learning strategy to maintain population diversity.

The literature also used comprehensive learning (CL) to improve the performance of MPA. For instance, in study [34], the CL approach was used to improve search and transition within the exploration and exploitation of MPA. In study [42], MPA was integrated with the CL approach and the memory aspect of fractional calculus.

Other approaches that were implemented to improve the performance of MPA include the use of Dynamic Foraging Strategy (DFS) to tackle sudden transition between the Levy Flight and Brownian Motion by study [46], Differential Evolution (DE) operator was integrated into the exploration face of the standard MPA by study [64] to escape local solution, and the use of teaching and learning mechanism was incorporated into MPA in study [47] where the teaching mechanism was integrated into the first phase of the MPA to promote its global search ability. In study [39], chaotic sequence parameters and an adaptive mechanism for velocity update were implemented to improve MPA's search exploitation and exploration. Also, group ranking of predator populations was proposed by study [48], incorporating a thorough learning approach implemented at stage 2 of MPA, and a variable step-size control approach.

Furthermore, time-delay polynomials were applied to improve the model prediction performance [49]. A local escaping operator (LEO) was incorporated into classical MPA [20] to tackle poor exploitation and exploration. In study [24], exploration was improved by replacing the Brownian motion's random walk of search agents with a high-tailed Weibull distribution. The exploitation stage in phase 3 was also modified to use PSO or MPA based on probability. The study in [51] used a ranking-based mutation operator to identify the most performing search agent, enhancing exploitation capabilities and preventing premature convergence.

In addition, [52] applied a strategy known as a “good point set” in the initial population stage for improvement by initializing a good point set and enhancing the convergence factor (CF) and Cauchy distribution. Learning automata (LA) was used in [41] to improve the artificial jellyfish search algorithm (JS) and MPA, reducing computational complexity while preserving their strengths. MPA is incorporated with a spiral complex path search strategy based on Archimedes’ spiral curve for perturbations in study [43], expanding the global exploration range and strengthening the algorithm's overall search capabilities. In study [55], HOGO was implemented which modifies the search transition in MPA to gradually shift from exploration to exploitation as iterations progress, utilizing the global best solution at each iteration. In study [56], MPA was enhanced by incorporating a linear flight strategy in the middle stage to enhance predator interaction. Reinforcement learning (RL) was also integrated into MPA [44] to improve global searchability.

VII. Future Research Direction

The application of the MPA is predominant in engineering and real-world design. However, researchers need to extend it to other disciplines and optimization problems. Additional variants of MPA, such as Constrained MPA (CMPA), Mixed-Integer MPA (MIMPA), and Parameter Less MPA (PMPA), warrant exploration, alongside dynamic applications like Mobile or dynamic MPA in robotics. Moreover, MPA shows potential in diverse areas like knowledge discovery, power systems, signal processing, DNA assembly, and medical diagnostics. However, variants like MpNMRA still face challenges such as potential entrapment in local optima and inefficient optimization of all test functions, necessitating improvements in control parameter selection and solution retention. In addition, the expansion of MPA into multi-objective problems, alongside enhanced stability and convergence analysis remains an area for future research. Other proposed methods, such as DAMPA and MTLMPA, also require comprehensive testing in various domains to assess their efficacy. Additionally, the scalability of dataset testing for algorithms like IMPA-ResNet50 and exploration of their performance in regression tasks, computational efficiency enhancements, and generalization to different CNN configurations are suggested. Further research efforts should aim to integrate MPA with deep learning and machine learning techniques, explore its potential in renewable energy systems – with emphasis on solar radiation forecasting, refine its application in real-world scenarios, and investigate its hybridization with other metaheuristic methods for improved optimization outcomes.

VIII. Conclusion

This systematic review of MPA presents a wide panorama concerning its theoretical formulation, practical implementations, and novel improvements. Current research synthesizes studies undertaken during the last five years that underline, among others, the flexibility and efficiency of the MPA approach as a metaheuristic optimization method but with peculiar efficacy in handling complex, high-dimensional, and multimodal optimization problems. From its principle of inspiration to its adaptive nature, MPA has always shown robust performance in diverse fields, ranging from real-world engineering design, image segmentation, and PV system modeling, indicating its wide acceptance and high applications. It also identifies the critical design parameters and their influence on the convergence and performance of the algorithm, thus contributing to the deeper theoretical understanding of the method.

This research significantly contributes to the optimization literature by systematically categorizing MPA variants based on their core improvements, including parameter tuning, hybridization, and other modification mechanisms. The review delineates the strengths and limitations of each approach by comparing these variants across benchmark problems, thus providing a roadmap for future research. We also find gaps in the current literature, such as a need for more rigorous theoretical analysis regarding convergence properties and scalability in dynamic environments. These insights pave the way for developing more efficient, adaptive, and robust MPA variants that can address emerging challenges in optimization.

MPA provides several practical benefits over other optimization algorithms, including ease of implementation and minimal parameter-tuning requirements to escape local optima using a form of collective intelligence. Computationally efficient with adaptability toward real-time application, such as resource allocation and feature selection control system optimization is another added area of MPA. Besides, the ease with which the algorithm can be combined with other optimization techniques has favored its use in hybrid systems and further extended the usefulness of the MPA in solving complex, real-world problems. This review, therefore, highlights that the simplicity and flexibility of MPA make it a useful tool for practitioners from all walks of life in addressing optimization problems, both at the academic and applied levels.

This systematic review, therefore, underlines the continuous relevance and transformational potential of MPA as an optimization technique. By connecting the dots between theoretical developments and practical applications, it provides a comprehensive overview of the algorithm's capabilities and limitations, thus laying the ground for future innovations in the field. We expect this work to be a reference point for researchers and practitioners alike, encouraging new contributions that tap into MPA's unique strengths to solve ever more complex optimization problems.

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