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Marine Predators Algorithm for discrete optimization problems: a review of the state-of-the-art

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Abstract

The Marine Predators Algorithm (MPA) is inspired by the hunting behavior of marine predators. This natural phenomenon involves both exploration and exploitation, mirroring the movement patterns of prey and predators. The MPA strategy optimizes solutions by balancing these two processes. It has been applied to various research fields, including Mathematics, Engineering, Medicine, Physics, and Astronomy. This research aims to categorize and investigate the application of MPA to discrete optimization problems. Data from studies published between 2020 and 2023 in the Scopus database were collected. Following the classification of problem types, we provide a summary of MPA's strengths and weaknesses. The critical analysis and investigation section addresses key questions and explores potential future work in the application of MPA to discrete problem-solving.

Keywords: Artificial intelligence, Metaheuristics, Nature-inspired, Comprehensive survey, Systematic literature review

1. INTRODUCTION

Real-world optimization involves finding the optimal values of variables within specified constraints. These constraints can be deterministic or non-deterministic, often leading to NP-hard problems, which are computationally complex. Such problems involve large datasets and search spaces that grow exponentially (Mann Z., 2017). Objective functions can be categorized into two types: maximization and minimization. The complexity of the study increases when multiple objective functions are involved. In terms of mathematical optimization problems, there are two primary categories: discrete and continuous optimization problems.

Discrete problems involve searching for solutions within a finite or countably infinite set of data, encompassing a wide range of problems such as scheduling, traveling salesman, vehicle routing, knapsack, and facility location problems (Bernhard K. and Jens V., 2012). These problems are often NP-hard, meaning they are computationally challenging (Ahmed Z.E. et al., 2020). Optimization techniques aim to find the best possible solutions. Exact optimization methods, such as branch and bound, linear programming, mixed-integer programming, and branch and cut, can guarantee optimal solutions but are often time-consuming. Approximate optimization algorithms, on the other hand, aim to find optimal solutions but may not always find the best possible one. These algorithms are often faster and are suitable for complex problems.

Approximate optimization algorithms can be divided into heuristics and metaheuristics. Heuristics are methods that focus on exploitation and may not guarantee optimal solutions. Metaheuristics incorporate both exploration and exploitation to avoid local optima and often find better solutions for complex problems. Metaheuristics can also be modified and hybridized with other algorithms.

Metaheuristics are inspired by various concepts. There are diverse processes, such as natural processes. Examples of natural process-inspired algorithms include the Artificial Hummingbird Algorithm (AHA), Elephant Herding Algorithm (EHA), Grey Wolf Optimizer (GWO), and Marine Predators Algorithm (MPA). The search process in metaheuristics involves an iterative optimization process that combines strategies from various algorithms to find the optimal solution. According to the Scopus database, the MPA has experienced a significant increase in usage over the years, with a total citation count of 929.

Faramarzi A. et al. (2020) introduced the Marine Predators Algorithm (MPA) as a novel approach to solving complex problems. The MPA has been successfully applied to various research fields, including photovoltaic systems, fog computing, scheduling problems, traveling salesman problems, and image processing. This demonstrates the algorithm's effectiveness and widespread interest.

This research study focuses on applying the Marine Predators Algorithm (MPA) to solve discrete optimization problems. The first section reviews and

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categorizes relevant literature on discrete problems. The second section provides a comprehensive overview of the MPA, including its strengths, weaknesses, and steps. The third section explores the application areas of MPA, as illustrated in Figure 1. The fourth section provides a critical analysis of the MPA. Finally, the conclusion summarizes the research findings.

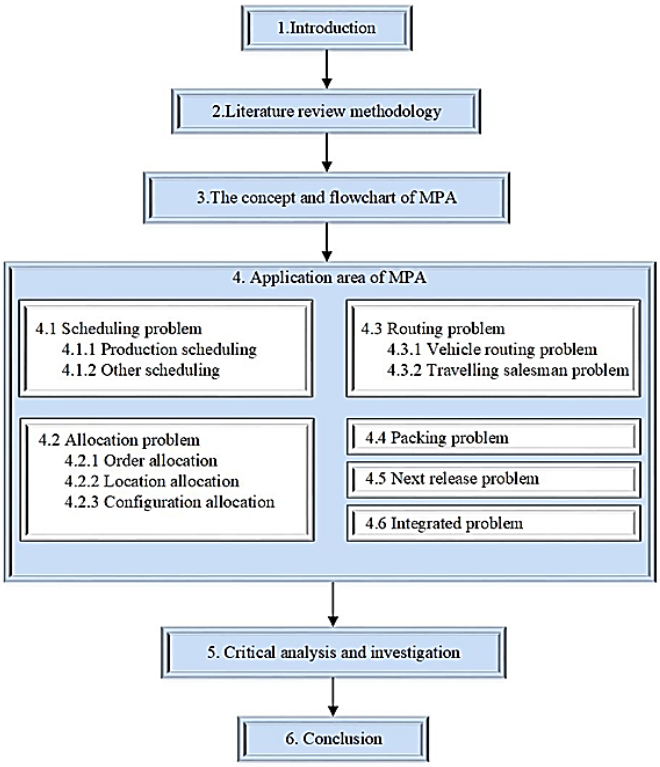

Figure 1 The main title of an article

2. Methodology of the Literature Review

2.1 PRISMA flow review step

The research data was sourced from the Scopus database, which enables filtering results based on criteria like topics, author names, document types, and languages (Burnham J.F., 2006). By specifying relevant criteria, the search can be narrowed down to include only pertinent information, such as abstracts, author names, and publication years. Scopus is a comprehensive database encompassing academic articles from various disciplines, including medicine, technology, agriculture, social sciences, and humanities. This allows for a wide range of research topics to be explored. The keywords used for literature search consist of two main parts, all connected by "and." The first keyword is "Marine Predators *" the second is "Metaheuristics*" A total of 244 related literatures were found shown as figure 2. When considering the period of 2020-2023, the number was reduced to 182. The next step involved selecting works related to engineering and research in English. By examining the titles and abstracts, 72 papers that directly addressed the six discrete problems were identified. This process initially focused on the direct problem titles and their objectives. Subsequently, full-text papers were selected, resulting in a final count of 35 relevant literatures shown as Table 1.

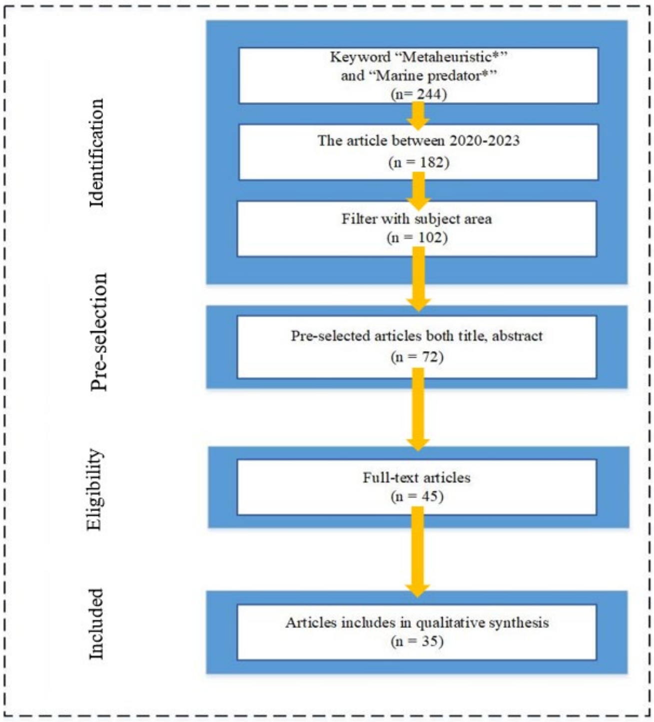

Figure 2 PRISMA flow diagram

Table 1 Literature database

Journals name	Quantity per journal	Total
Computational Intelligence and Neuroscience, IEEE Transactions on Industrial Informatics, Neural Computing and Applications, Energy Reports, Biosensors, Energy, Ecology and Environment, Process Integration and Optimization for Sustainability , China Communications ,	1	25

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Table 1 (Continuous)

Journals name	Quantity per journal	Total
International Journal of Hydrogen Energy, Journal of Renewable and Sustainable Energy, Neural Computing and Applications, Computers and Electrical Engineering, International Journal of Intelligent Transportation Systems Research, Expert Systems with Applications, Engineering Optimization, Results in Control and Optimization, International Journal of Energy Research, Energies, Entropy, Agricultural Water Management, International Journal of Intelligent Engineering and Systems, Electric Power Components and Systems, KSII Transactions on Internet and Information Systems, International Journal of Renewable Energy Research and GMSARN International Journal, International Journal of Intelligent Engineering and Systems, Electric Power Components and Systems, KSII Transactions on Internet and Information Systems, International Journal of Renewable Energy Research and GMSARN International Journal		
Computers and Industrial Engineering, IEEE Access, Mathematics, Pervasive and Mobile Computing, Alexandria Engineering Journal	2	10
Total	**35**	

As summarized in Table 1, the conclusions of all 35 articles were analyzed. The journals most frequently associated with research on DOPs were Computers and Industrial Engineering , IEEE Access, Mathematics, Pervasive and Mobile Computing, and Alexandria Engineering Journal, each contributing 2 articles, representing 5.71% of the total. Other journals from diverse sources each contributed 1 article, making up 2.86% of the total.

2.2 Literature review of DOPs

The research conducted by Liu Q. et al. (2020) focuses on Metaheuristics for discrete optimization problems (DOPs). They categorized these discrete problems into six categories: Scheduling problems, Allocation problems, Routing problems, Next release problems, Integrated problems, and Packing problems. Within these categories, three specific problems were further divided into sub-problems.

Scheduling problems were classified into two types: production scheduling problems and other scheduling problems. Allocation problems were divided into order allocation, location-allocation, and configuration. The routing sub-problems were the traveling salesman problem and the vehicle routing problem, as shown in Table 2.

Table 2 Classification of DOPs from literature review

Type of Problems	Sub-Problems	Number of papers
Allocation problem	Order allocation	1
	Location allocation	13
	Configuration allocation	1
Scheduling problem	Production scheduling	1
	Other scheduling	12
Integrated problem	No sub-problem	3
Packing Problem	Knapsack problem	2
	Bin packing problem	-
Routing problem	Vehicle routing problem	-
	Travelling salesman problem	1
Next Release problem	No sub-problem	1
Total		**35**

2.3 Classification of DOPs

The classification criteria for the six distinct types of discrete problems, based on the literature by Liu Q. et al. (2020), are outlined as follows:

Problem 1: Scheduling Problem.

The subproblem of Production Scheduling is classified based on objective functions related to job sequencing on machines, aiming to minimize working time, costs, or expenses incurred during production.

In the Other scheduling category, the focus is on the operation of the power system, combining water discharge and power generation. The objective functions prioritize managing power generation for maximum efficiency, minimizing carbon emission rates, and reducing power loss.

Problem 2: Allocation Problem.

Allocation problems focus on the allocation of limited resources. They are categorized into three sub-problems:

- **Location Allocation:** This subproblem focuses on finding optimal locations to enhance operational efficiency, such as the placement of distribution centers, service facilities, and distributed generation sources.
- **Order Allocation:** This subproblem involves studying literature related to disassembly processes and balanced lines.
- **Configuration Allocation:** This subproblem examines objective functions related to reconfiguration.

Problem 3: Routing Problems.

Routing problems can be categorized based on their objective functions. Both the Traveling Salesman Problem (TSP) and the Vehicle Routing Problem (VRP) focus on minimizing delivery costs and total distance, but they differ in key aspects. TSP involves finding a single route that visits each customer exactly once and returns to the starting point, with fewer constraints and types compared to VRP. In contrast, VRP involves multiple routes for servicing multiple customers, and its constraints can vary depending on the specific type of VRP.

Problem 4: Packing Problem.

The scope of the packing problem studied includes two sub-problems: the knapsack problem and the bin packing problem. The primary objective is to plan the packing of goods according to orders while optimizing the use of packing space.

Problem 5: Next Release Problem.

The next release problem is relevant to the software industry, which involves creating or developing products tailored to the specific needs of customers.

Problem 6: Integrated Problem.

An integrated problem involves combining multiple objective functions into a single issue. For example, when an allocation problem is combined with a scheduling problem, the goal is to study how to reduce production costs and optimize generation planning for maximum efficiency and cost-effectiveness.

3. THE ORIGINAL OF MPA

3.1 The original of MPA

The Marine Predators Algorithm (MPA) was developed in 2020. This population-based metaheuristic algorithm is inspired by the collective intelligence observed in the hunting behaviors of marine predators in the ocean. MPA utilizes the strategies of intelligent group hunting to tackle optimization problems.

MPA employs two types of movement strategies: Brownian motion, suitable for environments with abundant prey, and Levy motion, more suitable for environments where prey is scarce or difficult to find (Rai R. et al., 2023). The solution search process can be visualized in Figure 3.

Step 1-2: Data Collection

The necessary data collection varies for each problem. For example, the Vehicle Routing Problem requires essential information such as product demands, vehicle types, vehicle capacities, product types, and costs.

Step 3: Parameter Setting

Determine the parameters of the MPA method. There are two primary variables: the number of preys (p) and the number of iterations (i). These variables significantly impact the efficiency of the search for optimal solutions. Additionally, set other essential parameters specific to each problem.

Step 4 Initial Step

The process of randomly a set of initial solution responses to use for refining and evaluating responses in each iteration loop.

Step 5-6: Solution Repair, Evaluation, and Ranking

Calculate the fitness values based on the objective function and refine the initial solutions by incorporating the problem's essential conditions. Subsequently, rank the best solution values and select them as the search agent matrix (SAM) and contract the elite matrix.

Initial Step $$\mathrm{M_0 = M_{min} + rand(M_{max} - M_{min})} \qquad (1)$$

In this context, the variable 'rand' represents a random number generated from a Uniform distribution, with values ranging from 0 to 1. M_{max} and M_{min} values are used as the upper and lower bounds of variables representing the positions of predators and prey, as depicted in Equations (2) and Equations (3), respectively.

$$\text{Elite Matrix} = \begin{bmatrix} \mathrm{M^I_{1,1}} & \mathrm{M^I_{1,2}} & \cdots & \mathrm{M^I_{1,d}} \\ \mathrm{M^I_{2,1}} & \mathrm{M^I_{2,2}} & \cdots & \mathrm{M^I_{2,d}} \\ \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots \\ \mathrm{M^I_{n,1}} & \mathrm{M^I_{n,2}} & \cdots & \mathrm{M^I_{n,d}} \end{bmatrix}_{n*d} \qquad (2)$$

$\mathrm{M^I_{n,d}}$ = the top predator vector replicated n times
n = the number of search agents
d = the number of dimensions

$$\text{Prey Matrix} = \begin{bmatrix} \mathrm{M_{1,1}} & \mathrm{M_{1,2}} & \cdots & \mathrm{M_{1,d}} \\ \mathrm{M_{2,1}} & \mathrm{M_{2,2}} & \cdots & \mathrm{M_{2,d}} \\ \mathrm{M_{3,1}} & \mathrm{M_{3,2}} & \cdots & \mathrm{M_{3,d}} \\ \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots \\ \mathrm{M_{n,1}} & \mathrm{M_{n,2}} & \cdots & \mathrm{M_{n,d}} \end{bmatrix}_{n*d} \qquad (3)$$

$\mathrm{M_{n,d}}$ = presents the $\mathrm{j^{th}}$ dimension of $\mathrm{i^{th}}$ preys
n = the number of search agents
d = the number of dimensions

Step 7-12: Improving Solutions with MPA

Initiating the first iteration based on the core mechanisms of MPA, the process is divided into three primary phases: the Initial Step, the Optimization Step, and the Development Step. This step falls within the Optimization phase.

Stage 1: In this phase, all fish species are designated as search agents that explore the environment for food using Brownian motion or by improving solutions through population-wide exploration using Equation (5). Equation (4) represents Brownian motion. During this stage, prey move at a faster pace than predators, and remaining stationary is generally the optimal strategy for predators.

$$f_B(x;\mu,\sigma) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\left(\frac{(x-\mu)^2}{2\sigma^2}\right)} = \frac{1}{\sqrt{2\pi}} e^{-\left(\frac{x^2}{2}\right)} \quad (4)$$

When $\sigma^2 = 1$ and $\mu = 0$.

While iteration < $\frac{1}{3}$ Max_ iteration

$$\overrightarrow{sz} = \vec{B} \otimes (\vec{E} - \vec{B} \otimes \vec{p}) \quad i = 1,\ldots,N$$
$$\vec{p} = \vec{p} + P.\vec{R} \otimes \overrightarrow{sz}_i \quad (5)$$

sz = The magnitude of the step movement
B = Random vector representing Brownian motion
E = Matrix of the best fitness value
p = Matrix of the random fitness value except the best fitness value
P = Constant value (The suggested value is 0.5)
R = Uniform random vector ranging from [0, 1]
N = Number of the populations

Stage 2: When approximately two-thirds of the total iterations have been completed, the hunting proficiency of each fish species can be assessed. This determines whether each type exhibits high or lower hunting skills. The population is then divided, with the top half classified as predators and the bottom half as prey. Subsequently, the entire population of predators will move to search for food using Brownian motion from Equation (4) and randomly select the best solution using Equation (6).

While $\frac{1}{3}$ Max_iteration < iteration < $\frac{2}{3}$ Max_iteration

$$\overrightarrow{sz} = \vec{B} \otimes (\vec{B} \otimes \vec{E} - \vec{p}) \quad i = 1,\ldots,\frac{N}{2}$$
$$\vec{p} = \vec{E} + P.CF \otimes \overrightarrow{sz} \quad (6)$$

When $CF = \left(1 - \frac{iteration}{Max\ iteration}\right)^{\left(2\frac{iteration}{Max\ iteration}\right)}$

Prey refer to solutions that have not performed well in the past 50%. These preys will use Levy movement, represented by Equation (8), to hunt for food or explore solutions according to Equation (12).

$$f_L(x;\alpha,\gamma) \approx \frac{\gamma\Gamma(1+\alpha)\sin\left(\frac{\pi\alpha}{2}\right)}{\pi x^{(1+\alpha)}} \quad (7)$$

$$levy\ (\alpha) = 0.05\frac{x}{|y|^{\frac{1}{\alpha}}} \quad (8)$$

$$x = \text{Normal}\ (0,\sigma_x^2) \quad (9)$$

$$y = \text{Normal}\ (0,\sigma_y^2) \quad (10)$$

$$\sigma_x = \left[\frac{\Gamma(1+\alpha)\sin\left(\frac{\pi\alpha}{2}\right)}{\Gamma\frac{(1+\alpha)}{2}\alpha\, 2^{\frac{(\alpha-1)}{2}}}\right]^{\frac{1}{\alpha}} \quad (11)$$

When $\alpha = 1.5$ and $\sigma_y = 1$

$$\overrightarrow{sz} = \vec{L} \otimes (\vec{E} - \vec{L} \otimes \vec{p}) \quad i = \frac{N}{2},\ldots,N$$
$$\vec{p} = \vec{p} + P.\vec{R} \otimes \overrightarrow{sz} \quad (12)$$

L = Random vector of levy motion

Mantegna R.N. (1994) introduced a random variable with a probability density function that closely resembles a Levy stable distribution. This distribution is characterized by control parameters that can be arbitrarily set within the range of [0.3,1.99].

Stage 3: When the number of iterations surpasses two-thirds of the total iterations, predators will actively hunt prey while the prey consume their own food. Subsequently, both predators and prey will move using Levy motion for the entire population, as described in Equation (13).

While iteration > $\frac{2}{3}$ Max_iteration

$$\overrightarrow{sz} = \vec{L} \otimes (\vec{L} \otimes \vec{E} - \vec{p}) \quad i = 1,\ldots,N$$
$$\vec{p} = \vec{E} + P.CF \otimes \overrightarrow{sz} \quad (13)$$

The Development Step of MPA involves predators, generally at an 80% hunting proficiency level, facing disturbances from fishing gear or water currents in their marine environment. To escape local optima, similar to the effect of Fish Aggregating Devices (FADs), predators may venture outside this area 20% of the time to hunt prey. The following mathematical equations are used for solution improvement:

$$\vec{p} = \begin{cases} \vec{p} + CF\left[\vec{X}_{min} + \vec{R} \otimes (\vec{X}_{max} - \vec{X}_{min})\right] \otimes \vec{U} & \text{if } r \leq FADs \\ \vec{p} + [FADs(1-r) + r]\,(\overrightarrow{p_{r1}} - \overrightarrow{p_{r2}}) & \text{if } r > FADs \end{cases} \quad (14)$$

FADs = the probability of an effect occurring in the optimization process, with a value of 0.2. If a randomly sampled value of r is less than or equal to 0.2, use the equation corresponding to the condition r ≤ FADs. Otherwise, use another equation.
U = The binary vector with array of zero and one.
r = the uniform random number between 0 to 1
r_1 , r_2 = random indexes of prey matrix

Step 13-18 The evaluation of answers and ranking them based on quality and improve answers with FADs equation.

When iterating according to the MPA conditions, starting from each round following step 7, values evaluated and adjusted to arrange the best fitness value for comparison with the post-adjustment answer using the FAD's effect. A random value of r generated to use in Equation (14). After adjustment, if researcher found that the answer has improved compared to the previous one by utilizing this equation, replace this answer in the search agent matrix and iterate in the next round.

Steps 19-20: Repeat until completing the iteration.

Display the best answer value (minimum or maximum value) obtained after iterating until reaching the maximum iterations.

3.2 The strength and weakness of MPA

Each algorithm was developed based on different inspirations. The strengths of each algorithm, if improved upon, could enhance the quality of the best solution. Conversely, integrating other algorithms through hybrid approaches could also improve the best solution. Table 3 illustrates the strengths and weaknesses of the Marine Predators Algorithm as follows.

Table 3 The strength and weakness of MPA

Strength	Weakness
- Easy to modify - Flexible for modification and integration with other algorithms - Few parameters - An effective process for memory saving - Includes both Exploration and Exploitation processes and features a single phase where both strategies are executed simultaneously - FAD's effect on escaping local optima	- Fast convergence to local optima

4. APPLICATION AREAS OF MPA

The categorization of the application area is based on data from the research in Table 4, with details outlined in the following sections.

4.1 Scheduling problem

The study by Smanchat S. and Viriyapant K. (2015) identified five key components of scheduling criteria: Time, Cost, Reliability, Energy consumption, and Security. These components were used to categorize scheduling problems into Production scheduling and other scheduling. The research aim focused on investigating these components within the context of Production scheduling. Power system-related research was classified as other scheduling.

4.1.1 Production scheduling

Production scheduling involves organizing schedules for all types of production, whether related to machinery or various operations. In the study by Liu Q. et al. (2020), Production scheduling is divided into two categories: Job shop scheduling problems (JSPs) and Flow shop problems (FSPs).

JSPs refer to non-continuous production where multiple machines are involved and multiple jobs are processed by one machine without a strict order (Ullah H. and Parveen S., 2011). For example, jobs can be newly introduced, come from previous machines, arrive from WIP (work in progress), or be completed products. In general, the arrangement of jobs in JSPs aims to minimize production costs. This includes reducing production time, improving machine efficiency, and optimizing various time-related metrics such as Flow time, Latency, Tardiness, and Makespan.

FSPs, on the other hand, involve continuous production with five main objectives: Completion times, Punctuality, Environmental sustainability, Cost, and others (minimizing work in progress, noise, and pollution). Production in FSPs follows a strict sequence, meaning all jobs must pass through the same machines in a predetermined order (Ribas I. et al., 2010). Due to the inherent complexity of Production scheduling as a NP-Hard problem, the use of Metaheuristics to search for solutions has gained popularity for this type of problem.

Wei Y. et al. (2022) proposed a hybrid method called EOSMA to reduce completion time. In addition, Centroid Opposition-based Computation (COBC) was utilized in specific iterations to enhance exploration and exploitation efficiency, thereby avoiding getting stuck in local optimal solutions. The results obtained from EOSMA were compared with those from MPA and other algorithms to assess the effectiveness of the proposed approach in job shop scheduling.

4.1.2 Other scheduling

The categorization of other scheduling includes the study of hydrothermal scheduling, task scheduling for IoT, and other energy-related activities.

Hydrothermal scheduling is crucial to the power sector, as it significantly impacts the overall cost and profitability of exporting electricity generated from hydropower, a popular renewable energy source. The working principle of hydrothermal scheduling involves releasing water from a higher elevation to generate electricity in hydropower plants. Key components in this process include the power generator, turbine, transformer, and other equipment that facilitate the transmission of electricity based on demand. There are two types of scheduling: short-term and long-term planning. Short-term planning involves the organization of schedules on a daily or weekly basis, including the hourly generation of power system data. In contrast, long-term scheduling involves annual planning, considering variables such as water flow rates and seasonal load demands. Hydrothermal scheduling aims to minimize production and thermal costs while maximizing hydroelectric power generation. (Gupta S.K. and Malik M., 2016). The constraints of the hydrothermal model include

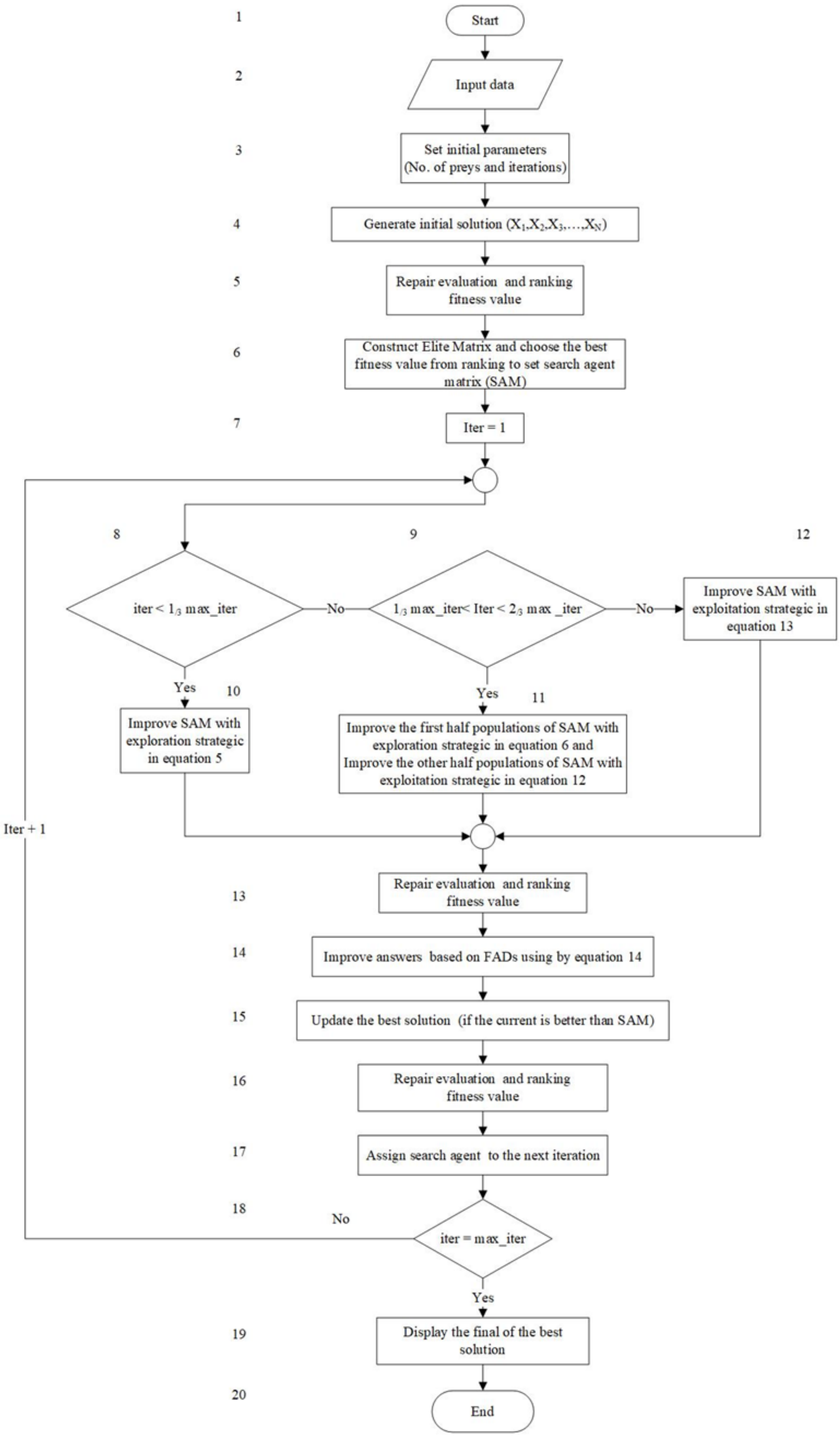

Figure 3 Flow chart of MPA

Table 4 Application area of MPA

Author & year	Application area	Objective function	Type of MPA approach	Results
Wei Y. et al. (2022)	Scheduling Problem (Production Scheduling)	Optimize for reduced the completion time	MPA	The results and statistical evaluation demonstrate that the suggested EOSMA outperforms alternative algorithms
Abd Elaziz M. et al. (2021)	Scheduling Problem (Others Scheduling)	Reduce both completion time and overall energy usage	Modified MPA	AOAM exhibits promise and effectively tackles task scheduling compared to other comparative methods
Abdel-Basset M.,Mohamed R.,Elhoseny M., et al. (2021)	Scheduling Problem (Others Scheduling)	Optimize for reduced energy usage, completion time, flow duration, and carbon emission rate	Modified MPA	The enhanced MMPA demonstrates superior performance over all other algorithms, including two previous versions
Abdel-Basset M.,Moustafa N., et al. (2021)	Scheduling Problem (Others Scheduling)	Optimize for reduced energy usage, completion time, flow duration, and carbon emission rate	Modified MPA	Experimental results indicate that MHMPA yields superior outcomes across various performance metrics
Attiya I. et al. (2022)	Scheduling Problem (Others Scheduling)	Optimize for reduced the completion time	Hybrids MPA	CHMPAD can achieve average makespan time superiority over alternative algorithm
Kuang F. et al. (2022)	Scheduling Problem (Others Scheduling)	ANN-based workload prediction and optimize resource provisioning	Modified MPA	The proposed scheme of the OMPA algorithm can yield superior outcomes when compared to alternative metaheuristic algorithms and scheduling strategies
Chen D. and Zhang Y. (2023)	Scheduling Problem (Others Scheduling)	Optimize for reduced energy usage, completion time, and throughput.	Modified MPA	In both scenarios, DAMPA algorithm achieved higher throughput
Shaker Y.O. et al. (2021)	Scheduling Problem (Others Scheduling)	Reducing operational expenses, emissions, and power supply failure likelihood while maximizing renewable energy utilization	MPA	The comparisons affirmed the superior performance of the proposed MOHGS over another algorithm proposed

Table 4 (Continued)

Author & year	Application area	Objective function	Type of MPA approach	Results
Ferahtia S. et al. (2022)	Scheduling Problem (Others Scheduling)	Reducing overall operational expenses	MPA	The proposed EMS decreases operating expenses, enhances economic gains, and mitigates problem complexity
Kong F. et al. (2022)	Scheduling Problem (Others Scheduling)	Optimizing the power output of cascade hydropower plants while minimizing the ecological impact on water volume	Modified MPA	MOIMPA can proficiently address conflicting power generation and ecological objectives
Sowmya R. and Sankaranarayanan V. (2022a)	Scheduling Problem (Others Scheduling)	Optimize travel efficiency by minimizing time spent enroute to the charging station, waiting, and charging, while maximizing financial gains	Modified MPA	The outcomes of OBMPA demonstrate a substantial decrease in travel time, queue time, recharging time, and energy costs
Sowmya R. and Sankaranarayanan V. (2022b)	Scheduling Problem (Others Scheduling)	Optimize electricity cost for charging/discharging while accounting for battery capacity, C-rating, and physical limitations	Modified MPA	The statistical analysis indicates that IMPA outperforms other algorithms
Shaheen A.M.,Elsayed A.M.,Ginidi A.R., et al. (2022)	Scheduling Problem (Others Scheduling)	Optimize for minimal total fuel expenses	Modified MPA	The proposed IMPOA exhibits stability, with the optimal solution arriving faster than conventional MPOA
Eid A. et al. (2021)	Allocation Problem (Location Allocation)	Optimize to reduce overall reactive power losses	Modified MPA	IMPA yields superior results compared to MPA, AEO, and PSO algorithms
Amroune M. (2022)	Allocation Problem (Location Allocation)	Optimize for reduced power loss, voltage variance, and enhanced voltage stability	MPA	AEO algorithm achieves a higher success rate than the competition algorithms
Dai Y. et al. (2022)	Allocation problem (Location allocation)	Optimize to reduce the discrepancy in state estimation	Modified MPA	The enhanced MPA for mobile edge computing outperforms PSO and Random algorithms
Dharavat N. et al. (2022)	Allocation Problem (Location Allocation)	Optimize to reduce energy wastage and improve voltage stability across the distribution network	MPA	MPA algorithm minimizes power loss to the maximum extent compared to other algorithms

Table 4 (Continued)

Author & year	Application area	Objective function	Type of MPA approach	Results
Sadiq A.S. et al. (2022)	Allocation problem (Location allocation)	Efficient power distribution to accommodate maximum users while minimizing expenses	Modified MPA	The NMPA algorithm demonstrates its superiority when compared with MPA, GWO, SSA, MVO, and MFO
Shaheen A.M.,Elsayed A.M.,El-Sehiemy R.A., et al. (2022)	Allocation Problem (Location Allocation)	Optimizing to reduce overall active power dissipation and improve voltage stability	Modified MPA	MMPO yields superior results over conventional MPO and previous techniques in terms of minimizing overall
Su Y. et al. (2022)	Allocation Problem (Location Allocation)	Optimizing to achieve maximum secrecy capacity and energy efficiency in secure communication	Modified MPA	QMPA yields better results than other algorithms
Sulaiman M.H. and Mustaffa Z. (2022a)	Allocation Problem (Location Allocation)	Optimizing to reduce both energy wastage and expenses	MPA	TLBO and HBO outperform competitive algorithms
Vijayalakshmi V.J. et al. (2022)	Allocation problem (Location allocation)	Optimizing to reduce energy wastage, voltage fluctuations, land expenses, and installation expenses for EV charging infrastructure	Modified MPA	The m2MPA outperform competitive algorithms
Belbachir N. et al. (2023)	Allocation Problem (Location Allocation)	Optimizing to reduce technical indices such overall power and time	MPA	MPA achieves the best results across all cases
Hoballah A. and Azmy A.M. (2023a)	Allocation Problem (Location Allocation)	Reducing operational expenses, curtailing electric load, minimizing power loss, and optimizing the allocation of reactive power	Hybrids MPA	The HSRA is economically managed using optimization algorithms, notably HGWO and MPA, to minimize operational costs while considering power system constraints
Jain S. et al. (2023)	Allocation problem (Location allocation)	Optimizing crop yield to maximize net returns under varying water conditions	MPA	MPA demonstrates superiority in water resource allocation
Pratap A. et al. (2023b)	Allocation problem (Location allocation)	Reducing voltage fluctuations, overall power loss, and investment expenses to enhance voltage stability	MPA	The effectiveness and performance of the HAVOPS algorithm surpass AVOPS, MPA, AGTO, and GA

Table 4 (Continued)

Author & year	Application area	Objective function	Type of MPA approach	Results
Kusuma P.D. and Novianty A. (2023)	Allocation Problem (Order Allocation)	Reducing overall expenses, delays, and defects	MPA	MIO also achieving minimum cost, minimum lateness, and minimum total defects in solving order allocation problems
Rezk H. et al. (2021)	Allocation Problem (Configuration Allocation)	Optimizing to extract the maximum global power from the array	MPA	The efficiency of COA in optimally reconfiguring the shaded array.
Amroune M. (2022)	Integrated Problem	Optimizing to minimize generation expenses, covering thermal and stochastic wind power generation costs, active power losses, voltage deviations, and emissions	MPA	The EO algorithm delivers the most favorable outcomes
Pham L.H. et al. (2022)	Integrated Problem	Optimize for the lowest overall cost of the facilities	MPA	Comparative analysis of results reveals that ECSA is more efficient than these methods, and ECSA can minimize the operation cost of the system
Vo V.S. et al. (2023)	Integrated problem	Optimizing to reduce the cost of generation	MPA	SMA yields the lowest cost among the compared methods.
Al-qaness M.A.A. et al. (2022)	Next Release Problem	Maximizing the accuracy and efficiency of fall detection with data from body-worn sensors	MPA	The modified algorithm exhibited superior accuracy solution
Liang S. et al. (2022a)	Routing Problems (Travelling salesman problem)	Minimizing the path length	Modified MPA	The utilization of ACMPA is most suitable for addressing the Travelling Salesman Problem
Abdel-Basset M.,Mohamed R.,Chakrabortty R.K., et al. (2021)	Packing Problems (The knapsack problem)	Optimize earnings. (Do not exceed the knapsack limit)	Modified MPA	The results of the BMPA are better than competitive algorithms
Ervural B. and Hakli H. (2023)	Packing Problems (The knapsack problem)	Optimize earnings. (Do not exceed the knapsack limit)	MPA	Experimental findings demonstrate that BinRSA significantly enhances solution accuracy and robustness compared to other methods for solving 0–1 KP

water discharge rate, power generation, volume of water reservoirs, power balance, water spillage, and the operating capacity of hydro and thermal units. As a result, extensive research has been conducted on Fog computing in IoT environments. These studies aim to improve efficiency by optimizing task scheduling and identifying optimal values for four key metrics: makespan, energy usage, flow duration, and emission rate. The findings of these studies contribute to more efficient task distribution among devices, allowing users to specify desired reductions in energy consumption and emissions. An enhanced version of MPA has been developed, incorporating the latest positions rather than relying solely on the previous best position. A rank-based approach is integrated to reset and mutate towards the optimal solution. Additionally, to address local optima, half of the population is randomly reset after a certain number of iterations, while the remaining half mutates towards the best solution found so far. Upon evaluation of performance metrics such as makespan, energy usage, flow duration, emission rate, and fitness against competing algorithms, it became apparent that the Adapted Marine Predators algorithm outperforms others in addressing these challenges.

Abd Elaziz M. et al. (2021) aimed to address the job scheduling problem in fog computing and maximize the makespan measure, thereby providing customers with the highest possible service quality while minimizing total energy consumption. To achieve this, AOA with MPA enhances the best solution, outperforming the original AOA.

Abdel-Basset M.,Mohamed R.,Elhoseny M., et al. (2021) conducted a study on task scheduling in IoT environments. Fog computing was developed to reduce latency, improve real-time response to users, and enhance Quality-of-Service (QoS), among other benefits. The improved MPA approach involves reinitializing and mutating based on a ranking strategy to converge towards the best solution. Additionally, it entails randomly reinitializing half of the population after a set number of iterations to avoid becoming trapped in local optimal solutions and mutating the remaining half towards the best solution achieved so far. Das R. and Inuwa M.M. (2023) designed a system to manage data distribution from the Cloud, which can be overloaded due to a large number of users. Fog nodes play a crucial role in data management by dividing tasks into smaller subgroups based on usage.

Abdel-Basset M.,Moustafa N., et al. (2021) aimed to minimizing flow time, energy consumption, and makespan. This paper explores the enhancement of MPA through its integration with the polynomial mutation mechanism, denoted as MHMPA. The algorithm's performance is improved by substituting the Cauchy distribution for the Levy motion. The aim is to enhance the algorithm's convergence and reduce its susceptibility to becoming trapped in local minima.

Attiya I. et al. (2022) aimed to minimize completion time or makespan when scheduling IoT applications. To achieve this, researchers propose a hybrid algorithm, CHMPAD, which is utilized to circumvent local optima by enhancing the fundamental ChOA's exploitation potential.

Edge computing, a processing paradigm that provides real-time processing capabilities near the network edge, is central to this approach. The primary concept involves deploying Edge devices close to end-user devices to maximize data availability for rapid data processing and minimize delays. Edge computing collaborates with the central Cloud system, acting as a hub. With the increasing adoption of 5G technology in modern smartphones, the adoption of Edge computing has experienced significant growth.

Kuang F. et al. (2022) investigated task scheduling and resource allocation within Mobile Edge Computing (MEC), aiming to minimize the makespan, the number of deployed Virtual Machines (VMs), and the instances of missed deadlines for workflows during scheduling. To achieve these goals, the scholars propose an enhanced version of the Marine Predators Algorithm (MPA) incorporating Local Attraction (LA) and multiple Oblivious-Based Learning (OBL) techniques. These modifications are designed to address the local optima encountered in the MPA algorithm and improve its effectiveness. Additionally, the study introduces a multi-layer feed-forward Artificial Neural Network (ANN) model for workload prediction in MEC. This model enables the provisioning of necessary virtualized resources based on workload predictions, thereby streamlining the overall scheduling process.

Chen D. and Zhang Y. (2023) aimed to cloud computing is the convergence of hardware and software to provide users with limitless services, enabling secure data storage. It comprises four main components: Network, Service, Storage, and Application (Sadashiv and S. M. D. Kumar, 2011). However, typical usage necessitates the utilization of a web browser to access the services. In cloud computing scheduling, tasks are segregated into two tiers: the initial phase involves allocating suitable virtual resources for tasks submitted by users. In contrast, the subsequent phase involves assigning appropriate hosts for these virtual resources. The goal is to optimize and minimize makespan, energy consumption, and throughput. DAMPA integrates advanced tactics such as the predator crowding degree ranking strategy, comprehensive learning strategy, and stage-independent control of the stepsize-scaling strategy. Moreover, other scheduling techniques also enhance operations' stability during fluctuating power sources and load changes. This includes reducing electricity grid disturbances and enabling the integration of multiple energy sources, including renewable energy and distributed energy generation systems. The distribution system is divided into three forms: DC Microgrid, AC Microgrid, and Hybrid Microgrid (Santoso H. et al., 2013). The case study entails a Hybrid Microgrid System with a blend of fuel cells, photovoltaic, wind power, batteries, and supercapacitors. Another scenario comprises a standalone microgrid powered by environmentally friendly alternative energy sources such as photovoltaic arrays, wind turbines, fuel cell systems, microturbines, and battery storage systems. The selection of WT/PV/FC/Battery is a management strategy for handling the Microgrid, with particular emphasis placed on battery maintenance to extend their lifespan, as frequent replacements may result in higher costs than other equipment.

Shaker Y.O. et al. (2021) focuses on a Hybrid Microgrid System that leverages localized renewable energy resources across individual DC or AC microgrids. The aim is to minimize four parameters: operational costs, gas emissions, power supply loss probability, and maximize the renewable factor through utilizing the HGSO. This methodology is compared with alternative algorithms, including MPA, to determine which algorithm achieves the lowest values across the four parameters.

Ferahtia S. et al. (2022) focuses on minimizing daily operation costs using the Marine Predators Algorithm to optimize energy-related parameters such as energy storage, load profiles, and other factors daily to achieve the lowest cost based on the objective function. Research in energy-related technologies coupled with environmental conservation has gained significant attention in recent times due to environmental degradation caused by human activities. Air pollution is a primary environmental concern, with approximately 60-70% of gases emitted from vehicles. The pollutants can have severe consequences on human health, with an estimated 9 million deaths related to poor air quality in 2019, of which the highest proportion is attributed to air pollution, accounting for 6.7 million deaths (Parvez S.M. et al., 2021). Consequently, efforts have been directed towards advancing Electric Vehicles (EVs) technology to conserve fuel, reduce costs, and improve air quality. EVs provide benefits such as savings on fuel expenditure, reduced electricity rates, and higher energy efficiency per kilometer compared to traditional fuel-based vehicles. Additionally, electric vehicles offer the advantage of zero emissions, as they do not release harmful gases that contribute to environmental degradation (Sanguesa J.A. et al., 2021). EVs are classified into five categories based on their engine and configuration: Battery Electric Vehicle, Plug-in Hybrid Electric Vehicle, Hybrid Electric Vehicle, Fuel Cell Electric Vehicle, and Extended range Electric.

Sowmya R. and Sankaranarayanan V. (2022a) aimed to the charging schedule for EVs involves assigning charging stations to each vehicle to inform users about the charging queue. The objective is to minimize travel time by selecting the nearest charging station. This procedure incorporates the enhanced MPA with the Opposition-Based Learning (OBL) mechanism during initial solution generation. Additionally, OBL is employed to select the best solution before computing the Fitness value. The final step involves establishing the Elite matrix for further optimization.

Sowmya R. and Sankaranarayanan V. (2022b) focuses on the objective of electric vehicle scheduling is to decrease the overall electricity cost associated with charging and discharging the battery capacity while maintaining the minimum allowable State-of-Charge deviation limit. This optimization is achieved through the enhanced Marine Predator algorithm, incorporating the Opposition-Based Learning mechanism strategy. By using the OBL Strategy, the algorithm gains improved exploration and exploitation capabilities.

Kong F. et al. (2022) aimed to enhance overall cascade power generation while minimizing the negative impact on ecological water volume. The researchers employ the "Enhanced Marine Predators Algorithm" combined with the Fast-Sorting approach to achieve this goal.

Shaheen A.M.,Elsayed A.M.,Ginidi A.R., et al. (2022) investigated power plants that generate heat energy through fossil fuel combustion experience high heat energy losses, in addition to causing environmental destruction and delivering electricity to end-users, resulting in wasted fuel costs. The equation also achieved an improved MPA to update the prey position after three phases of the original MPA. The Combined Heat and Power (CHP) system contributes to a higher overall fuel utilization efficiency of 70-90% (Wu D.W. and Wang R.Z., 2006). This is achieved by simultaneously producing electricity and heat energy from the same engine, reducing fuel consumption. The objective function of this study is to optimize the heat and power generation schedule using an improved marine predators algorithm. Part of the optimization involves updating the prey's position using equations after iteratively looping under three specified conditions. This modification allows for the movement of prey and predators beyond their original positions, as defined in the original algorithm.

4.2 Allocation problem

Allocated various limited tasks or resources to achieve maximum efficiency or performance while minimizing losses. From collecting research papers related to the Allocation problem, there were 15 papers, accounting for 42.86%. These papers are categorized into

Order allocation, Location Allocation, and Configuration allocation.

4.2.1 Order allocation

Supplier search and order allocation are critical business processes that directly affect costs. According to Naqvi M.A. and Amin S.H. (2021) examples of single objective functions include minimizing cost, maximizing profit, and maximizing performance. On the other hand, multiple objective functions involve studying multiple objectives simultaneously, such as pairing Min. Cost or Max. Profit with Max. Quantity, the best quality, and green value in the manufacturing industry.

In the study conducted by Kusuma P.D. and Novianty A. (2023) , order allocation problems were addressed using the Multiple Interaction Optimizer (MIO). The MIO generates random values to optimize cost, lateness, and defects. The results were compared with other algorithms like PSO, MPA, GWO, SMA, and GSO. The search process is influenced by factors like the number of customers, suppliers, production capacity, order quantity, and the manufacturer's capacity.

4.2.2 Location Allocation

Distributed generation (DG) is a power distribution system that can both supply and receive electricity, integrating multiple technologies. DG sources can provide three types of energy: renewable (biomass, solar, wind, hydro), non-renewable (gas turbines, microturbine, combustion turbines), and energy storage (batteries, flywheels, supercapacitors) (Adajah Y.Y. et al., 2021). DG technology aims to distribute electricity widely, even in remote areas, using renewable sources and reducing voltage losses. The general objective function of DG models often involves random value generation to optimize the allocation of DG resources. This includes minimizing energy losses, improving voltage regulation, reducing investment costs, and minimizing operational expenses. The goal is to determine the optimal location and size of DG resources to maximize efficiency and minimize overall costs.

Eid A. et al. (2021) investigated the optimal placement and sizing of distributed generation (DG) units to achieve multiple objectives, including minimizing total voltage deviation, enhancing network reliability, and improving system security. The study varied the number of shunt capacitors and DG units, considering both unity and optimal power factors. The Improved Marine Predators Algorithm combined with the Multi-Verse Optimizer (MVO) equation was employed in the post-iteration step to refine the solutions after each iteration.

Younesi S. et al. (2021) aimed to minimize energy consumption by combining the Marine Predators Algorithm (MPA) with parallel computation to reduce solution time (Dharavat N. et al., 2022). The study analyzed the allocation of distributed generation (DG) units, shunt capacitors (SCs), and electric vehicles (EVs) in various scenarios: single/multiple DG, DG with SCs, and DG without SCs. MPA was used to determine suitable locations for DGs, SCs, and EVs. Following the MPA steps, the best solutions from each round were used to calculate minimum power loss and establish the optimal positions and capacities for DGs and SCs.

Vijayalakshmi V.J. et al. (2022) used the Marine Predators Algorithm (MPA) and Symbiotic Organisms Search (SOS) to optimize the placement and capacity of rapid electric vehicle charging stations powered by renewable sources. These algorithms were applied in both the exploration and exploitation phases, with SOS being used after updating the solutions using the FADs equation. This approach enabled the efficient allocation of fast electric vehicle charging stations and the effective utilization of available energy resources.

Pratap A. et al. (2023a) aimed to enhance the efficiency of distributed generation (DG) and distribution static compensators (DSTATCOMs) by minimizing energy loss, voltage fluctuation, land expenses, and installation costs for electric vehicle charging stations. In contrast, Zellagui M. et al. (2022) used MPA to determine the optimal placement and sizing of renewable DG units within a smart grid, focusing on reducing the cost associated with location and sizing while improving system security and defense. In a separate study, Belbachir N. et al. (2023) employed MPA to allocate renewable DG between photovoltaic and wind turbine generators, considering specific locations that deviate from the general allocation problem by incorporating the operating time index and coordination time interval index. Additionally, Hoballah A. and Azmy A.M. (2023b) utilized MPA to allocate power during peak demand for hot spinning amidst disturbances among power generators, determining appropriate parameters for various objectives such as generator scheduling, reactive power distribution, voltage stability (regarding power flow constraints), and load reduction to prevent cascading failures. Beyond power source allocation, alternative resources like water were also investigated. Jain S. et al. (2023) studied water resource distribution in three forms—seasonal rainfall, groundwater, and surface water—in each region to maximize agricultural productivity.

Shaheen A.M.,Elsayed A.M.,El-Sehiemy R.A., et al. (2022) investigated methods to improve photovoltaic hosting capacity using a two-stage approach. In the first stage, fixed photovoltaic sizes were varied to reduce the total sum of voltage violations. In the second stage, the Marine Predators Algorithm (MPA) was used to optimize locations and determine the optimal sizes and operation strategies of static var compensator units for the photovoltaic locations.

Amroune M. et al. (2022) determined the optimal location and sizing of distributed generation (DG). The objective function incorporated active power

loss, voltage deviation, and the voltage stability index to select the most optimal solutions for each algorithm.
In terms of technology, edge computing was developed to process data locally at the enterprise, gateway, and device levels. This allows all components of the system to perform data processing tasks previously dependent on transmitting extensive data to the cloud.

Sulaiman M.H. and Mustaffa Z. (2022b) additionally addressed the allocation issues of Flexible AC Transmission Systems (FACTS) devices in Optimal Power Flow (OPF) to minimize power loss and cost. Four case studies were conducted, considering two approaches for power loss minimization: one involving Static VAR Compensators (SVCs) and Thyristor-Controlled Series Compensation (TCSC) or Thyristor Controlled Phase Shifters (TCPSs), and the other focusing on cost minimization.

Currently, mobile phones are the most popular IoT devices, primarily used for work and communication (Ahmed A. and Ahmed E., 2016). The objective function of mobile edge computing aims to minimize latency, energy consumption, and radio utilization while maximizing throughput and optimizing resource allocation (Dai Y. et al., 2022). In optimal cooperative sensing and resource allocation, the goal is to minimize estimation errors related to transmission delay, sensor-edge association, computed resource allocation, and subcarrier allocation. Due to the complexity of the problem, the Marine Predators Algorithm (MPA) is applied to determine the relationship between the sensor and the edge estimator, as well as subcarrier allocation (Sadiq A.S. et al. (2022). Non-orthogonal multiple access (NOMA) on 5G networks is developed to support high data transmission in densely populated areas. Power allocation for NOMA and visible light communications on 5G networks is achieved using the New Modified Predator Algorithm in the exploration and exploitation steps. Additional equations are included in the original MPA to control the step size of predators and introduce parameter 'w' for balancing exploration and exploitation (Mei W. et al., 2021). In the context of IRS-assisted IoT systems, location-allocation is optimized to maximize capacity and energy efficiency using the quantum-inspired marine predator algorithm (Su Y. et al., 2022). This involves additional parameters in the initial step and evaluation, mainly updating quantum rotation angles and quantum positions during exploration.

4.2.3 Configuration allocation

Configuration allocation is a specific type of allocation problem that involves optimizing the arrangement or configuration of elements to achieve a desired outcome. An example is the inventory configuration problem, where the goal is to rearrange production monitors to minimize costs. Currently, the use of fossil fuels has significant long-term consequences, such as releasing greenhouse gases into the atmosphere. Alternative energy sources or green energy are being used in various aspects, including solar energy to reduce energy losses in electronic devices, there is a need to study and determine critical values within circuit boards (Sharma D. et al., 2023). Rezk H. et al. (2021) performed reconfiguration on a 9x9 photovoltaic array with the objective of maximizing global power. They used the coyote optimization algorithm (COA) and compared its performance to the Marine Predators Algorithm (MPA).

4.3 Routing problem

4.3.1 Travelling salesman problem

Liang S. et al. (2022b) improved the Marine Predators Algorithm (MPA) for the Travelling Salesman Problem (TSP) by introducing Adaptive Weights and Logistic Chaos Factors in the exploration and exploitation steps. Adaptive Weights enhance the efficiency of the global search, making it faster and covering a broader area. Logistic Chaos Factors help the algorithm escape local optima by using the R-value equation to minimize the total path. The objective function considers two critical variables: the distance between cities and the city node. TSP, being an NP-hard problem, is typically solved using metaheuristics. To compare the performance of MPA, other algorithms such as Sine Cosine Algorithm (SCA), Moth Flame Optimization (MFO), and Chaos Optimization Algorithm (ChOA) were incorporated for testing.

4.4 Next release problem

The primary objective of this study is to identify the optimal decision points that maximize customer satisfaction. This can be achieved by continuously developing internal software within the organization responsible for collecting, analyzing, and storing various documents (Marghny M.H. et al., 2022). The software should be responsive to customer needs and ensure convenient working hours, considering the resources available for each project. In the context of fall detection and daily activity recognition (walking, running, sitting, standing), algorithms can be used to optimize sensor datasets through feature extraction. This aims to reduce processing time, enhance data accuracy, and improve activity categorization efficiency. The related optimization equation focuses on minimizing costs, which impacts both manufacturers and users (Al-qaness M.A.A. et al., 2022).

4.5 Integrated problem

In this type of problem categorization, the classification is based on the combination of study topics, including Scheduling, Allocation, Routing, and Next Release problems. When two or more of these problems are combined, it is referred to as an Integrated Problem Amroune M. (2022) integrated wind power with generators. Pham L.H. et al. (2022) integrated wind

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power, photovoltaic power, hydropower, and thermal power with generators. Vo V.S. et al. (2023) studied the generation problem integrated with three power plants (thermal power, hydropower, and photovoltaic power) to find values that minimize the cost of generators, stochastic wind power generation, total power losses, voltage deviation, and emission rate.

4.6 Packing problem

The knapsack problem involves efficiently packing items of different weights into containers to maximize value while minimizing total weight. In one scenario, the items' weights do not exceed the knapsack's capacity constraint, resulting in maximum profit (Pradhan T. et al., 2014). The 0-1 knapsack problem is a variant where items are either selected or not. The Marine Predators Algorithm (MPA) was developed as a binary algorithm for solving this problem. Important variables in the objective function include the weight and profit of each item, the knapsack's capacity, and binary variables indicating whether an item is selected or not. Abdel-Basset M.,Mohamed R.,Chakrabortty R.K., et al. (2021) introduced V-Shaped and S-Shaped transfer functions to the Binary Marine Predators Algorithm to aid in finding positions. If the best hunter does not meet the specified conditions, repair and improved algorithms are used before proceeding with the general MPA steps (Ervural B. and Hakli H. (2023). Additionally, the Binary Reptile Search Algorithm (BinRSA) was introduced to solve the 0-1 knapsack problem, including new shapes U, T, Z, and O to measure the performance of the algorithms, including MPA.

5. CRITICAL ANALYSIS AND INVESTIGATION

5.1 Q1: What are the proportion of each type of MPA?

Three types of MPA were studied: The Original, The Modified, and The Hybrid MPA. As shown in Figure 4

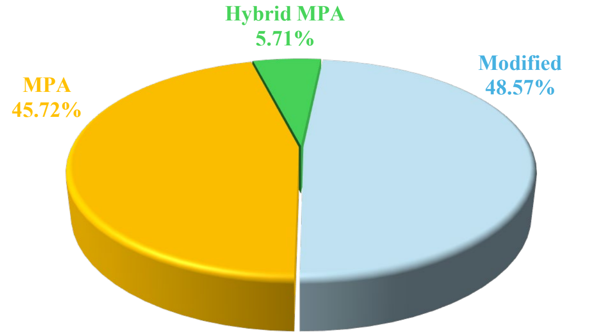

Figure 4 Types of marine predators algorithm from research

The Modified MPA was used the most, with a proportion of 48.57%. This is because the modification process is simple and not complicated. In some literature, parameters or processes may be changed or repositioned. For example, the modification of MPA involves adjusting FAD's Effect from 0.2 to 0.5 to increase the proportion of escaping local optima. The Original MPA is the next most used, following Modified MPA, due to its completeness in all processes. The strengths of MPA, as outlined in Table 3, may yield better results compared to other algorithms. The least used is Hybrid MPA, as integrating MPA with other algorithms might result in a worse best solution. An example of Hybrid MPA is Attiya I. et al. (2022), who combined the Chimp Optimization Algorithm with the Marine Predators Algorithm. This hybrid approach aimed to leverage the strengths of MPA to enhance its exploitation capability and employed a disruption operator to boost exploration effectiveness, thereby increasing the efficiency of finding better solutions and hybridization involves a more complex process and takes more time than modification. It requires a thorough examination of each algorithm to be used, to carefully evaluate their strengths and weaknesses and address them in detail. Examples of delivery costs are provided to illustrate question 1, as shown in Figure 5 and 6.

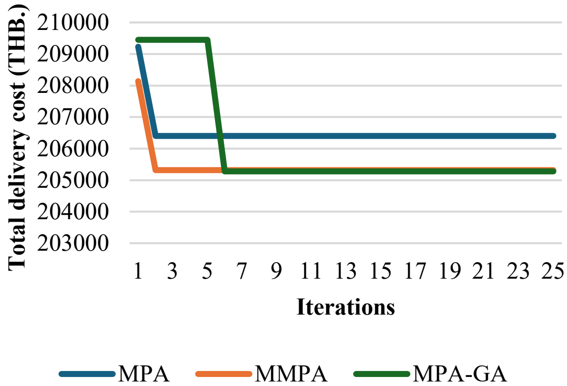

Figure 5 The total delivery cost of MPA, MMPA and MPA-GA (Example 1)

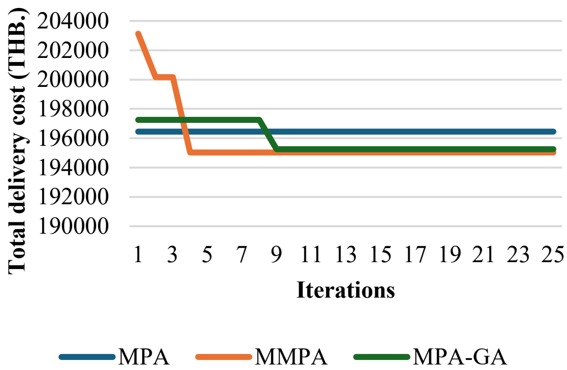

Figure 6 The total delivery cost of MPA, MMPA and MPA-GA (Example 2)

Figure 5 presents a sample of total delivery costs generated from a real-world VRP problem (Niracha, 2024), using the traditional CVRP with a capacity constraint. These costs were derived from a literature review and experimental implementation using three mutation with the top 50% of the population (predators). This combination significantly reduced costs, comparable to the modified MPA. By adjusting the FAD value from 0.2 to 0.9, the modified MPA also exhibited lower costs compared to the original MPA, indicating the effectiveness of the FAD's effect in cost reduction.

Figure 6 further reinforces these findings by showcasing the lowest delivery costs among the three algorithms. The modified MPA consistently outperformed the original MPA. Given these results, it's evident why modified and hybrid MPA variants are more prevalent in research. Beyond the effectiveness of modified and hybrid MPA, their simplicity and computational efficiency contribute to their popularity. The modified MPA requires fewer steps and processes compared to hybrid MPA, resulting in shorter computation times.

5.2 Q2: What are the differences between MPA, SSO, WOA and AHA?

According to the data in Table 5, the comparison involves three marine-based algorithms and one nature-inspired algorithm: the Marine Predators Algorithm (MPA), Shark Smell Optimization Algorithm (SSO), Whale Optimization Algorithm (WOA), and the Artificial Hummingbird Algorithm (AHA). A notable feature of all four algorithms is their mechanism for balancing SSO employs a strategy based on detecting the blood of injured prey. MPA has the fewest parameters, with only two: methods: the Marine Predators Algorithm (MPA), its modified version, and a hybrid of MPA. The results are based on 25 iterations with a population of 100 (prey) and 30 replications. The lowest delivery cost was achieved by MPA-GA, a hybrid combining MPA's second stage the number of iterations and the number of preys.MPA, WOA, and AHA are similar in that they seek optimal solutions based on the position of prey, while exploration and exploitation in the search for solutions. All algorithms have the potential to encounter local optima. To address this, MPA utilizes the FAD's effect to avoid repeatedly converging on the same solution, thereby increasing the chance of discovering a potentially better solution by up to 20% (according to the original MPA). This is a notable strength and advantage compared to SSO and WOA. Additionally, MPA includes a mechanism for updating the best solution, employing a marine memory-saving strategy to remember the positions that yield the best fitness values in each iteration, ensuring continuous improvement of solutions. Similarly, SSO uses a mechanism to remember the best positions, but WOA lacks a process for remembering the best solutions. In conclusion, MPA is a marine-based algorithm that is both interesting and comprehensive in its approach.

Upon comparing MPA and AHA, it is evident that both methodologies are quite similar and incorporate elements of both exploitation and exploration. The primary distinction lies in the number of parameters; MPA has fewer parameters than AHA. However, MPA has the advantage of integrating both strategies within a single phase, potentially leading to more diverse solutions. Furthermore, both algorithms share a common issue tend to converge on the optimal solution too rapidly.

Table 5 The differences between MPA, SSO, WOA and AHA

	MPA	WOA	SSO	AHA
No. of parameters of the algorithm	2	3	5	3
Inspiration for finding solutions	The position of prey	The position of prey	The scent of blood from the injured prey	The position of hummingbird
Representation	Prey	Prey	Injured prey	Hummingbird
Exploration Strategies	Brownian motion	Search for prey	Rotational motion	The territorial foraging
Exploitation Strategies	Levy motion	Spiral bubble-net attacking	Forward Motion	The guide foraging
Escape local optimal	Eddy and FAD's effect	-	-	The migration foraging strategy
Improving best solution	3 Phases of max iterations	Use parameter A to select between exploration and exploitation.	Both exploration and exploitation are represented in the same way.	3 Flight movement: Axial flight, diagonal flight, and omnidirectional flight
The strategy for updating the best solution	Memory saving	-	Considering the position of the best prey	Updating the best position in the visit table

Figures 7, 8, and 9 present the insights generated by the MPA for questions 3, 5, and 6, respectively.

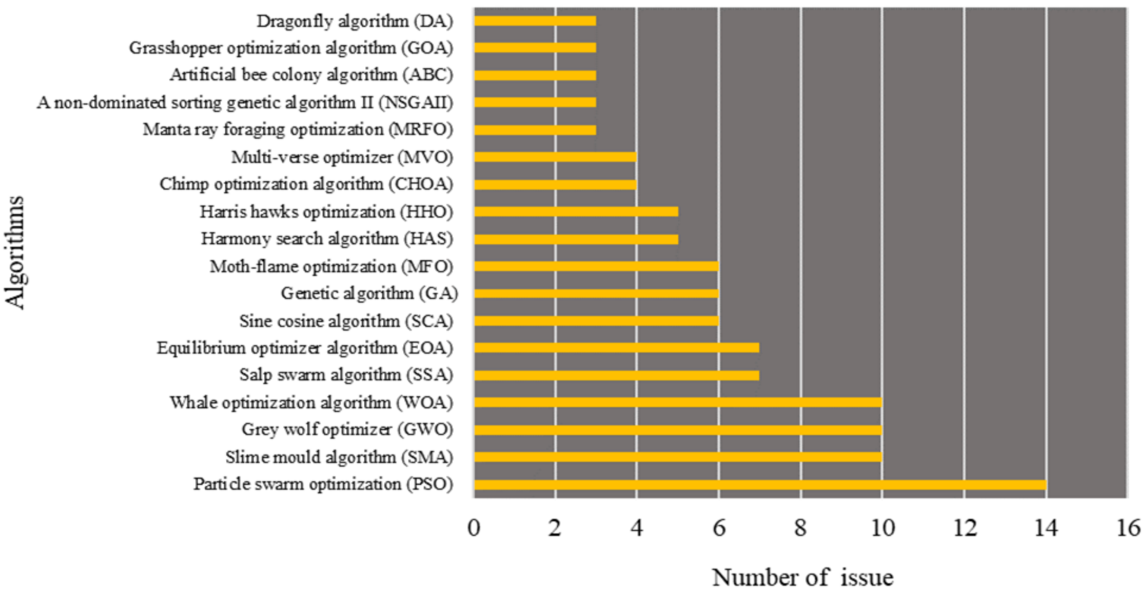

Figure 7 Top 7 algorithms for comparing performance of MPA

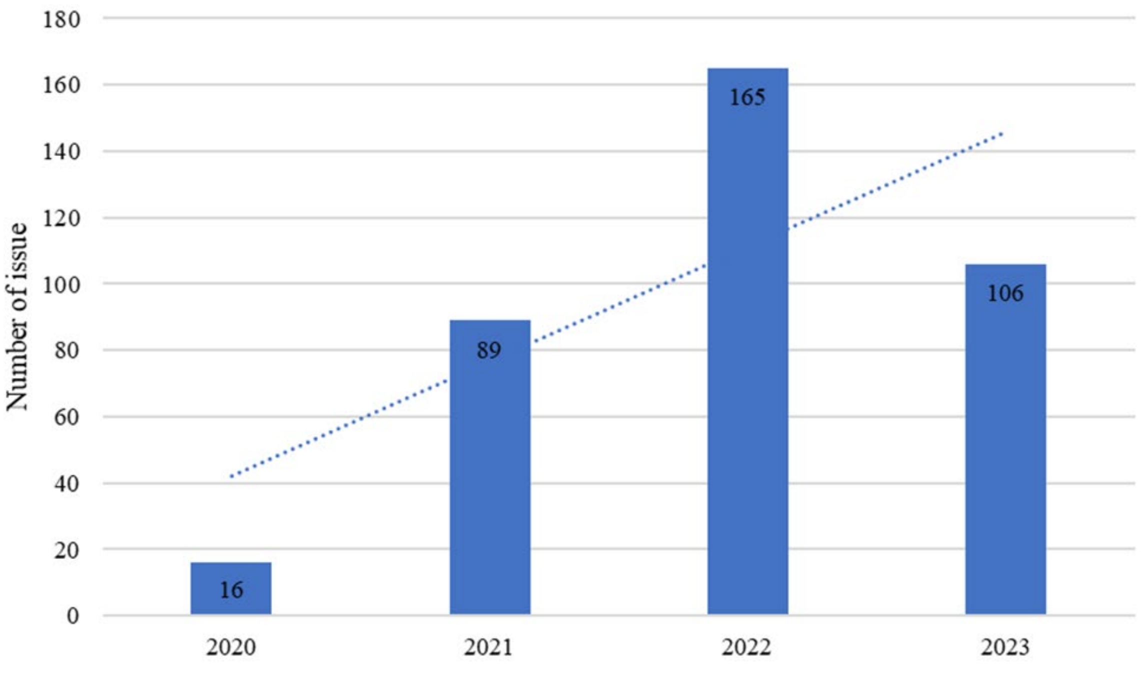

Figure 8 The trend of using MPA per year.

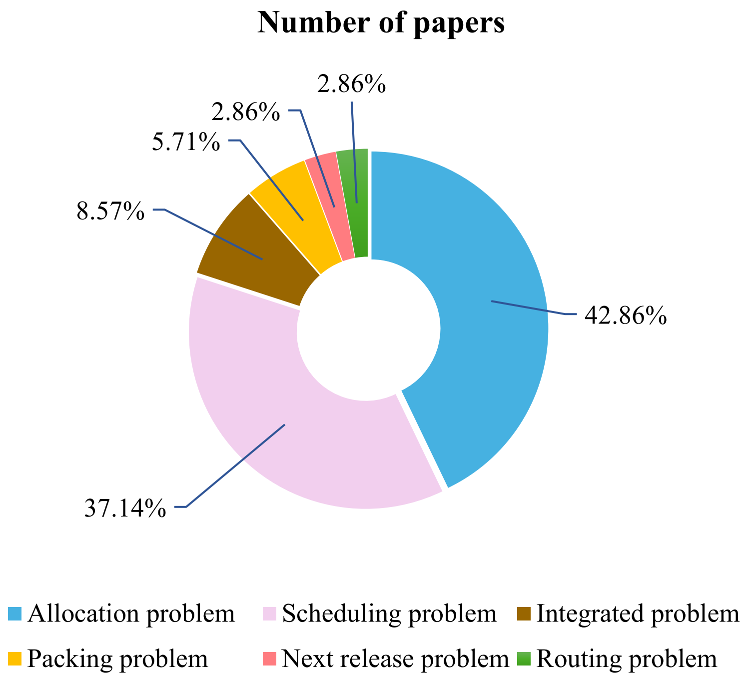

Figure 9 Literature distribution of DOPs of Engineering Problems

5.3 Q3: Which "Algorithm" is the most popular to compare the performance with MPA?

From Figure 7, the top 7 algorithms that are commonly used to compare the performance of MPA are as follows:

PSO (Particle Swarm Optimization) - used in 14 editions.

SMA (Social-Molecule Algorithm), GWO (Grey Wolf Optimizer), and WOA (Whale Optimization Algorithm) are tied for the second rank, with three editions each.

SSA (Sine Cosine Algorithm) and EOA (Elephant Optimization Algorithm) - ranked third.

SCA (Sine Cosine Algorithm), GA (Genetic Algorithm), and MFO (Moth Flame Optimization) - ranked fourth.

HAS (Harris Hawks Optimization) and HHO (Harris Hawks Optimization) - ranked fifth.

CHOA (Cuckoo Search with Hybrid Optimization Algorithm) and MVO (Multiverse Optimization) - ranked sixth.

MRFO (Manta Ray Foraging Optimization), NSGAII (Non-dominated Sorting Genetic Algorithm II), ABC (Artificial Bee Colony), GOA (Grasshopper Optimization Algorithm), and DA (Differential Evolution Algorithm) - ranked last.

Other algorithms have limited usage, typically around 1 or 2 articles. For researchers seeking novel approaches, there are opportunities to explore hybrid algorithms that combine MPA with other techniques, such as the Firefly Algorithm (FF), Butterfly Optimization Algorithm (BOA), or Flower Pollination Algorithm (FPA)

5.4 Q4: What are the differences between MPA, WOA, and other population-based metaheuristics?

The Marine Predators Algorithm (MPA) employs a nature inspired by the hunting behaviors of marine predators. Belongs to the family of population-based metaheuristics. For example, other population-based metaheuristic, the Genetic Algorithm (GA) is based on genetic processes, utilizing crossover and mutation to enhance the search for optimal solutions. However, MPA offers a unique approach.

While both crossover and mutation involve exploration and exploitation, GA typically performs these processes separately in distinct phases. Consequently, the diversity of solutions generated by GA may be limited. In contrast, MPA integrates exploration and exploitation within a single phase, allowing for a more comprehensive search. This means MPA can explore the entire solution space, exploit promising regions, and balance both strategies effectively.

MPA further stands out with its ability to perform exploration of the entire population, exploitation of the entire population, and a combination of both, all within a single framework. This versatility contributes to its efficiency in finding optimal solutions. Additionally, unlike some algorithms that may get trapped in local optima, MPA incorporates the FAD's effect equation to refine solutions iteratively, ensuring that the final solution

5.5 Q5: What is the trend in the use of MPA each year?

The trend described by Figure 8 regarding the utilization of the Marine Predators Algorithm between 2020 and 2023 suggests a consistent rise in interest among researchers across the specified years. Nevertheless, the extent of MPA usage in 2023 remains to be determined due to its inclusion within the paper review period. The distribution of MPA usage for addressing different issues annually stands at 4.26%, 23.67%, 43.88%, and 28.19%, respectively.

In conclusion, future predictions indicate the growing popularity of MPA, demonstrating its effectiveness as an algorithm. The outcomes are expected to be promising.

5.6 Q6: What are the proportion of discrete problems?

From Figure 9, the most prevalent issue encountered in using MPA is the Allocation problem, with a total of 15 articles, constituting 42.86%. Following this is the Scheduling problem, with 13 articles accounting for 37.14%. As for integrated problems, three editions were encountered, representing 8.57%, while the Packing problem was found in 2 articles, amounting to 5.71%. The discrete problem, utilizing MPA in only one edition, accounts for 2.86% of the total, encompassing the routing problem and the next release problem.

Based on a search in the same database used for the literature review, namely Scopus, from 2020 to the present, and using keywords related to problem names and metaheuristics, all six problems were specifically explored within the field of engineering literature. It was found that the Scheduling problem is the most popular, followed by the Allocation problem. However, a review of this research indicates that MPA is most applied to Allocation problems, which may be due to the criteria used for categorizing these problems.

5.7 Q7: What are the research gaps?

While the reviewer has conducted experiments on the CVRP problem using MPA, MMPA, and MPA-GA, there is significant potential for further development and refinement of the conditions and constraints. Real-world delivery scenarios often involve time windows, varying customer demands, and fluctuating production capacities. Integrating production planning with demand forecasting could optimize inventory levels and align transportation schedules. Additionally, considering environmental concerns and energy efficiency, future research could focus on minimizing carbon emissions and developing tailored VRP models to meet specific company requirements.

Both benchmark and real-world datasets can be utilized for these advancements. To introduce novelty and assess the capabilities of emerging algorithms like MPA-AHA, future research could explore hybrid approaches. By combining algorithms, it may be possible to achieve even better solution quality compared to traditional methods. Additionally, the Bin Packing Problem, which involves packing items of different sizes into the fewest number of containers, was not found within the scope of the discrete problems studied. This suggests that future research could explore the application of all three MPA methods to this specific problem.

6. CONCLUSION

The Marine Predators Algorithm (MPA) is a nature-inspired metaheuristic that imitate the hunting behavior of marine predators. It offers several advantages, including a few of parameters, easy to adaptability, and suitability for complex, large-scale problems. Notably, MPA effectively balances exploration and exploitation within a single phase and incorporates the FAD's equation in every iteration, ensuring thorough solution refinement.

There are three methods of MPA: the original, modified, and hybrid versions. Modified MPA is particularly popular among researchers due to its simplicity, flexibility in parameter tuning, and faster convergence compared to hybrid MPA. While hybrid MPA offers more customization options by combining MPA with other algorithms, it often involves more complex procedures and longer computational times. Both modified and hybrid MPA generally outperform the original MPA, making them preferred choices for obtaining high-quality solutions.

A review of 35 papers on discrete engineering problems revealed gaps in the application of MPA to vehicle routing problems (VRP). Various VRP types, such as capacitated vehicle routing, vehicle routing with time windows, and green vehicle routing, present opportunities for MPA-based solutions. While MPA can be applied to VRP, modified and hybrid MPA variants are recommended for achieving optimal results. Furthermore, the Bin Packing Problem can be addressed using MPA, allowing researchers to explore novel modifications or hybrids with algorithms such as SSO, AHA, and ECO to optimize the number and sizes of containers for packaging items, ultimately reducing costs and material usage.

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