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REVIEW ARTICLE

An Inclusive Survey on Marine Predators Algorithm: Variants and Applications

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Abstract

Marine Predators Algorithm (MPA) is the existing population-based meta-heuristic algorithms that falls under the category of Nature-Inspired Optimization Algorithm (NIOA) enthused by the foraging actions of the marine predators that principally pursues Levy or Brownian approach as its foraging strategy. Furthermore, it employs the optimal encounter rate stratagem involving both the predator as well as prey. Since its introduction by Faramarzi in the year 2020, MPA has gained enormous popularity and has been employed in numerous application areas ranging from Mathematical and Engineering Optimization problems to Fog Computing to Image Processing to Photovoltaic System to Wind-Solar Generation System for resolving continuous optimization problems. Such huge interest from the research fraternity or the massive recognition of MPA is due to several factors such as its simplicity, ease of application, realistic execution time, superior convergence acceleration rate, soaring effectiveness, its ability to unravel continuous, multi-objective and binary problems when compared with other renowned optimization algorithms existing in the literature. This paper offers a detailed summary of the Marine Predators Algorithm (MPA) and its variants. Furthermore, the applications of MPA in a number of spheres such as Image processing, classification, electrical power system, Photovoltaic models, structural damage detection, distribution networks, engineering applications, Task Scheduling, optimization problems etc., are illustrated. To conclude, the paper highlights and thereby advocates few of the potential future research directions for MPA.

1 Introduction

Meta-heuristic is one of the striking research areas accompanied by exceptionally significant progress with regard to generation of solution for numerous firm optimization problems. In the year 1976, the term "Meta-heuristic" was coined by Fred Glover [1] basically to exemplify heuristic method with no problem-specific characteristic. Over the last few decades, more attention is paid to the field of optimization using meta-heuristic and huge progress has been made from the time when the first meta-heuristic was anticipated and several novel algorithms are endorsed each day for resolving intricate and real-world predicaments. Appropriate trade-off among exploration and exploitation (chief functions of meta-heuristics) is the key to a proficient search process. Numerous ways of classifications of meta-heuristics have been offered based on utilization of exploration and exploitation mechanism, and the metaphor of the search procedures. In that regard, quite a few algorithms typically instigated by the natural phenomenon has been anticipated and exist in the literature and among those, meta-heuristic search algorithms with population-based outline [2] have revealed pleasing potential to crack high dimension optimization problems [3–5] appropriate for global searches due to global exploration and local exploitation capability. It involves the production of a set of assorted solutions at each run and the classification of population-based meta-heuristic

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algorithm into two main categories namely Evolutionary-Based and Nature-Inspired Algorithms [6, 7]. Further, the nature-inspired algorithms are categorized into five different classes i.e., Swarm-Based, Physics/Chemistry-Based, Human-Based [8], Plant-Based and Maths-Based Algorithms and the same is depicted in Fig. 1.

Evolutionary Algorithms (EA) is considered as the foremost class of population-based meta-heuristic optimization algorithms instigated from evolutionary phenomena of nature that make use of three main operators i.e., selection, recombination and mutation). A few popular EAs are: Genetic Algorithm [9], Differential Evolution [10], Evolutionary Programming [11], Evolution Strategies [12], Genetic Programming [13], Population-Based Incremental Learning [14], Biogeography-Based Optimizer [15], Memetic Algorithm [16] and Clonal Selection Algorithm [17]. The second class of population-based meta-heuristic optimization algorithms as depicted in Fig. 1 is *Swarm-Based algorithm* wherein the swarms (unsophisticated agents) tend to mimic the behavior of the social animals or agents available in our nature such as ants foraging, birds flocking, fish schooling, bacteria moulding, animals herding and many more. The algorithm basically emphasizes on direct and indirect interactions whereby the cooperative behavior of agent intermingling locally with the environment causes the comprehensible global pattern to arise. Some of the Swarm-Based algorithm that has been listed is: Ant Colony Optimization [18], Particle Swarm Optimization [19], Artificial Bee Colony Algorithm [20], Cuckoo Search [21], Firefly Algorithm [22], Bat Algorithm [23], Krill Herd Algorithm [24], Gray Wolf Optimization [25], Ant Lion Optimizer [26], Moth-Flame Optimization Algorithm [27], Dragonfly Algorithm [28], Whale Optimization Algorithm [29], Grasshopper Optimization Algorithm [30], Crow Search Algorithm [31], Salp Swarm Algorithm [32], Marine Predators Algorithm [2], Bee Algorithm [33], Harris Hawks Optimization [34], Social Spider Optimization [35], Intelligent Water Drop Algorithm [36], Glowworm

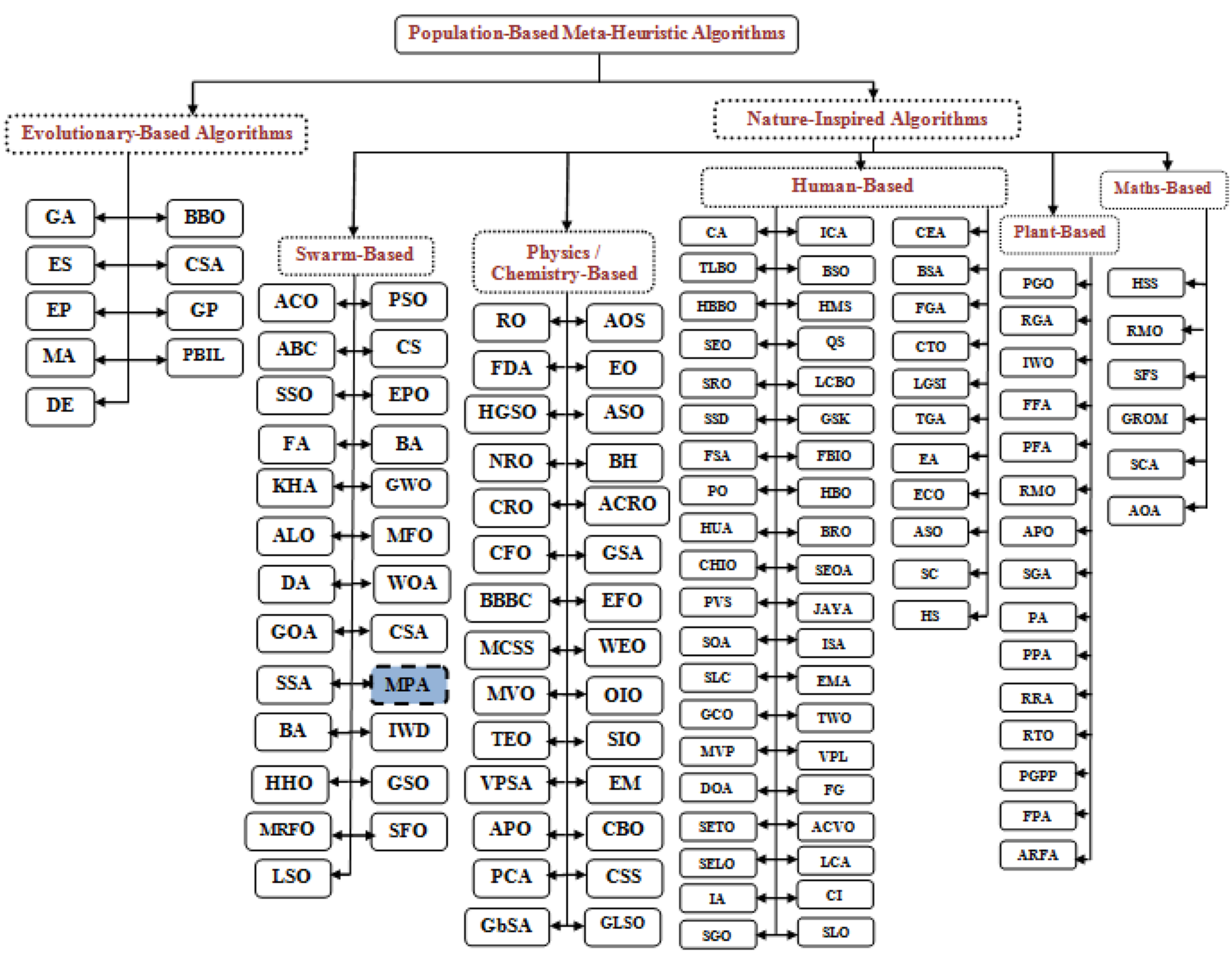

Fig. 1 Classification of population-based meta-heuristic algorithms

Swarm Optimization [37], Manta Ray Foraging Optimization [38], Sail Fish Optimizer [39], Lion Swarm Optimization [40] and Emperor Penguin Optimizer [41].The third class of population-based meta-heuristic optimization algorithms as highlighted in Fig. 1 is *Physics/Chemistry-Based algorithms* wherein the main source of inspirations is the physical processes or nature of chemical reactions which are further formulated into solutions to resolve the problems. Few popular physics/chemistry-based algorithms are: Photosynthetic Algorithm [42], Galaxy-based Search Algorithm [43], Flow Direction Algorithm [44], Henry Gas Solubility Optimization [45], Nuclear Reaction Optimization [46], Chemical Reaction Optimization [47], Central Force Optimization [48], Big Bang-Big Crunch Algorithm [49], Magnetic Charged System Search [50], Multi-Verse Optimization [51], Thermal Exchange Optimization [52], Vibrating Particle System Algorithm [53], Artificial Physicomimetics Optimization [54], Ray Optimization [55], Atomic Orbital Search [56], Equilibrium Optimizer [57], Atom Search Optimization [58], Black Hole Algorithm [59], Artificial Chemical Reaction Optimization [60], Gravitational Search Algorithm [61], Electromagnetic Field Optimization [62], Water Evaporation Optimization [63], Optics Inspired Optimization [64], Electromagnetism-like Algorithm [65], Colliding Bodies Optimization [66], Charged System Search [67], Gravitational Local Search Optimization [68].

The fourth class of population-based meta-heuristic optimization algorithm, *Human-Based algorithms* imitates human behaviour, supremacy and intelligence. Few of the human-based algorithms as depicted in the figure are listed below: Cultural Algorithm [69], Imperialist Competitive Algorithm [70], Teaching Learning-Based Optimization [71], Brain Storm Optimization [72], Human Behavior-Based Optimization [73], Human Mental Search [74], Social Engineering Optimizer [75], Queuing Search Algorithm [76], Search and Rescue Optimization [77], Life Choice-Based Optimization [78], Social Ski-Driver Optimization [79], Gaining Sharing Knowledge-Based Algorithm [80], Future Search Algorithm [81], Forensic-Based Investigation Optimization [82], Political Optimizer [83], Heap-Based Optimizer [84], Human Urbanization Algorithm [85], Battle Royale Optimization [86], Corona virus Herd Immunity Optimization [87], Passing Vehicle Search [88], Jaya Algorithm [89], Seeker Optimization Algorithm [90], Interior Search Algorithm [91], Soccer League Competition Algorithm [92], Exchange Market Algorithm [93], Group Counseling Optimization Algorithm [94], Tug of War Optimization [95], Most Valuable Player Algorithm [96], Volleyball Premier League Algorithm [97], Dynastic Optimization Algorithm [98], Focus Group [99], Stock Exchange Trading Optimization [100], Anti Corona virus Optimization Algorithm [101], Socio Evolution and Learning Optimization [102], League Championship Algorithm [103], Ideology Algorithm [104], Cohort Intelligence [105], Social Group Optimization [106], Social Learning Optimization [107], Cultural Evolution Algorithm [108], Backtracking Search Optimization Algorithm [109], Football Game Algorithm [110], Class Topper Optimization [111], Ludo Game-based Swarm Intelligence [112], Team Game Algorithm [113], Election Algorithm [114], Election Campaign Optimization Algorithm [115], Anarchic Society Optimization [116], Society and Civilization [117] and Social Emotional Optimization Algorithm [118]. *Plant-Based Algorithms* has been categorized as the fifth class of population-based meta-heuristic optimization algorithm that mimics the intelligent behavior exhibited by plants. Some of the renowned plant-based algorithms are: Plant Growth Optimization [119], Root Growth Algorithm [120], Invasive Weed Optimization [121], Fertile Field Algorithm [122], Flower Pollination Algorithm [123], Paddy Field Algorithm [124], Root Mass Optimization Algorithm [125], Artificial Plant Optimization Algorithm [126], Sapling Growing up Algorithm [127], Photosynthetic Algorithm [42], Plant Propagation Algorithm [128], Rooted Tree Optimization [129], Path Planning inspired by Plant Growth [130] and Artificial Root Foraging Algorithm [131]. The last category that falls under the population-based meta-heuristic optimization algorithm is the *Maths-Based Algorithms* that basically tend to imitate the procedure of numerical techniques, mathematical programming and its orientation to resolve numerous constraints and optimization issues of the real environment. Some of the widely known maths -based algorithms are Hyper-Spherical Search Algorithm [132], Radial Movement Optimization [133], Stochastic Fractal Search [134], Golden Ratio Optimization Method [135], Sine Cosine Algorithm [136] [137] and Arithmetic Optimization Algorithm [138].

Marine Predators Algorithm (*MPA*) as highlighted in Fig. 1 is the algorithm that is considered among the list of algorithms available in this paper. MPA is one of the potential population-based meta-heuristic optimization algorithms that come under the class known as Swarm-Based Algorithms. This algorithm is employed to work out on abundant optimization problems specifically Mathematical and Engineering Optimization problems, Image processing, Photovoltaic Systems, Fog Computing, Wind-Solar Generation System and many other as mentioned earlier. MPA is formulated based on the different foraging strategy opted by the ocean predators and optimal encounter rates policy in biological interaction. The Levy and Brownian motions are dual strategies preferred by predators intended for the purpose of optimal foraging. MPA has time and again proved its capacity to present a good number of effectual designs and also spawned efficient statistical results when matched up with other well-regarded existing methods. The different strategies involved in terms of foraging and memories makes Marine Predators and overall MPA slightly different [2] and acceptable when compared with the other meta-heuristics algorithms presented in the literature:

a. Marine Predators is well equipped with strategies for different scenarios. If the environment with less and sparse concentration of prey is encountered, MPA indulges in the usage of Levy strategy for foraging however, it navigates to Brownian movement on encountering of the environment [2] with higher and profuse concentration of prey.
b. Marine Predators apart from quickly fluctuating the foraging strategy as well changes their actions with the objective [2] to discovery the areas with different concentrations of prey.
c. In terms of memory, Marine predators are blessed with good memories [2] and predators takes the benefits of its skill to further track of the locations and additional help their subordinates to do the needful.
d. The minimalism, easier to implement in conjunction with effectual and competent outcomes unquestionably put forth Marine Predators Algorithm, as an alternate optimization procedure to conventional techniques available in the literature.

This article hereby exemplifies a crisp survey of MPA, variants of MPA and further highlights the applications of MPA in diverse fields of research. Furthermore, to assemble the numerous published articles related to MPA, quite a few acclaimed publishers specifically IEEE, Elsevier, Springer, MDPI, AIMS press, Nature Portfolio, Taylor & Francis, Wiley, Hindawi and many more has been considered and in order to do so one of the liberally reachable web search engine that provides the full text of scholarly literature across the range of publishing disciplines i.e. *Google Scholar* is employed and the searching is done based on few of the terminologies (Not limited to though) as projected in Fig. 2. Number of recent variants of MPA (Revised and Hybridized) published by different publishers as per surveyed is depicted in Fig. 3. Figure 4 elaborates the top 10 Journals ranked based on publications of variants of MPA. Number of publications of research papers related to variants of MPA per year is depicted in Fig. 5.

MPA is one of the prevalent swarm-based meta-heuristic and is considered as one of the exclusive members of NIOA family. The total number of citations of MPA (as per Google Scholar, dated: 19.10.2022) is 1040 (Only for the papers considered in this survey). As mentioned earlier, several variants of MPA have been proposed in the literature and applied in numerous application areas. However, as per the best of the knowledge there is no review or survey paper highlighting the different variants of MPA till date and this is the main objective behind the study i.e., basically reviews the existing work on MPA. This review article sheds lights on identifying, categorizing and further analyzing the different variants of MPA used in numerous application areas to resolve the real-world optimization issues. This review paper meticulously explores all research works linked with MPA thereby addressing five important pillars which is structured as follows:

The structure of the standard or original MPA is described in Sect. 2.

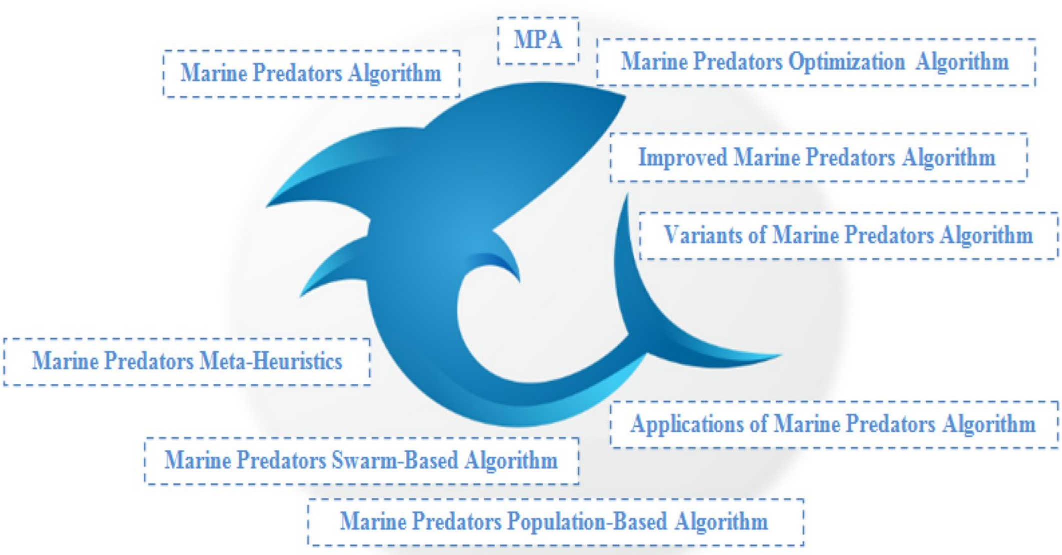

Fig. 2 Terminologies used to search the MPA research papers from google scholar

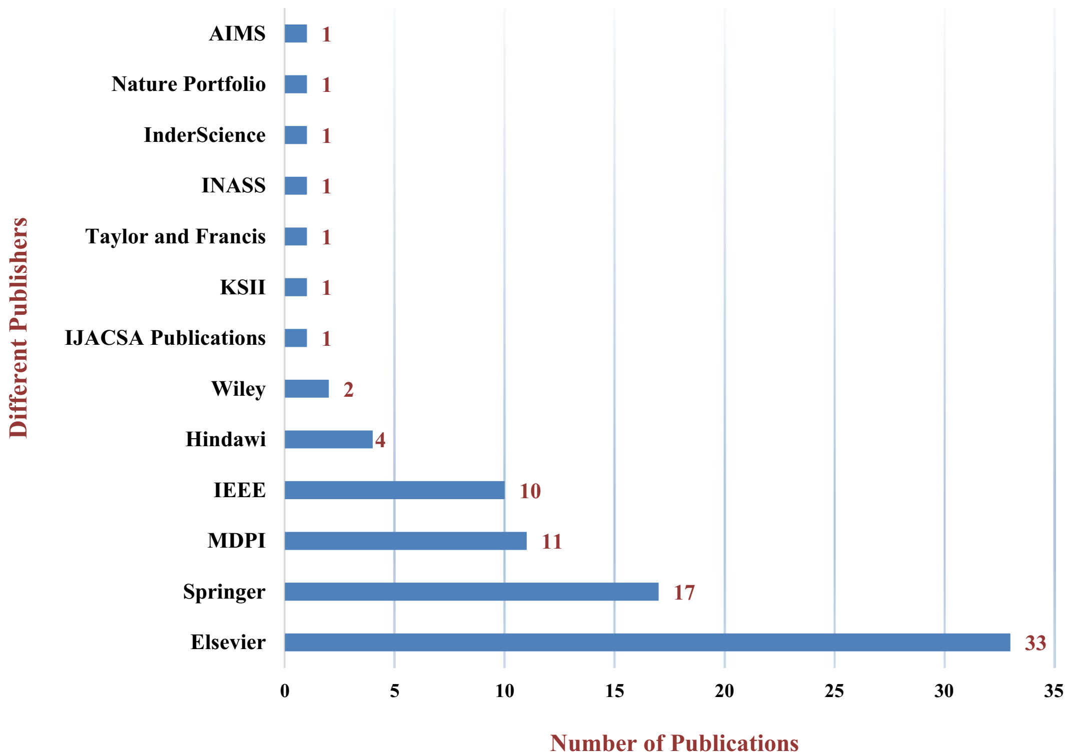

Fig. 3 Number of recent variants of MPA (Revised, Hybridized and Application based) published by different publishers (As per Surveyed)

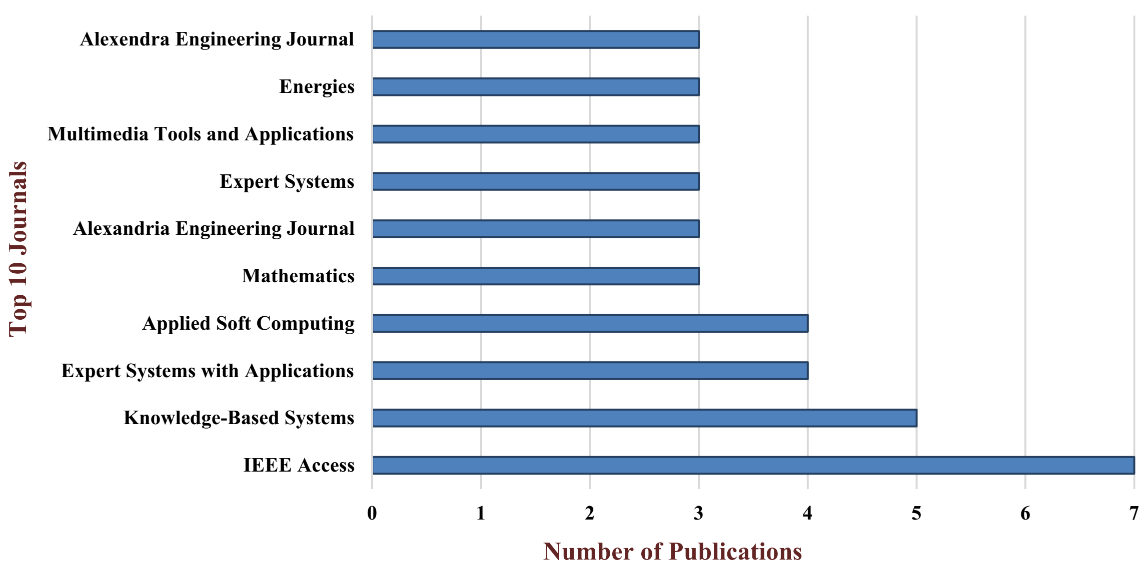

Fig. 4 Top 10 Journals ranked based on publications of variants of MPA (Revised, Hybridized and Application based) (As per Surveyed)

Section 3 highlights and further discusses the revised variants and hybrid version of MPA developed, introduced and applied so far.
The problem resolved by MPA that belongs to different applications areas are discussed in Sect. 4.
Section 5 highlights few representative articles of MPA used in the survey.
Finally, the paper is concluded and few potential future research directions for MPA is advocated in Sect. 6.

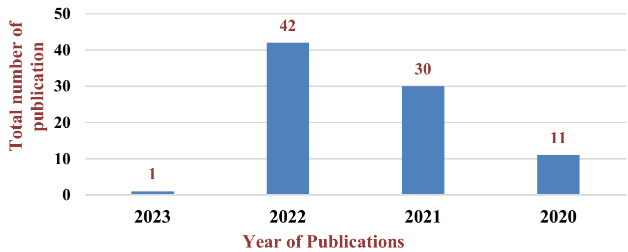

Fig. 5 Number of publications of recent variants of MPA (Revised, Hybridized and Application based) per year (As per Surveyed)

2 Original Marine Predators Algorithm (MPA)

Marine Predators Algorithm (*MPA*) is a popular nature-inspired swarm-based meta-heuristic optimization algorithm originally developed and introduced by Faramarzi and group in the year 2020 [2] based on foraging nature and meandering communications amongst the predators and prey in the oceanic ecological unit. The natural animals that tend to forage in groups basically employ the random walk strategy and one such exceptional variant of random walk strategy is Levy flight/move strategy that is typically grounded on the perception of optimal search. Several studies have clearly revealed and anticipated that many marine creatures including sharks, marlines, sunfish, tunas and swordfish make use of Levy strategy as the means to forage [139]. The other type of random walk strategy employed by the natural predators to traverse is popularly known as Brownian strategy and MPA during its life span thus uses both Levy as well as Brownian strategies to traverse or navigate diverse territories utilizing the first strategy i.e., Levy in the surroundings with inferior concentration of prey and the second strategy i.e., Brownian in the environment involving profuse number of preys. The pseudo-code for standard Marine Predators Algorithm is represented as Algorithm 1 and further Fig. 6 exemplifies the flowchart of the same. Like other population-based meta-heuristic algorithms, in MPA too, preliminary solution is unvaryingly disseminated over the search space and the same is depicted using Eq. 1. Two matrices of the same dimensions namely Elite and Prey is constructed [2] (as shown in Eqs. 2 and 3 respectively) that basically depicts the Predator's and the Prey's position that enables the predator to find its prey while the prey is in search for the food to survive as per the mechanism called "*survival of the fittest*". Both the predator as well as prey is the searching agent in this scenario as mentioned earlier that predator is searching for prey and in turn prey searches for its food. The entire procedure of optimization revolves around these two matrices i.e., Elite and Prey matrices as depicted below.

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

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

$$Prey = \begin{bmatrix} X_{1,1} & \cdots & X_{1,d} \\ \vdots & \ddots & \vdots \\ X_{n,1} & \cdots & X_{n,d} \end{bmatrix}_{n\times d} \tag{3}$$

Here, X_{min} denotes the lower variable bound, X_{max} the upper variable bound and *rand* is a random vector that is uniform in nature ranging from 0 to 1[2]. Here, $\overrightarrow{X^I}$ depicts the vector with regard to top predator that is simulated *n* times (reliant on the total search agent, *n*) to construct the Elite matrix with *d* as its dimension. In the entire process of searching the constructed Elite matrix keeps updating in search of the fittest predator. Further, $X_{i,j}$ corresponds to the location in the search space of the i^{th} Prey in j^{th} dimension.

Subsequently with the MPA formulation, MPA optimization needs to be addressed and, in this regard, the entire optimization procedure is divided broadly into three major stages taking into account different velocity ratio however yet impersonating the life-cycle of predator as well as prey. Three different stages are highlighted as Stage I, II and III [2].

Stage I: "Whenever the predator navigates quicker than prey". (High velocity ratio).

Stage II: "Whenever the predator and prey navigate almost with the same velocity". (Unit velocity ratio).

Stage III: "Whenever the predator navigates slower than prey". (Low velocity ratio).

In first stage, in a scenario wherein the predator is steering quicker than the prey, the velocity ratio is considered high, thereby the best strategy that can be adopted by the predator is to stop and not move at all. The mathematical formulation [2] of the same is depicted using Eq. 4.

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

$$\overrightarrow{Stepsize_l} = \overrightarrow{R_B} \otimes \left(\overrightarrow{Elite_l} - \overrightarrow{R_B} \otimes \overrightarrow{Prey_l}\right) \qquad i = 1, \dots\dots n \tag{4}$$

Here, $\overrightarrow{Prey_l} = \left(\overrightarrow{Prey} + P.\vec{R} \otimes \overrightarrow{Stepsize_l}\right)$; $\overrightarrow{R_B}$ is a vector comprising of random numbers built on Normal distribution symbolizing the Brownian motion; $\otimes$ denotes entry-wise multiplication; P represents constant number initialized to 0.5 [2]; Iter is the current iteration; Mar_Iter symbolizes the maximum number of iteration and R designates vector of uniform random number in the range [0,1].

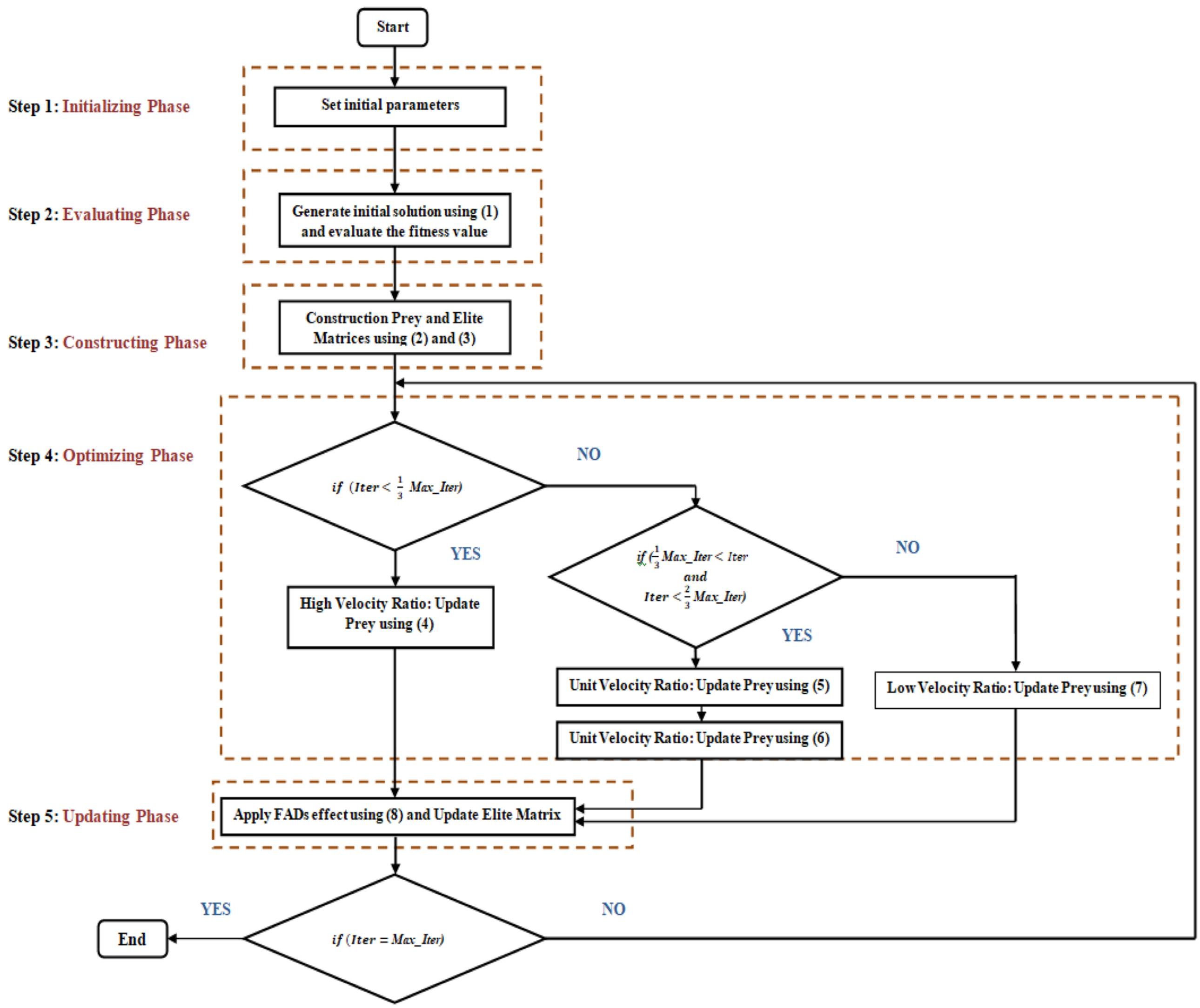

Fig. 6 Flowchart depicting the mechanism in Marine Predators Algorithm

In Stage II, the scenario wherein the pace of predator as well as prey is almost the same, the velocity ratio is considered to be a unit velocity ratio, thereby the best strategy that can be rather need to be opted by Predator is the Brownian move and by the Prey is Levy move [2]. Herein, predator is accountable for exploration nevertheless the prey is responsible for the exploitation, depicted using Eqs. 5 and 6.

$$While \tfrac{1}{3}\, Max\_Iter < Iter < \tfrac{2}{3}\, Max\_Iter\ then,$$

For the Population (Prey)

$$\overrightarrow{Stepsize_l} = \overrightarrow{R_L} \otimes \left(\overrightarrow{Elite_l} - \overrightarrow{R_L} \otimes \overrightarrow{Prey_l}\right) \qquad i = 1, ...n/2 \tag{5}$$

Here, $\overrightarrow{Prey_i} = \overrightarrow{Prey_i} + P.\vec{R} \otimes \overrightarrow{Stepsize_i})$; $\overrightarrow{R_L}$ is a vector based on Levy distribution representing the Levy motion;

For the Population (Predator)

$$\overrightarrow{Stepsize_l} = \overrightarrow{R_B} \otimes \left(\overrightarrow{R_B} \otimes \overrightarrow{Elite_l} - \overrightarrow{Prey_l}\right) \qquad i = n/2, ...n \tag{6}$$

Here,$\overrightarrow{Prey_i} = \overrightarrow{Elite} + P.CF \otimes \overrightarrow{Stepsize_i})$; CF is used to control the step size and is given as $CF = \left(1 - \frac{Iter}{Max_{Iter}}\right)^{\left(2\frac{Iter}{Max\_Iter}\right)}$; Multiplication $\overrightarrow{R_B} \otimes \overrightarrow{Elite_i}$ denotes the Brownian move of the predator.

Algorithm 1: Pseudocode of standard Marine Predators Algorithm.

Step 1: **Population Initializing Phase**
Initialize the parameters of the algorithm (Population size, dimensions, maximum Iterations)
Uniformly distribute the initial solution using **Equation 1**.
Step 2: **Evaluating Phase**
while (the termination condition does not satisfy)
    Evaluate the fitness of the solutions
Step 3: **Matrix Constructing Phase**
    Construct the **Elite matrix** using **Equation 2**
    Construct the **Prey matrix** using **Equation 3**
Step 4: **Optimizing 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,***
        For the first half of the population $(\mathbf{i = 1, \ldots . n/2})$
            Update Prey using **Equation 5**
        For the remaining half of the population $(\boldsymbol{i = n/2, \ldots . n})$
            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: **Updating Phase**
    Updation of the **Elite matrix** and carrying out memory saving
    Apply FADs effect, then update using **Equation 8**
    Further, **Update Elite matrix** and carry forward memory saving
end ***while***

In the third stage, in the scenario wherein predator moves slower than that of the prey, the velocity ratio is considered to be a low velocity ratio, thereby the best strategy [2] that can be opted by the predator is Levy motion and the same is clearly depicted using Eq. 7.

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

$$\overrightarrow{Stepsize_l} = \overrightarrow{R_L} \otimes \left(\overrightarrow{R_L} \otimes \overrightarrow{Elite_l} - \overrightarrow{Prey_l}\right) \qquad i = 1, \ldots\ldots n \tag{7}$$

Here, $\overrightarrow{Prey_i} = \overrightarrow{Elite} + P.CF \otimes \overrightarrow{Stepsize_i}$); Multiplication $\overrightarrow{R_L} \otimes \overrightarrow{Elite_i}$ denotes the Levy move of the predator. Lastly, one important component that needs to be considered here in MPA is the cause of the behavioral change among the marine predators i.e., the environment concerns such as Eddy Formation or Fish Aggregating Devices commonly known as FADs effects [2]. The FADs effect is mathematically depicted as shown in Eq. 8.

$$\overrightarrow{Prey_i} = \begin{cases} \overrightarrow{Prey_i} + CF\left[\overrightarrow{X_{min}} + \vec{R} \otimes \left(\overrightarrow{X_{max}} - \overrightarrow{X_{min}}\right)\right] \otimes \vec{U} if r \le FADs \\ \overrightarrow{Prey_i} + [FADs(1-r) + r](\overrightarrow{Prey_{r1}} - \overrightarrow{Prey_{r2}}) if r > FADs \end{cases} \tag{8}$$

Here, FADs denote the probability for FADs effect on the optimization procedure initialized with value 0.2; $\overrightarrow{U}$ denotes the binary vectors with value 0 [2] (if array is < FADs) and 1 otherwise; r depicts random number ranging between [0, 1] [2]; $\overrightarrow{X_{min}}$ and $\overrightarrow{X_{max}}$ are the vectors containing lower and

Table 1 Abbreviations of different algorithms along with its full form for algorithms projected in Fig. 1

Name of the algorithm	Abbreviation	Name of the algorithm	Abbreviation
Cultural algorithm	CA	Group counseling optimization algorithm	GCO
Imperialist competitive algorithm	ICA	Tug of war optimization	TWO
Teaching learning-based optimization	TLBO	Most valuable player algorithm	MVP
Brain storm optimization	BSO	Volleyball premier league algorithm	VPL
Human behavior-based optimization	HBBO	Dynastic optimization algorithm	DOA
Human mental search	HMS	Focus group	FG
Social engineering optimizer	SEO	Stock exchange trading optimization	SETO
Queuing search algorithm	QS	Anti-Corona virus optimization algorithm	ACVO
Search and rescue optimization	SRO	Socio evolution and learning optimization	SELO
Life choice-based optimization	LCBO	Election algorithm	EA
Social ski-driver optimization	SSD	Election campaign optimization algorithm	ECO
Gaining sharing knowledge-based algorithm	GSK	Anarchic society optimization	ASO
Future search algorithm	FSA	Society and civilization	SC
Forensic-based investigation optimization	FBIO	Social emotional optimization algorithm	SEOA
Political optimizer	PO	League championship algorithm	LCA
Heap-based optimizer	HBO	Ideology algorithm	IA
Human urbanization algorithm	HUA	Cohort intelligence	CI
Battle royale optimization	BRO	Social group optimization	SGO
Corona virus herd immunity optimization	CHIO	Social learning optimization	SLO
Harmony search algorithm	HS	Cultural evolution algorithm	CEA
Passing vehicle search	PVS	Backtracking search optimization algorithm	BSA
Jaya algorithm	JAYA	Football game algorithm	FGA
Seeker optimization algorithm	SOA	Class Topper optimization	CTO
Interior search algorithm	ISA	Ludo game-based swarm intelligence	LGSI
Soccer league competition algorithm	SLC	Team game algorithm	TGA
Exchange market algorithm	EMA	Ant colony optimization	ACO
Genetic algorithm	GA	Particle swarm optimization	PSO
Differential evolution	DE	Artificial bee colony algorithm	ABC
Evolutionary programming	EP	Cuckoo search	CS
Evolution strategies	ES	Firefly algorithm	FA
Genetic programming	GP	Bat algorithm	BA
Population-based incremental learning	PBIL	Krill herd algorithm	KHA
Biogeography-based optimizer	BBO	Gray wolf optimization	GWO
Memetic algorithm	MA	Ant lion optimizer	ALO
Harmony search	HS	Moth-flame optimization algorithm	MFO
Clonal selection algorithm	CSA	Dragonfly algorithm	DA
Social spider optimization	SSO	Whale optimization algorithm	WOA
Plant propagation algorithm	PPA	Grasshopper optimization algorithm	GOA
Manta ray foraging optimization	MRFO	Crow Search algorithm	CSA
Sail fish optimizer	SFO	Salp swarm algorithm	SSA
Lion swarm optimization	LSO	Marine predators algorithm	MPA
Emperor penguin optimizer	EPO	Bee algorithm	BA
Intelligent water drop algorithm	IWD	Harris hawks optimization	HHO
Glowworm Swarm Optimization	GSO	Plant growth optimization	PGO
Arithmetic Optimization Algorithm	AOA	Root growth algorithm	RGA
Hyper-Spherical Search Algorithm	HSS	Invasive weed optimization	IWO
Radial Movement Optimization	RMO	Fertile field algorithm	FFA
Stochastic Fractal Search	SFS	Flower pollination algorithm	FPA
Golden Ratio Optimization Method	GROM	Paddy field algorithm	PFA
Sine Cosine Algorithm	SCA	Root mass optimization algorithm	RMO

Table 1 (continued)

Name of the algorithm	Abbreviation	Name of the algorithm	Abbreviation
Runner Root Algorithm	RRA	Artificial plant optimization algorithm	APO
Rooted Tree Optimization	RTO	Sapling growing up algorithm	SGA
Path Planning inspired by Plant Growth	PGPP	Photosynthetic algorithm	PA
Artificial Root Foraging Algorithm	ARFA	Galaxy-based search algorithm	GbSA
Atomic Orbital Search	AOS	Flow direction algorithm	FDA
Equilibrium Optimizer	EO	Henry gas solubility optimization	HGSO
Atom Search Optimization	ASO	Nuclear reaction optimization	NRO
Black Hole Algorithm	BHA	Chemical reaction optimization	CRO
Artificial Chemical Reaction Optimization	ACRO	Central force optimization	CFO
Gravitational Search Algorithm	GSA	Big bang-big crunch algorithm	BBBC
Electromagnetic Field Optimization	EFO	Magnetic charged system search	MCSS
Water Evaporation Optimization	WEO	Multi-verse optimization	MVO
Optics Inspired Optimization	OIO	Thermal exchange optimization	TEO
Sonar Inspired Optimization	SIO	Vibrating particle system algorithm	VPSA
Electromagnetism-like Algorithm	EM	Artificial physicomimetics optimization	APO
Colliding Bodies Optimization	CBO	Ray optimization	RO
Charged system Search	CSS	Gravitational local Search optimization	GLSO

Table 2 Recent variants of marine predators algorithm (MPA)

Variants of marine predators algorithm (MPA)	
Revised variants	Hybridized variants
Modified MPA: MMPA-I, MMPA-II, MMPO, MMPA-SA, IMPA-I, IMPA-II, IMPA-III, IMPOA, IMMPA, EMPA, LEO-EMPA, EMPA, AMPA	**MPASSA**
Multi-Group MPA: MGMPA	**EGMPA**
Multi-Objective MPA: MOEMPA, MOMPA-I, MOMPA-II, MOMPA-III	**ODMPA**
Mutated MPA: MPAmu	**MMPA-OLGWO**
Binary MPA: BMPA, BMPA-TVSinV	**MPASCA**
IP Based MPA: IPMPA	**TLMPA**
Gold-Sine Dynamic MPA: GDMPA	**HMPA**
Fractional Order Comprehensive Learning MPA: FOCLMPA	**MPA-PO**
Fuzzy MPA: FMPA	**MPA-PSO**
Quantum MPA: QMPA	**IMPAPSO**
Fusion MPA: FMMPA	**MPA-MVO**
Chaos MPA: CMMPA	**MpNMRA**
Fractional MPA: FO-MPA	**MPAOA**
Stochastic MPA: SMPA-MC	**MPO-IPSO-OCR**
Non-Linear MPA: NMPA	**MMPA-TLBO**
Heterogeneous MPA: H-MPA	**DEMP**
Co-Evolutionary MPA: CECMPA	
Comprehensive Learning Dynamic Multi-Swarm MPA: CLDMMPA	
Adaptive Chaos MPA: ACMPA	
Opposition-Based MPA: MPA-OBL, OBL-MPA	
Multi-Strategy MPA: N-MPA, MSMPA- JRSSELM	
Lambert MPA: MPALW	
Harmonic MPA: SHE-MPA	
Ranking-Based MPA: IMPARDR	
Hybrid MPA: HMPA	
Comprehensive MPA: CLMPA	

Table 3 Abbreviations of revised MPA variants along with its full form for algorithms projected in Table 2

S. No	Revised MPA variants	Abbreviation
1	Improved Marine Predator Algorithm-I [147]	IMPA-I
2	Improved Marine Predator Algorithm-II [148]	IMPA-II
3	Improved Marine Predator Algorithm-III [167]	IMPA-III
4	Improved Marine Predators' Optimization Algorithm [148]	IMPOA
5	Improved Modified Marine Predators Algorithm [181]	IMMPA
6	Modified Marine Predator Algorithm [161]	MMPA-I
7	Modified Marine Predator Algorithm [169]	MMPA-II
8	Modified Marine Predator Optimizer [151]	MMPO
9	Modified Self Adaptive Marine Predators Algorithm [150]	MMPA-SA
10	Binary Marine Predator Algorithm using Time-Varying Sine and V-shaped transfer functions [149]	BMPA-TVSinV
11	Binary Marine Predator Algorithm [168]	BMPA
12	Multi-Objective Marine Predator Algorithm-I [170]	MOMPA-I
13	Multi-Objective Marine Predator Algorithm-II [171]	MOMPA-II
14	Multi-Objective Marine Predator Algorithm-III [175]	MOMPA-III
15	Multi-Objective Enhanced Marine Predators Algorithm [140]	MOEMPA
16	Enhanced Marine Predator Algorithm [172]	EMPA
17	Enhanced Marine Predator Algorithm with Local Escaping Operator [173]	LEO-EMPA
18	Multi-Strategy Marine Predator Algorithm [174]	MSMPA- JRSSELM
19	Multi-Strategy Marine Predator Algorithm (Neighborhood) [160]	N-MPA
20	Multi-Group Marine Predator Algorithm [176]	MGMPA
21	Quantum Marine Predator Algorithm [178]	QMPA
22	Advanced Marine Predator Algorithm [146]	AMPA
23	Fuzzy Marine Predator Algorithm [145]	FMPA
24	Chaos Embed Marine Predator Algorithm [141]	CMMPA
25	Stochastic Marine Predator Algorithm with Multiple Candidates [144]	SMPA-MC
26	Fusion Multi-Strategy Marine Predator Algorithm [142]	FMMPA
27	Fractional Order Marine Predators Algorithm [180]	FO-MPA
28	Co-Evolutionary Cultural mechanism-based Marine Predators Algorithm [143]	CECMPA
29	Comprehensive Learning Dynamic Multi-Swarm Marine Predators Algorithm [177]	CLDMMPA
30	Heterogeneous Marine Predators Algorithm [152]	H-MPA
31	Internet Protocol based Marine Predators Algorithm [153]	IPMPA
32	Marine Predators Algorithm Based on Adaptive Weight and Chaos Factor [154]	ACMPA
33	Opposition-based Marine Predators Algorithm [179]	MPA-OBL
34	Golden-Sine Dynamic Marine Predator Algorithm [155]	GDMPA
35	Marine Predator Algorithm with Mutation Operators [156]	MPAmu
36	Extended Marine Predator Algorithm [157]	EMPA
37	Non-Linear Marine Predator Algorithm [158]	NMPA
38	Fractional-Order Comprehensive Learning Marine Predators Algorithm [159]	FOCLMPA
39	Comprehensive Learning Marine Predator Algorithm [162]	CLMPA
40	Augmented Marine Predators Algorithm based on Opposition Based Learning [163]	OBL-MPA
41	Hybrid Marine Predators Algorithm [164]	HMPA
42	Improved Marine Predators Algorithm and a Ranking-Based Diversity Reduction Strategy [165]	IMPARDR
43	Selective Harmonic Elimination with Marine Predator Algorithm [166]	SHE-MPA
44	Marine Predators Algorithm and Lambert W function [182]	MPALW

upper bounds of the dimensions and r1 and r2 signifies the indexes of the prey matrix. (see Table 1).

3 Recent Variants of Marine Predators Algorithm

Since the inception of MPA, an extensive series of MPA's variants have been developed and further introduced in the

Table 4 Abbreviations of hybridized MPA variants along with its full form for algorithms projected in Table 2

S. No	Hybridized MPA variants	Abbreviation
1	Marine predator inspired naked Mole-Rat Algorithm [183]	MpNMRA
2	Marine Predators Algorithm and Multi-Verse Optimization Algorithm [184]	MPA-MVO
3	Boosting Marine Predators Algorithm by Salp Swarm Algorithm [185]	MPASSA
4	Hybrid Marine Predators Algorithm (MPA with AOA) [186]	MPAOA
5	Elite opposition-based learning strategy and the Golden Sine algorithm with Improved Marine Predators Algorithm [187]	EGMPA
6	Hybrid Marine Predators Optimization and Improved Particle Swarm Optimization-based Optimal Cluster Routing [188]	MPO-IPSO-OCR
7	Modified Marine Predator Algorithm with Teaching–Learning-Based Optimization [189]	MMPA-TLBO
8	Binary Differential Evolution and Marine Predators Algorithm [190]	DEMP
9	Improved Marine Predator Algorithm with Quasi-Opposition Strategy and Differential Evolution [191]	ODMPA
10	Modified Marine Predator Algorithm based on Opposition Learning and Grey Wolf Optimizer [192]	MMPA-OLGWO
11	Modified Marine Predators Algorithm with Sine–Cosine Algorithm [193]	MPASCA
12	Teaching–Learning-based Marine Predators Algorithm [194]	TLMPA
13	Hybrid Marine Predators-Slime Mould Algorithm [195]	HMPA
14	Marine Predators and Political Optimizers [196]	MPA-PO
15	Integrating Marine Predators Algorithm and Particle Swarm Optimization [197]	MPA-PSO
16	Improved Marine Predators Algorithm and Particle Swarm Optimization [198]	IMPAPSO

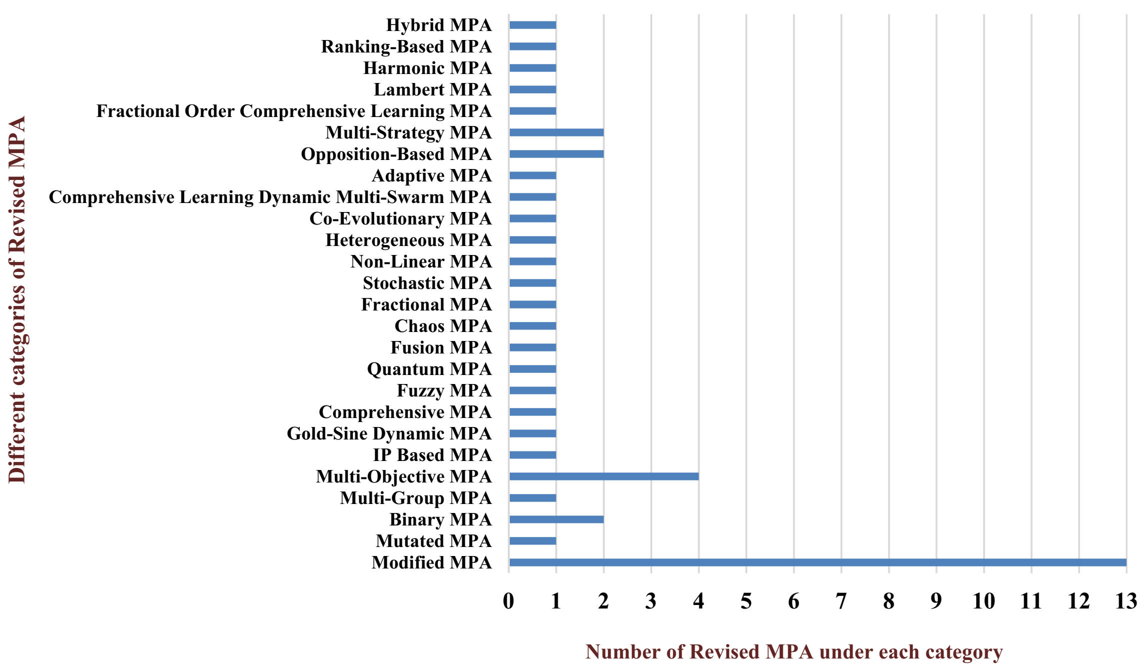

Fig. 7 Proposed methods belonging to categories of revised MPA

literature. Based on the same, recent variants of MPA are divided into two important categories namely: Revised variants of MPA and Hybridized variants of MPA and the same are illustrated in Table 2. The details in regard to the two categories as depicted in Table 2 are discussed in the subsequent sections. Furthermore, Abbreviations of different MPA variants along with its full form for algorithms projected in Fig. 4 is tabulated in Tables 3 and 4.

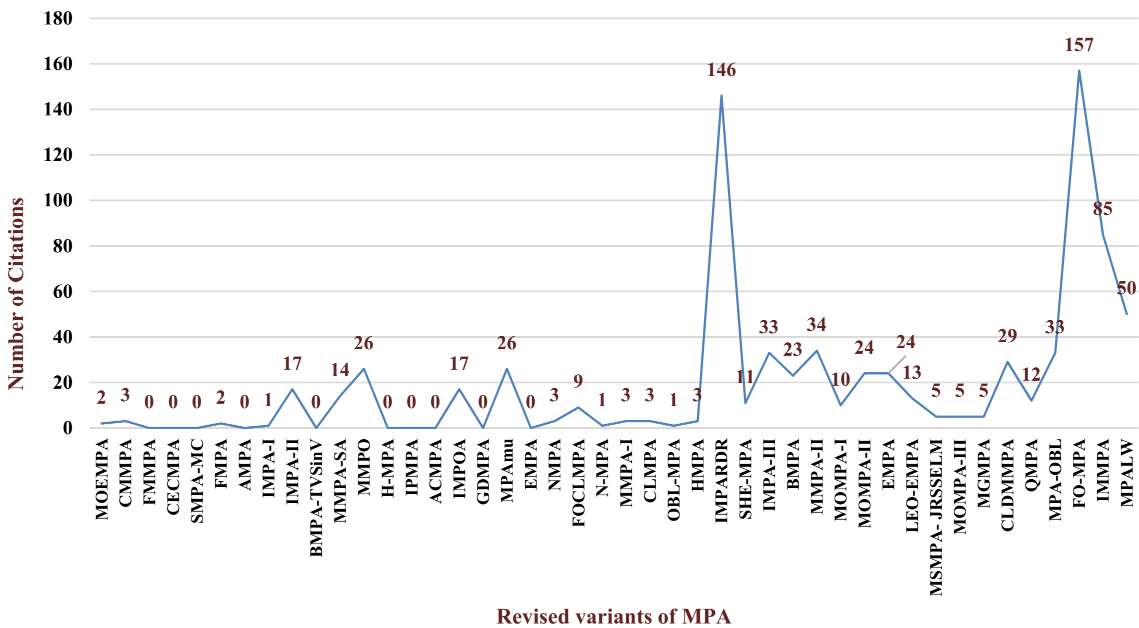

Fig. 8 The citations as per Google scholar for different revised variants of MPA

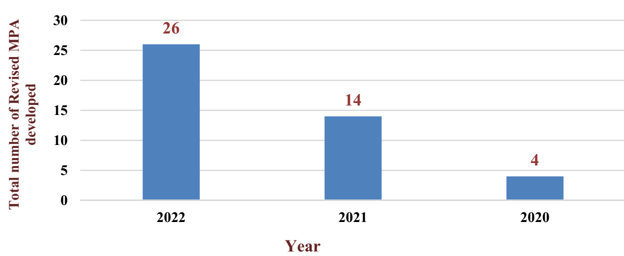

Fig. 9 Total number of revised variants of MPA developed over years

3.1 Revised Variants of Marine Predators Algorithm

The revised variants of MPA as per Fig. 7 has been categorized into different categories. The name of each category is devised as per the nomenclature provided by the different authors in their research papers and has not been altered. It is clear from given figure that around **26** different categories of the revised variants (with sub-variants) of MPA has been introduced since its development namely, Modified MPA, Improved MPA, Mutated MPA, Enhanced MPA, Binary MPA, Multi-Group, Multi-Objective, Extended MPA, IP Based MPA, Gold-Sine Dynamic MPA, Advanced MPA, Comprehensive MPA, Fuzzy MPA, Quantum MPA, Fusion MPA, Chaos MPA, Fractional MPA, Stochastic MPA, Non-Linear MPA, Heterogeneous MPA, Co-Evolutionary MPA, Comprehensive Learning Dynamic Multi-Swarm MPA, Adaptive MPA, Opposition-Based MPA, Multi-Strategy MPA, Fractional Order Comprehensive Learning MPA, Lambert MPA, Harmonic MPA, Ranking-Based MPA and Hybrid MPA. Further, depending on the different mechanism / operators / transfer functions used to resolve the problem under consideration, various sub-variants have been introduced under each category. There are **44** different revised version of MPA belonging to different categories that is IMPA-I, IMPA-II, IMPA-III, IMPOA, IMMPA, MMPA-I, MMPA-II, MMPO, MMPA-SA, BMPA-TVSinV, BMPA, MOMPA-I, MOMPA-II, MOMPA-III, MOEMPA, EMPA, LEO-EMPA, MSMPA-JRSSELM, MGMPA, QMPA, AMPA, FMPA, CMMPA, SMPA-MC, FMMPA, FO-MPA, CECMPA, CLDMMPA, H-MPA, IPMPA, MPA-OBL, GDMPA, MPAmu, N-MPA, EMPA, NMPA, FOCLMPA, CLMPA, ACMPA, OBL-MPA, HMPA, IMPARDR, SHE-MPA and MPALW. The same is depicted in Fig. 7. The citations as per Google scholar for different revised variants of MPA belonging to different categories is portrayed in Fig. 8. The total number of revised variants of MPA developed over years is highlighted in Fig. 9. The full-form of the same is depicted in Table 3. The details of each of the variants such as revised variants name, Methods / Mechanism used, application areas, results, citation (as per Google Scholar, dated: 19.10.2022) and publisher are tabulated in Table 5. Full form of the different terminologies used in Table 5 is projected in Table 7.

3.2 Hybridized Variants of Marine Predators Algorithm

On the other hand, **16** research papers has been listed that focuses on the hybridization of MPA with numerous

Table 5 Various revised MPA variants along with other related details

SI	Revised MPA	Author (Year)	Methods/Transfer Function/ Operators /Mechanism	Results	Citation	Journal	Publisher
1	Multi-Objective Enhanced Marine Predators Algorithm (MOEMPA)	Yousri et. al. [140]	Non-Uniform mutation operator	The MOEMPA method proves to be efficient when compared with current multi-objective optimization algorithms namely MOMPA, MOGOA, MOSMA, MOGWO, MOALO and MOMVO	2	Energy Conversion and Management	Elsevier
2	Chaos Embed Marine Predator Algorithm (CMMPA)	Alrasheedi et. al. [141]	Chaos strategy	The CMMPA method attains better results than MPA, ALO, GA and PSO in regard to fitness function, selected features and accuracy in terms of classification	3	Mathematics	MDPI
3	Fusion Multi-Strategy Marine Predator Algorithm (FMMPA)	Yang et. al. [142]	Strategy: Spiral complex path search	The FMMPA method is compared with MPA, WOA, SCA, AO, EO and GWO	0	Applied Sciences	MDPI
4	Co-Evolutionary Cultural mechanism-based Marine Predators Algorithm (CEC-MPA)	Jia et. al. [143]	Co-Evolutionary cultural mechanism	The CECMPA method when compared to PSO, GOA, SSA, WOASAT-2 and SOA-TEO3 achieves either alike or enhanced outcome with regard to classification accuracy and identification of optimal feature	0	KSII Transactions on Internet and Information Systems (TIIS)	Korea Society of Internet Information
5	Stochastic Marine Predator Algorithm with Multiple Candidates (SMPA-MC)	Kusuma et. al. [144]	Linear probability, Stochastic approach and Exploration dominant strategy	The SMPA-MC method performs better in terms of average fitness score parameter for solving multimodal functions in comparison to PSO, MPA and KMA	0	International Journal of Advanced Computer Science and Applications	IJACSA publications
6	Fuzzy Marine Predator Algorithm (FMPA)	Cuevas et. al. [145]	Strategy: Best feeding, Type 2 Fuzzy parameter adaption	The FMPA method outperforms HS method considering different of numerous comprehensive performance metrics	2	Symmetry	MDPI
7	Advanced Marine Predator Algorithm (AMPA)	Owoola et. al. [146]	Mechanism: Adaptive velocity update	The AMPA method accomplishes superior performances in terms of convergence rate when compared to other algorithms	0	Sensors	MDPI

Table 5 (continued)

SI	Revised MPA	Author (Year)	Methods/Transfer Function/ Operators /Mechanism	Results	Citation	Journal	Publisher
8	Improved Marine Predator Algorithm (IMPA-I)	He et al. [147]	Strategy: Dynamic inertia weight adjustment, multi-elite	The IMPA method outperforms other classical meta-heuristic algorithms such as SCA, TSA, MA and EO	1	Sustainability	MDPI
9	Improved Marine Predator Algorithm (IMPA-II)	Shaheen et. al. [148]	Levy and Brownian movement	The IMPA generates better result when compared with IMPA HS, EDHS, CPSO, TVAC-PSO, WVO, MPA and WVO-PSO	17	Alexandria Engineering Journal	Elsevier
10	Binary MPA using Time-Varying Sine and V-shaped transfer functions (BMPA-TVSinV)	Behesti [149]	Time-Varying Sine along with V-shaped	The BMPA-TVSinV archives a higher accuracy and feature reduction rate on datasets when compared with recent binary meta-heuristic algorithms	0	Knowledge-Based Systems	Elsevier
11	Modified Self-Adaptive Marine Predator Algorithm (MMPA-SA)	Fan et. al. [150]	Opposition-Based Learning, Inertia weight coefficient and nonlinear step size control parameter strategies	The MMPA method when compared with PRO, GOA, MFO, ALO, MBA, PSO-DE, BA, and DEDS reveals finer performance considering accuracy, stability and convergence speed as performance parameters	14	Engineering with Computers	Springer
12	Modified Marine Predator Optimizer (MMPO)	Shaheen et. al. [151]	Predator's strategies	The MMPO method outperforms other methods as compared with the original MPO, GA, HSA, FWO, FF and ISCA	26	Engineering Optimization	Taylor and Francis
13	Heterogeneous Marine Predators Algorithm (H-MPA)	Zaky et. al. [152]	Triple Diode Model (TDM) parameters as decision variables	The H-MPA method is compared with SMA, TSO, MRFO, FBI, EO and AEO thus proving its supremacy in designing a reliable and robust model	0	Mathematics	MDPI
14	Internet Protocol based Marine Predators Algorithm (IPMPA)	Liu et. al. [153]	IP address: Encoding strategy	The IPMPA method when compared with IPPSO, VLGA, VLNSGA-II, VLBSO, IPMPSO and VLACO proved itself to be proficient in regard to the accuracy score	0	Journal of Ambient Intelligence and Humanized Computing	Springer

Table 5 (continued)

SI	Revised MPA	Author (Year)	Methods/Transfer Function/ Operators /Mechanism	Results	Citation	Journal	Publisher
15	Marine Predators Algorithm Based on Adaptive Weight and Chaos Factor (ACMPA)	Liang et. al. [154]	Adaptive weight and Chaos factor	The ACMPA method when compared with ChoA, MPA, MFO and SCA accomplishes healthier results proving it to be having a superior outcome especially in the problem related to shortest path	0	Scientific Programming	Hindawi
16	Improved Marine Predators' Optimization Algorithm (IMPOA)	Shaheen et. al. [148]	Levy and Brownian movement, Operating point setup, Boundary check	The IMPOA method generates stable convergence characteristics and the advent of most favorable outcome is faster than MPOA, WOA, TVAC-PSO, RCGA-IMM and MPHS	17	Alexandria Engineering Journal	Elsevier
17	Golden-Sine Dynamic Marine Predator Algorithm (GDMPA)	Han et. al. [155]	Sigmoid function, Gold-Sine factor	The GDMPA method is comparatively better than that of MPA, BOA, SSA, SOA and HHO thereby paving its way towards structural design and optimization	0	Expert Systems with Applications	Elsevier
18	Marine Predator Algorithm with Mutation Operators (MPAmu)	Qaness et. al. [156]	Mutation operator	The MPAmu method is compared with SVM, FNN and LSTM and extensively boost the prediction accuracy of the underlying model	26	Applied Energy	Elsevier
19	Extended Marine Predator Algorithm (EMPA)	Adnan et. al. [157]	Predator strategies	The EMPA method is compared with MPA, PSO, GA and GWO	0	Applied Soft Computing	Elsevier
20	Nonlinear Marine Predators Algorithm (NMPA)	Sadiq et. al. [158]	Set of nonlinear functions	The NMPA method could effectively find the minimum rate and is further compared with MVO, MFO, SSA, GWO, PSO and DE	3	Expert Systems with Applications	Elsevier
21	Fractional-Order Comprehensive Learning Marine Predators Algorithm (FOCLMPA)	Yousri et. al. [159]	Comprehensive Learning and Memory perspective of the Fractional Calculus strategies	The FOCLMPA method is compared with several optimization algorithms using statistical and non-parametric and attains a superior and stable result generating incredible convergence curves	9	Knowledge-Based Systems	Elsevier

Table 5 (continued)

SI	Revised MPA	Author (Year)	Methods/Transfer Function/ Operators /Mechanism	Results	Citation	Journal	Publisher
22	Multi-Strategy boosted Marine Predator Algorithm (N-MPA)	Hu et al. [160]	Neighborhood-based learning and the adaptive population size strategies	The NMPA method confirm to be advanced over other algorithms in terms of accuracy and convergence rate	1	Knowledge-Based Systems	Elsevier
23	Modified Marine Predator Algorithm (MMPA-I)	Hassan et al. [161]	Comprehensive Learning strategy, Pareto approach, Fuzzy method	The MMPA-I method has better performance relative to other techniques	3	Computers & Industrial Engineering	Elsevier
24	Comprehensive Learning Marine Predator Algorithm (CLMPA)	Yousri et al. [162]	Comprehensive Learning strategy	The CLMPA method is compared with MRFO, WCA, MVO, VSA, MPA, AOA, JS and RUN which further substantiate its skill in creating trustworthy corresponding circuit	3	Journal of Energy Storage	Elsevier
25	Augmented Marine Predators Algorithm based on Opposition Based Learning (OBL-MPA)	Balakrishnan et al. [163]	High-Dimensional Microarray Datasets	The OBL-MPA method is compared with other methods such as WOA, GWO, HHO, iWOA, and MPA Thereby successfully exploring the entire search space considered	1	Expert Systems	Wiley
26	Hybrid Marine Predators Algorithm (MPA with LIS and RUS) (HMPA)	Basset et al. [164]	Gray Scale Images	The HMPA method proved to be superior for the high threshold levels and is compared with EO, SMA, ITSA, HHA, FPA, IMPA and WOA	3	Artificial Intelligence Review	Springer
27	Improved Marine Predators Algorithm and a Ranking-Based Diversity Reduction Strategy (IMPARDR)	Basset et al. [165]	X-Ray Images	The IMPARDR method outperforms all other algorithms namely EO, WOA, SCA, HHA and SSA for a range of metrics	146	IEEE Access	IEEE
28	Selective Harmonic Elimination with Marine Predator Algorithm (SHE-MPA)	Riad et al. [166]	Cascaded H-Bridge (CHB) topology	The SHE-MPA method outperforms TLBO, FPA and PSOGWO in terms of efficiency and accuracy	11	Electronics	MDPI
29	Improved Marine Predator Algorithm (IMPA-III)	Eid et al. [167]	Reactive power control strategy, Predator strategies	The IMPA-III method finds optimal solution and beats other methods such as MPA, AEO and PSO	33	Neural Computing and Applications	Springer

Table 5 (continued)

SI	Revised MPA	Author (Year)	Methods/Transfer Function/ Operators /Mechanism	Results	Citation	Journal	Publisher
30	Binary Marine Predators Algorithm (BMPA)	Abdel-Basset et al. [168]	V-shaped and S-shaped	The BMPA outperformed BHHA, BWOA, BSCA and other optimization algorithms for tackling Knapsack Problem	23	Computers & Industrial Engineering	Elsevier
31	Modified Marine Predator Algorithm (MMPA-II)	Ramezani et al. [169]	Opposition-based learning, Self-adaptive population method and Chaos map	The MMPA generates better result when compared with PSO, HHA, DS, JAYA, WOA, LCA, GOA and EO	34	Arabian Journal for Science and Engineering	Springer
32	Multi-Objective Marine Predator Algorithm (MOMPA-I)	Jangir et al. [170]	Elitist Non-dominated Sorting and Crowding Distance mechanisms	The MOMPA method excel the other methods namely MOWCA, MOSOS and MOMFO in regard to numerous performance indicators	10	Evolutionary Intelligence	Springer
33	Multi-Objective Marine Predator Algorithm (MOMPA-II)	Zhong et al. [171]	Top predator selection	The MOMPA method provides very competitive results when compared with MOPSO, PESA-II, MOALO, MODA, MOGWO, MOBO, MOMVO, MSSA and MOEA/D	24	Computer Methods in Applied Mechanics and Engineering	Elsevier
34	Enhanced Marine Predator Algorithm (EMPA)	Elaziz et al. [172]	Differential Evolution operators	The EMPA method generates outstanding results when compared to MPA, EPSO, GA, CSA, HCLPSO, PGJAYA, CWOA, PSO-WOA, STLBO, ELPSO, HFAPS, MLBSA, TVACPSO, CPSO and ICSA considering data fitting, convergence rate, stability and consistency	24	Energy Conversion and Management	Elsevier

Table 5 (continued)

SI	Revised MPA	Author (Year)	Methods/Transfer Function/ Operators /Mechanism	Results	Citation	Journal	Publisher
35	Enhanced Marine Predator Algorithm with Local Escaping Operator (LEO-EMPA)	Oszust [173]	Local Escaping Operator	The LEO-EMPA method proves to be efficient when compared with MPA and other state-of-arts algorithms such as PSO, IGWO, ChOA, SSA, BOA, GOA, MPA, WDO, AOA, GBO, DDAO, HBO, ASO, SMA, CGO, FDBSOS, and PO	13	Knowledge-Based Systems	Elsevier
36	Multi-Strategy Marine Predator Algorithm (MSMPA-JRSSELM)	Yang et al. [174]	Hessian and supervised information regularization	The MSMPA- JRSSELM shows excellent classification performance in regard to ACC, MAE and RMSE when compared with SSELM, PSO, GWO, WOA, MFO, SOA, and SCA	5	Mathematics	MDPI
37	Multi-Objective Marine Predator Algorithm (MOMPA-III)	Chen et al. [175]	Non-Dominated Sorting approach and Reference Point strategy	The MOMPA-III method outperforms other methods such as NSGA-II, NSGA-III, MOEA/D, PESA-II, CMOPSO and NSLS	5	Proceedings of the Genetic and Evolutionary Computation Conference Companion	Springer
38	Multi-Group Marine Predator Algorithm (MGMPA)	Pan et al. [176]	Maximum and average of same group, maximum and average of different groups	The MGMPA method is compared to PSO, PPSO, SSA and MPA and thereby achieves the supreme economic profits	5	Energy Science & Engineering	Wiley
39	Comprehensive Learning Dynamic Multi-Swarm Marine Predators Algorithm (CLDMMPA)	Yousri et al. [177]	SOFC steady-state and dynamic state-based models	The CLDMMPA method reveals the minimum deviation amongst the measured and estimated stack current–voltage and current–power curves proving it to be finer than other counterparts	29	Alexandria Engineering Journal	Elsevier
40	Quantum Maine Predators Algorithm (QMPA)	Elaziz et al. [178]	Schrodinger wave function	The QMPA method outperforms other methods like MPA, WOA, SCA, SSA, GOA, ALO, MFO and GWO to uncover optimal threshold that show the way towards enhancing the worth of the segmented images	12	Applied Soft Computing	Elsevier

Table 5 (continued)

SI	Revised MPA	Author (Year)	Methods/Transfer Function/ Operators /Mechanism	Results	Citation	Journal	Publisher
41	Opposition-Based Marine Predators Algorithm (MPA-OBL)	Houssein et al. [179]	Opposition-based learning	The MPAO-OBL method generates exceedingly proficient and consistent outcomes in contrast with the other competitor algorithms such as LSHADE-SPACMAOBL, CMA_ES-OBL, DE-OBL, HHO-OBL, SCA-OBL, SSA-OBL and MPA	33	Knowledge-Based Systems	Elsevier
42	Fractional Order Marine Predators Algorithm (FO-MPA)	Sahlol et. al. [180]	Fractional Order Calculus	The FO-MPA method generated promising result in terms of both classification and feature extraction when compared with SMA, HHO, HGSO, WOA, SCA, bGWO, SGA, BPSO, besides the classic MPA	157	Scientific reports	Nature Portfolio
43	Improved Modified Marine Predators Algorithm (IMMPA)	Basset et. al. [181]	Last updated positions usage strategy, ranking strategy-based re-initialization and mutation	The IMMPA method outperformed other methods such as MPA, MMPA, WOA, SCA, SSA, GA and EOA	85	IEEE Transactions on Industrial Informatics	IEEE
44	Marine Predators Algorithm and Lambert W function (MPALW)	Ridha [182]	Single diode and double diode PV models	The MPALW method outperforms various methods such as MPA, IEM, BHHO, DEAM, EO and SMA considering accuracy and reliability	50	Solar Energy	Elsevier

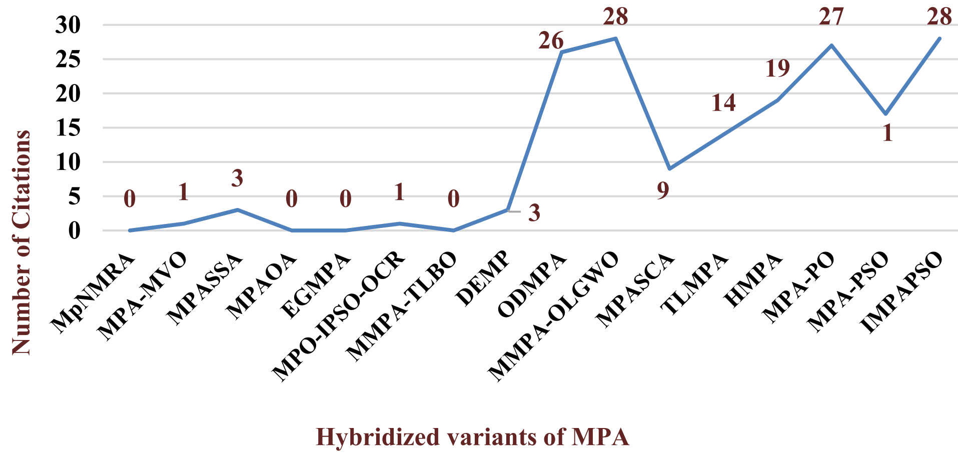

Fig. 10 The citations as per Google scholar for different hybridized variants of MPA

Fig. 11 Total number of revised variants of MPA developed over years

metaheuristic algorithms such as Salp Swarm Algorithm, Teaching–Learning mechanism, Golden Sine algorithm, Differential Evolution, Grey Wolf Optimizer, Sine–Cosine Algorithm, Slime Mould Algorithm, Mole Rat algorithm, Multi-Verse Optimization algorithm, Political Optimizers and Particle Swarm Optimization. The hybridization of MPA with all these algorithms has generated around **16** new algorithms that can applied to wide range of applications ranging from Image classification to Segmentation to Image Synthesis to Feature Selection to Optimization problems and many more. The hybridized algorithms are: MPASSA, EGMPA, ODMPA, MMPA-OLGWO, MPASCA, TLMPA, HMPA, MPA-PO, MPA-PSO, IMPAPSO, MPA-MVO, MpNMRA, MPAOA, DEMP, MMPA-TLBO and MPO-IPSO-OCR. The citations as per Google scholar for different hybridized variants of MPA belonging to different categories is depicted in Fig. 10. Various hybridized variants of MPA build up and projected over years since 2020 till date (as surveyed) is provided in Fig. 11. Full form of the same is highlighted in Table 4 and the hybridized variants of MPA and its related details are illustrated in Table 6. Full form of the different terminologies used in Table 6 is projected in Table 7.

4 Application Areas of Different Variants of Marine Predators Algorithm

Since its inception in the year 2020, Marine Predators Algorithm (MPA) has been employed to unravel assorted problems that belong to different application areas. The wide range of problems resolved by the algorithm and the details of the entire scenario are tabulated in Table 8. Full form of the different terminologies used in Table 8 is projected in Table 9. Also, kindly refer to Tables 3 and 4 for the remaining full forms of the different terminologies used in Table 8.

5 Representative Articles of MPA Used in the Survey

This section briefly describes few articles used in the survey in the above sections that has been highlighted as a representative article in the manuscript. The choice of the articles is done on the basis of the highest number of citations done so far. The articles described in this section comprised of both the revised variant as well as the hybridized variant of Marine Predators algorithm developed so far and has been referred by many researchers to carry forth their research activities.

In the work of Basset et al. [165] a hybridized variant of MPA called as Improved Marine Predators Algorithm and a Ranking-Based Diversity Reduction Strategy (IMPARDR) to develop hybrid COVID-19 Detection model is proposed. The proposed method employs Improved Marine Predators Algorithm (IMPA) and a Ranking-Based Diversity Reduction Strategy (RDR). The RDR strategy is employed for the enhancement of the performance of IMPA to get better solution in lesser number of iterations. RDR basically identifies incompetent particles that cannot reach the better solutions within a specified number of iterations, thus moving those inept particles towards the best solutions generated

Table 6 Various Hybridized MPA variants along with other related details

SI	Hybridized MPA	Author (Year)	Dataset/Test Cases/Image Type/Models/Topology used	Results	Citation	Journal	Publisher
1	Marine predator inspired naked mole-rat algorithm (MpNMRA)	Salgotra et. al. [183]	CEC2005, CEC2014 and CEC 2019 test suites	The MpNMRA method is efficient and effective thereby providing superior results	0	Expert Systems with Applications	Elsevier
2	Marine Predators Algorithm and Multi-Verse Optimization Algorithm (MPA-MVO)	Yildiz [184]	Kriging Surrogate modelling	The MPA-MVO method when compared to other methods generates the best result	1	Journal of Vehicle Design	InderScience Online
3	Boosting Marine Predators Algorithm by Salp Swarm Algorithm (MPASSA)	Abualigah et al. [185]	Gray Scale Images	The MPASSA method generates healthier results than WOA, SSA, AOA, MPA and PSO	3	Multimedia Tools and Applications	Springer
4	Hybrid Marine Predators Algorithm (MPA with AOA) (MPAOA)	Hai et al. [186]	Thermal-aware Routing Scheme	The MPAOA method surpasses other algorithms such as BA, GA, AOA and MPA in regard the different metrics	0	Journal of Bionic Engineering	Springer
5	Elite opposition-based learning strategy and the Golden Sine algorithm with Improved Marine Predators Algorithm (EGMPA)	Qin et. al. [187]	Carbon dioxide emissions model	The EGMPA achieves appreciably superior results when compared with MPA, DE, CS, MVO, SCA, MFO, SSA and GWO	0	Environmental Science and Pollution Research	Springer
6	Hybrid Marine Predators Optimization and Improved Particle Swarm Optimization-based Optimal Cluster Routing (MPO-IPSO-OCR)	Balamurugan et al. [188]	Simulation environment	The MPO-IPSO-OCR method improves the energy stability, prolongs network lifetime and offers maximum throughput when compared other methods	1	China Communications	IEEE
7	Modified Marine Predator Algorithm with Teaching–Learning-Based Optimization (MMPA-TLBO)	Gao et. al. (2022) [189]	CEC'17 test suite	The MPA-TLBO method outperform other methods especially in terms of tracking the abrupt motion	0	Multimedia Tools and Applications	Springer
8	Binary Differential Evolution and Marine Predators Algorithm (DEMP)	Ghoneimy et al. [190]	Multi-omics datasets from TCGA	The DEMP method outperforms other methods such as FFA, EO, MPA and SMA considering the clustering ability and execution time	3	International Journal of Intelligent Engineering and Systems	INASS
9	Improved Marine Predator Algorithm with Quasi-Opposition Strategy and Differential Evolution (ODMPA)	G.Hu et al. [191]	CEC'17 test suite	ODMPA provides best results when compared to methods such as MPA, MMPA and other intelligent algorithms	26	Engineering Applications of Artificial Intelligence	Elsevier

Table 6 (continued)

SI	Hybridized MPA	Author (Year)	Dataset/Test Cases/Image Type/Models/Topology used	Results	Citation	Journal	Publisher
10	Modified Marine Predator Algorithm based on Opposition Learning and Grey Wolf Optimizer (MMPA-OLGWO)	Houssein et. al. [192]	CEC'17 test suite	MPAOBL-GWO method outperforms other methods namely original MPA, GWO and PSO achieving the required optimal solution	28	Expert Systems with Applications	Elsevier
11	Modified marine predators' algorithm with Sine–Cosine Algorithm (MPASCA)	Elaziz et al. [193]	UCI datasets	MPASCA method highlights significant performance thereby outperforming the compared methods such as MPA, HHO, HGSO, WOA, GWO, GA and SSA in terms of classification measures	9	Knowledge and Information Systems	Springer
12	Teaching–Learning-based Marine Predators Algorithm (TLMPA)	Zhong et al. [194]	CEC'17 test suite	The TLMPA method outperformed the other methods in terms of searching efficiency generating optimal solution when compared with PSO, DE, SSA, LSHADE-cnEpSin, GWO and TLBO	14	AIMS Mathematics	AIMS press
13	Hybrid Marine Predators-Slime Mould Algorithm (HMPA)	Yousri et. al. [195]	Triple Diode Model (TDM)	The HMPA method Outperformed other methods namely SMA, EO, MRFO, TSO, JS and FBI	19	Energy Conversion and Management	Elsevier
14	Marine Predators and Political Optimizers (MPA-PO)	Diab et al. [196]	Proton Exchange Membrane Fuel Cells (PEMFC) model	The MPA-PO method proved its efficiency by reaching the optimal solution when compared with the results of HHO, MAEO, HGWO, HADE, JAYA, CS-EO	27	IEEE Access	IEEE
15	Integrating Marine Predators Algorithm and Particle Swarm Optimization (MPA-PSO)	Wang et al. [197]	UCI database	The MPA-PSO is not just capable of finding number of clusters but also obtain stable results when compared with PSO, MPA, DE, SHO, LSA and EO	17	IEEE Access	IEEE
16	Improved Marine Predators Algorithm and Particle Swarm Optimization (IMPAPSO)	Shaheen et. al. [198]	IEEE 30 bus, IEEE 57 bus and IEEE 118 bus systems	The IMPAPSO method when compared with MPA and PSO resulting in low power loss and high convergence speed	28	Energies	MDPI

Table 7 Full form of the different algorithms or terminologies as mentioned in Table 5 and 6

Full form of different algorithms / Terminologies	Abbreviation	Full form of different algorithms/Terminologies	Abbreviation
Marine Predator Algorithm	MPA	Structured similarity index metric	SSIM
Harris Hawks Optimization	HHO	Universal quality index	UQI
Henry Gas Solubility Optimization	HGSO	Optimal reactive power dispatch	ORPD
Improved Grey Wolf Optimizer	IGWO	Binary whale optimization algorithm	BWOA
Chimp Optimization Algorithm	ChOA	Binary sine cosine algorithm	BSCA
Moth-Flame Optimization Algorithm	MFO	Binary harris-hawks algorithm	BHHA
Seagull Optimization Algorithm	SOA	Grasshopper optimization algorithm	GOA
Butterfly Optimization Algorithm	BOA	Jaya algorithm	JAYA
Wind Driven Optimization	WDO	Equilibrium optimizer algorithm	EO
Arithmetic Optimization Algorithm	AOA	Differential search algorithm	DS
Gradient-Based Optimizer	GBO	League championship algorithm	LCA
Slime Mould Algorithm	SMA	combined heat and power	CHP
Chaos Game Optimization	CGO	Harmony search	HS
Fitness-Distance Balance Symbiotic Organism Search	FDBSOS	Economic dispatch harmony search	EDHS
Atom Search Optimization	ASO	Classical particle swarm optimization	CPSO
Dynamic Differential Annealed Optimization	DDAO	Heap-based optimizer	HBO
Time-Varying Acceleration Coefficients PSO	TVAC-PSO	Genetic algorithm	GA
Weighted Vertices Optimizer	WVO	Particle swarm optimization	PSO
Weighted Vertices Optimizer—PSO	WVO-PSO	equilibrium optimizer	EO
Opposition Strategy and Differential Evolution MPA	ODMPA	Whale optimization algorithm	WOA
Poor and Rich Optimization Algorithm	PRO	Sine cosine algorithm	SCA
Performance-Guided JAYA	PGJAYA	Harris-Hawks algorithm	HHA
Heterogeneous Comprehensive Learning PSO	HCLPSO	Salp swarm algorithms	SSA
Self-adaptive Teaching–Learning-Based Optimization	STLBO	Differential evolution	DE
Improved Whale Optimization Algorithm variants	CWOA	Ensemble particle swarm optimizer	EPSO
Particle Swarm Optimizer-Whale Optimization Algorithm	PSO-WOA	Grey wolf optimizer	GWO
Multi-Objective Multi-Verse Optimizer	MOMVO	Chaos particle swarm optimization	CPSO
Teaching Learning Based Optimization	TLBO	Photo voltaic	PV
Non-dominated Sorting and Local Search	NSLS	Battle royale optimization	BRO
Modified Artificial Ecosystem Optimization	MAEO	Tunicate swarm algorithm	TSA
Semi-Supervised Extreme Learning Machine	SSELM	Mayfly algorithm	MA
Multi-Objective Water-Cycle Algorithm	MOWCA	Equilibrium optimizer algorithm	EO
Multi-Objective Symbiotic-Organism Search	MOSOS	Firefly algorithm	FFA
Multi-Objective Moth-Flame Optimizer Algorithm	MOMFO	Improved sine cosine algorithm	ISCA
Multi-Objective Particle Swarm Optimization	MOPSO	Harmony search algorithm	HSA
Pareto Envelope-Based Selection Algorithm 2	PESA-II	Fire works optimizer	FWO
Multi-Objective Ant Lion Optimizer	MOALO	Human urbanization algorithm	HUA
Multi-Objective Dragonfly Algorithm	MODA	Genetic algorithm	GA
Multi-Objective Grey Wolf Optimizer	MOGWO	Cuckoo search algorithm	CSA
Multi-Objective Bonobo Optimizer	MOBO	Improved cuckoo search algorithm	ICSA
Multi-Objective Salp Swarm Algorithm	MSSA	Spotted hyena optimizer	SHO
Enhanced Leader Particle Swarm Optimization	ELPSO	Accuracy	ACC
Hybrid Firefly and Pattern Search Algorithms	HFAPS	Mean absolute error	MAE
Multiple Learning Backtracking Search Algorithm	MLBSA	Root mean square error	RMSE
Non-dominated Sorting Genetic Algorithm II	NSGA-II	Bat algorithm	BA
Non-dominated Sorting Genetic Algorithm III	NSGA-III	Parallel particle swarm optimization	PPSO

Table 7 (continued)

Full form of different algorithms / Terminologies	Abbreviation	Full form of different algorithms/Terminologies	Abbreviation
Pareto Envelope-based Selection Algorithm II	PESA-II	Side lobe level	SLL
Multi-Objective Grasshopper Optimization Algorithm	MOGOA	Support vector machine	SVM
Multi-Objective Marine Predators Algorithm	MOMPA	Komodo Mlipir algorithm	KMA
Multi-Objective Slime Mould Algorithm	MOSMO	Multi-objective ant lion optimizer	MOALO
Multi-Objective Multi-Verse Optimizer	MOMVO	gravitational search algorithm	GSA
Improved Whale Optimization Algorithm	iWOA	Kill herd algorithm	KH
Artificial Ecosystem-based Optimization	AEO	convolutional neural networks	CNN
Lightning Searching Algorithm	LSA	Equilibrium optimizer	EO
Improved Electromagnetism-like algorithm	IEM	boosted harris hawks optimizer	BHHO
Differential Evolution with Adaptive Mutation	DEAM	Paddy field algorithm	PFA
Plant Propagation Algorithm	PPA	Flower pollination algorithm	FPA
Non-Sub Sampling Contour Transform	NSCT	convolutional sparse representation	CSR
Artificial Bee Colony-based Support Vector Machine	ABC-SVM	Manta ray foraging optimization	MRFO
Simulated Annealing-based Support Vector Machine	SA-SVM	Jellyfish optimizer	JS
Stacked Sparse Auto Encoder	SSAE	Jaya algorithm	JAYA
Transient Search Optimization	TSO	Variable-length genetic algorithm	VLGA
Forensic-based Investigation Optimizer	FBI	Hybrid grey wolf optimizer	HGWO
Variable-Length Ant Colony Optimization	VLACO	hybrid adaptive differential evolution	HADE
Variable-Length Biogeography-Based Optimizer	VLBBO	Ip-modified particle swarm optimization	IPMPSO
Variable-Length Non-dominated Sorting Genetic Algorithm-II	VLNSGA-II	Convolutional sparsity based morphological component analysis	CSMCA
Multi-Objective Evolutionary Algorithm based on Decomposition	MOEA/D	Artificial fish swarm algorithm-based support vector machine	AFSA-SVM
Time Varying Acceleration Coefficients Particle Swarm Optimization	TVACPSO	The cuckoo search algorithm with explosion operator	CS-EO
Differential Evolution with Dynamic Stochastic Selection	DEDS	Particle swarm optimization-differential evolution	PSO-DE
Whale Optimization Algorithm with Simulated Annealing	WOASAT-2	Sea gull optimization algorithm- thermal exchange optimization	SOA-TEO3
Particle Swarm Optimization- Gravitational Search Algorithm	PSOGSA	Joint regularized semi-supervised extreme learning machine	JRSSELM
Non-Sub sampled Shearlet Transform with Multi-Scale Morphological Gradient using a pulse-Coupled Neural Network	NSST-MSMG-CNN	Competition multi-objective particle swarm optimization	CMOPSO
Hybrid Paddy Field Algorithm and Plant Propagation Algorithm with Disruption Operator	HPFAPPA-D	Hybrid particle swarm optimization with gray wolf optimization	PSOGWO
Non-Sub sampled Shearlet Transform with a Parameter-Adaptive Pulse Coupled Neural Network	NSST-PA-PCNN	Linearly increased worst solutions improvement strategy	LIS
Ranking-based Updating Strategy	RUS	shrimp freshness detection using Artificial neural network and k-neighbor network	SFD-ANN-KNN
Coefficient-based Particle Swarm Optimization and Chaotic Gravitational Search Algorithm-Artificial Neural Network	CPSOCGSA-ANN	Slime mold algorithm-artificial neural network	SMA-ANN
Shrimp Freshness Detection using Deep shrimp Net	SFD-D-SHNet	Differential evolution-opposition based learning	DE-OBL
Harris Hawk Optimization- Opposition Based Learning	HHO-OBL	Sine cosine algorithm-opposition based learning	SCA-OBL
Salp Swarm Algorithm- Opposition Based Learning	SSA-OBL	Long short-term memory	LSTM
Manta Ray Foraging Optimizer	MRFO	Water cycle algorithm	WCA

Table 7 (continued)

Full form of different algorithms / Terminologies	Abbreviation	Full form of different algorithms/Terminologies	Abbreviation
Multi-Verse Optimizer	MVO	Vortex search algorithm	VSA
Jellyfish Search Algorithm	JS	Runge–Kutta based algorithm	RUN

so far. The proposed method is validated using the medical images i.e., nine chest X-Ray images with threshold levels amid 10 and 100 and is further equated with five state-of-art algorithms namely EO, WOA, SCA, HHA, and SSA. The experimental outcome clearly exposes that the hybrid model, IMPARDR outdoes other algorithms mentioned above in terms of fitness values, Std, and a range of threshold metrics. The paper further advocates a path to the interested researcher that the proposed method can be worked on with color image segmentation and other medical applications thus paving a way for more investigation.

Sahlol et al. [180] anticipated a revised variant of MPA called Fractional Order Marine Predators Algorithm (FO-MPA) for COVID-19 image classification. The proposed method uses CNN mechanism for feature extraction and Fractional Order (FO) with enhanced version of Marine Predators Algorithm (MPA) to choose the pertinent features. The proposed method's performance is validated on two public COVID-19 X-ray datasets and the proposed FO-MPA method is compared with nine state-of-art algorithms namely SMA, HHO, HGSO, WOA, SCA, bGWO, SGA, BPSO, besides the classic MPA. The experimental result clearly highlights that the proposed method produces efficient result in terms of both classification as well as feature extraction when compared with the above-mentioned algorithms. The paper further suggests a direction to the researcher that the proposed method can be further applied for numerous image classification tasks and possibly will be decent alternative to other feature extractor and selector methods.

In the work of Basset et al. [181], Improved Modified Marine Predators Algorithm (IMMPA), a revised variants of MPA for the purpose of task scheduling in IoT based Fog Computing application is anticipated. The proposed method employs Modified MPA (MMPA) to improve the exploitation capability of the traditional MPA and ranking strategy-based initialization and mutation to get rid of the local optima and move towards the best so-far solution achieved. The IMMPA method is thereby compared with seven state-of-arts algorithms namely MPA, MMPA, WOA, SCA, SSA, GA and EOA and the experimental results clearly reveals the fact that the proposed method outperforms the above-mentioned algorithms. The evaluation has been performed based on five performance metrics such as energy consumed, make-span, cost, flow time and carbon dioxide emission rate. The paper further suggests a direction to the researcher that the proposed method can be further applied to schedule the dependent task in fog system and for answering multi-dimensional knapsack problems and DNA fragment assembly problem.

In the work of Elaziz et al. [217] a hybridized variant of MPA is proposed known as Random Vector Functional Link integrated with Marine Predators Algorithm (RVFL-MPA) for the tensile behavior prediction of dissimilar friction stir welded aluminum alloy joints. The proposed method employs MPA with RVFL to improve the prediction accuracy by employing the input parameters such as rotational speed, welding speed, tool axial force and pin profile with Tensile Elongation (TE) and Ultimate Tensile strength (UTS) as the output parameters. The RVFL-MPA method confirmed boundless promise amongst the experimental and projected outcomes which further indicates that it is not just precise but unfailing as well to expect the tensile behavior of welded aluminum joints.

In the work of Ridha [182] a hybridized variant of MPA is proposed known as Marine Predators Algorithm and Lambert W function (MPALW) for parameters extraction of single and double diodes photovoltaic models. The proposed method employs MPA with Lambert W function to tackle the parameter extraction optimization problem. The MPALW method is compared with six state-of-arts methods namely MPA, IEM, BHHO, DEAM, EO and SMA. The experimental result further clearly divulges the fact that the MPLW outperforms the other methods mentioned above in terms of accuracy as well as reliability. The paper further suggested the interested researchers that the proposed method can be applied to real engineering applications such as smart grids, energy sector, and fault error detection in future.

Ramezani et al [169]. in his work proposed a revised variant of MPA known as Modified Marine Predator Algorithm (MMPA) for the purpose of a real-world optimization problem based on PID control applied to a DC motor (PID controller tuning problem). The proposed method employs opposition-based learning method to improvise the initial population, population diversity as well as productivity; chaotic map function to discover the search space; self-adaptive population method to inevitably regulate the size of the population and adaptive method to switch amongst exploration and exploitation phases. The validation of the performance of MMPA is performed on the simulated MATLAB environment on standard test functions including

Table 8 The applications areas of Marine Predator Algorithm to solve various problems

SI	Application areas	Proposed Method	Variant of MPA	Type of MPA	Comparison	Year	References
1	Micro Grid	MOEMPA	Revised variant	Multi-Objective MPA	The MOEMPA method is compared with MOMPA, MOGOA, MOSMA, MOGWO, MOALO and MOMVO	2022	[140]
2	Feature Selection	CMMPA	Revised variant	Chaos MPA	The CMMPA method is compared to MPA, ALO, GA and PSO	2022	[141]
3	Robot Path Planning	FMMPA	Revised variant	Fusion MPA	The FMMPA method is compared with original MPA, WOA, SCA, AO, EO and GWO	2022	[142]
4	Feature Selection and SVM Optimization	CECMPA	Revised variant	Co-Evolutionary Cultural MPA	The CECMPA method is compared with PSO, GOA, SSA, WOASAT-2 and SOA-TEO3	2022	[143]
5	Production Planning	SMPA-MC	Revised variant	Stochastic MPA	The SMPA-MC method is compared with PSO, MPA and KMA	2022	[144]
6	Mobile Robots	FMPA	Revised variant	Fuzzy MPA	The FMPA method is compared with HS	2022	[145]
7	Circular Antenna Array	AMPA	Revised variant	Advanced MPA	The AMPA method is compared with recent binary meta-heuristic algorithms	2022	[146]
8	Wireless Sensor Network Coverage Optimization Problem	IMPA-I	Revised variant	Improved MPA	The IMPA method is compared with SCA, TSA, MA and EO	2022	[147]
9	CHP Economic Dispatch Problem	IMPA-II	Revised variant	Improved MPA	The IMPA method is compared with IMPA HS, EDHS, CPSO, TVAC-PSO, WVO, MPA and WVO-PSO	2022	[148]
10	Feature Selection and Classification	BMPA-TVSinV	Revised variant	Binary MPA	The BMPA-TVSinV method is compared with numerous binary meta-heuristic algorithms	2022	[149]
11	Engineering design	MMPA-SA	Revised variant	Modified MPA	The MMPA method is compared with recent binary meta-heuristic algorithms.PRO, GOA, MFO, ALO, MBA, PSO-DE, BA, and DEDS	2022	[150]
12	Network reconfiguration and Distributed Generator Allocation in Distribution Systems	MMPO	Revised variant	Modified MPA	The MMPO method is compared with the original MPO, GA, HSA, FWO, FF and ISCA	2022	[151]
13	Triple Diode Model	H-MPA	Revised variant	Heterogeneous MPA	The H-MPA method is compared with SMA, TSO, MRFO, FBI, EO and AEO	2022	[152]
14	COVID-19 Diagnosis	IPMPA	Revised variant	IP Based MPA	The IPMPA method is compared with IPPSO, VLGA, VLNSGA-II, VLBSO, IPMPSO and VLACO	2022	[153]
15	Travelling Salesman Problem (TSP)	ACMPA	Revised variant	Adaptive Chaos MPA	The ACMPA method is compared with ChoA, MPA, MFO and SCA	2022	[154]

Table 8 (continued)

SI	Application areas	Proposed Method	Variant of MPA	Type of MPA	Comparison	Year	References
16	CHP Economic Dispatch Problem	IMPOA	Revised variant	Improved MPA	The IMPOA method is compared with MPOA, WOA, TVAC-PSO, RCGA-IMM and MPHS	2022	[148]
17	Engineering Design Optimizations	GDMPA	Revised variant	Golden-Sine Dynamic MPA	The GDMPA method is compared with MPA, BOA, SSA, SOA and HHO	2022	[155]
18	Wind Power Forecasting	MPAmu	Revised variant	Mutation MPA	The MPAmu method is compared with SVM, FNN and LSTM	2022	[156]
19	Stream flow Prediction	EMPA	Revised variant	Extended MPA	The EMPA method is compared with MPA, PSO, GA and GWO	2022	[157]
20	Fair Power Allocation in NOMA-VLC-B5G networks	NMPA	Revised variant	Non-Linear MPA	The NMPA method is compared with MVO, MFO, SSA, GWO, PSO and DE	2022	[158]
21	Global Optimization and Feature Selections	FOCLMPA	Revised variant	Fractional-Order Comprehensive Learning MPA	The FOCLMPA method is compared with several well-regarded optimization algorithms	2022	[159]
22	Engineering Design Optimizations	N-MPA	Revised variant	Multi-Strategy MPA	The NMPA method is compared with more than a few popular optimization algorithms	2022	[160]
23	Combined Economic Emission Dispatch (CEED) problems	MMPA-I	Revised variant	Modified MPA	The MMPA-I method is compared with several well-regarded optimization algorithms	2022	[161]
24	Extracting parameters of Super Capacitor (SC) model	CLMPA	Revised variant	Comprehensive Learning MPA	The CLMPA method is compared with MRFO, WCA, MVO, VSA, MPA, AOA, JS and RUN	2022	[162]
25	Feature Selection	OBL-MPA	Revised variant	Opposition-Based MPA	The OBL-MPA method is compared with WOA, GWO, HHO, iWOA, and MPA	2022	[163]
26	Image Segmentation	HMPA	Revised variant	Hybrid MPA	The HMPA method is compared with EO, SMA, ITSA, HHA, FPA, IMPA and WOA	2022	[164]
27	COVID-19 detection	IMPARDR	Revised variant	Ranking-Based MPA	The IMPARDR method is compared with EO, WOA, SCA, HHA and SSA	2021	[165]
28	Three-Phase Multilevel Inverter	SHE-MPA	Revised variant	Harmonic MPA	The SHE-MPA method is compared with TLBO, FPA and PSOGWO	2021	[166]
29	Photovoltaic Models, Fault Error Detection, Engineering Applications	MPALW	Revised variant	Lambert MPA	The MPALW method is compared with MPA, IEM, BHHO, DEAM, EO and SMA	2020	[167]
30	Distribution Networks	IMPA-III	Revised variant	Improved MPA	The IMPA-III method is compared with MPA, AEO and PSO	2021	[168]

Table 8 (continued)

SI	Application areas	Proposed Method	Variant of MPA	Type of MPA	Comparison	Year	References
31	Optimization Problems with Discrete or Binary parameters (Knapsack Problem)	BMPA	Revised variant	Binary MPA	The BMPA is compared with BHHA, BWOA, BSCA and other optimization algorithms	2021	[169]
32	Engineering design/Tuning problems	MMPA-II	Revised variant	Modified	The MMPA method is compared with PSO, HHA, DS, JAYA, WOA, LCA, GOA and EO	2021	[170]
33	Multi-Objective Optimization Problem	MOMPA-I	Revised variant	Multi-Objective MPA	The MOMPA method is compared with MOWCA, MOSOS and MOMFO	2021	[171]
34	Engineering Design	MOMPA-II	Revised variant	Multi-Objective MPA	The MOMPA method is compared with MOPSO, PESA-II, MOALO, MODA, MOGWO, MOBO, MOMVO, MSSA and MOEA/D	2021	[172]
35	PV System / Models	EMPA	Revised variant	Enhanced MPA	The EMPA method is compared with MPA, EPSO, GA, CSA, HCLPSO, PGJAYA, CWOA, PSO-WOA, STLBO, ELPSO, HFAPS, MLBSA, TVACPSO, CPSO and ICSA	2021	[173]
36	Engineering Problems	LEO-EMPA	Revised variant	Enhanced MPA	The LEO-EMPA method is compared with MPA and other state-of-arts algorithms such as PSO, IGWO, ChOA, SSA, BOA, GOA, MPA, WDO, AOA, GBO, DDAO, HBO, ASO, SMA, CGO, FDBSOS, and PO	2021	[174]
37	Oil Logging Oil Layer Identification Applications	MSMPA- JRSSELM	Revised variant	Multi-Strategy MPA	The MSMPA- JRSSELM method is compared with SSELM, PSO, GWO, WOA, MFO, SOA, and SCA	2021	[175]
38	Multi-Objective Optimization problems	MOMPA-III	Revised variant	Multi-Objective MPA	The MOMPA-III method is compared with NSGA-II, NSGA-III, MOEA/D, PESA-II, CMOPSO and NSLS	2021	[176]
39	Power system Economic Load Dispatch	MGMPA	Revised variant	Multi-Group MPA	The MGMPA method is compared with PSO, PPSO, SSA and MPA	2021	[177]
40	Solid Oxide Fuel Cell	CLDMMPA	Revised variant	ComprehensiveLearning Dynamic Multi-Swarm MPA	The CLDMMPA is compared with recent state-of arts methods	2021	[178]
41	Image Segmentation	QMPA	Revised variant	Quantum MPA	The QMPA method is compared with MPA, WOA, SCA, SSA, GOA, ALO, MFO and GWO	2021	[179]

Table 8 (continued)

SI	Application areas	Proposed Method	Variant of MPA	Type of MPA	Comparison	Year	References
42	Image Segmentation	MPA-OBL	Revised variant	Opposition-Based MPA	The MPAO-OBL method is compared with as LSHADE-SPACMAOBL, CMA_ES-OBL, DE-OBL, HHO-OBL, SCA-OBL, SSA-OBL and MPA	2020	[180]
43	Image Classification	FO-MPA	Revised variant	Fractional Order MPA	The FO-MPA method is compared with SMA, HHO, HGSO, WOA, SCA, bGWO, SGA, BPSO, besides the classic MPA	2020	[181]
44	Task Scheduling in IoT-based Fog Computing Applications	IMMPA	Revised variant	Improved MPA	The IMMPA method is compared with MPA, MMPA, WOA, SCA, SSA, GA and EOA	2020	[182]
45	Engineering Design problems	MpNMRA	Hybridized variant	Standard MPA	The MpNMRA method is compared with CPSOCGSA-ANN and SMA-ANN	2023	[183]
46	Electric Car components design	MPA-MVO	Hybridized variant	Standard MPA	The MPA-MVO method is compared with other recent hybrid methods and standard MPA	2022	[187]
47	Image Segmentation	MPASSA	Hybridized variant	Standard MPA	The MPASSA method is compared with WOA, SSA, AOA, MPA and PSO	2022	[185]
48	Wireless Body Area Networks	MPAOA	Hybridized variant	Standard MPA	The MPAOA method is compared with BA, GA, AOA and MPA	2022	[186]
49	Carbon Dioxide Emission Forecast	EGMPA	Hybridized variant	Improved MPA	The EGMPA method is compared with MPA, DE, CS, MVO, SCA, MFO, SSA and GWO	2022	[187]
50	Wireless Sensor Networks (WSNs)	MPO-IPSO-OCR	Hybridized variant	Improved MPA	The MPO-IPSO-OCR method is compared to the numerous benchmarked cluster-based routing algorithms	2022	[188]
51	Engineering Design Problems, Abrupt Motion Tracking	MMPA-TLBO	Hybridized variant	Modified MPA	The MPA-TLBO method is compared with other trackers and MPA	2022	[189]
52	Data Clustering	DEMP	Hybridized variant	Standard MPA	The DEMP method is compared with FFA, EO, MPA and SMA	2021	[190]
53	Shape Optimization problems	ODMPA	Hybridized variant	Improved MPA	The ODMPA method is compared with MPA, MMPA and other intelligent algorithms	2021	[191]
54	PV System	MMPA-OLGWO	Hybridized variant	Modified MPA	The MPAOBL-GWO method is compared with the original MPA, GWO and PSO	2021	[192]

Table 8 (continued)

SI	Application areas	Proposed Method	Variant of MPA	Type of MPA	Comparison	Year	References
55	Image Processing (Feature Selection)	MPASCA	Hybridized variant	Modified MPA	MPASCA method is compared with MPA, HHO, HGSO, WOA, GWO, GA and SSA	2021	[193]
56	Engineering Design problems	TLMPA	Hybridized variant	Standard MPA	The TLMPA method is compared with PSO, DE, SSA, LSHADE-cnEpSin, GWO and TLBO	2021	[194]
57	Photovoltaic Models	HMPA	Hybridized variant	Standard MPA	The HMPA method is compared with SMA, EO, MRFO, TSO, JS and FBI	2021	[195]
58	Fuel Cell Parameters Estimation	MPA-PO	Hybridized variant	Standard MPA	The MPA-PO method is compared with HHO, MAEO, HGWO, HADE, JAYA, CS-EO	2020	[196]
59	Data Clustering	MPA-PSO	Hybridized variant	Standard MPA	The MPA-PSO algorithm is compared with several clustering algorithms	2020	[197]
60	ORPD Problem, Electricity Grid Problem	IMPAPSO	Hybridized variant	Improved MPA	The IMPAPSO method is compared with MPA and PSO	2020	[198]
61	River Water Level Forecasting	MPA-ANN	–	Standard MPA	The MPA-ANN method is compared with CPSOCGSA-ANN and SMA-ANN	2022	[199]
62	Arrhythmia Classification	IMPACNN	–	Improved MPA	The IMPACNN method is compared with other recent hybrid methods and standard MPA	2022	[200]
63	Multilevel Inverter	MGMPA-ERNN	–	Multi-Group MPA	The MGMPA-ERNN method is compared with MPA, HHO and WOA	2022	[201]
64	Image Synthesis	MPA-MGE	–	Standard MPA	The MPA-MGE method is compared with MPA, PSO, ACO, GA, MVO and SSA	2022	[202]
65	Photovoltaic (PV) Systems	MPA-MPPT	–	Standard MPA	The MPA-MPPT method is compared with standard MPA	2022	[203]
66	Stream flow Prediction	ANN-EMPA	–	Extended MPA	The ANN-EMPA method is compared with ANN-PSO ANN-GA, ANN-GWO and ANN-MPA	2022	[157]
67	Shrimp freshness detection	SFD-Hyb-CNN-SVM-MPA	–	Standard MPA	The SFD-Hyb-CNN-SVM-MPA method is SFD-D-SHNet, SFD-ANN-KNN and SVM-FCCD compared with	2022	[204]
68	Stream flow Prediction	ANN-EMPA	–	Standard MPA	The ANN-EMPA method is compared with MPA, PSO, GA and GWO	2022	[205]
69	Photo Voltaic models	–	–	Standard MPA	The proposed method is compared with GWO, SSA, PSO, and SCA	2022	[206]

Table 8 (continued)

SI	Application areas	Proposed Method	Variant of MPA	Type of MPA	Comparison	Year	References
70	Optimization Problems	QMPA	–	Standard MPA	The QMPA method is compared with GWO, PSO, SMA, SCA, RSA and AO	2022	[207]
71	Structural Health Monitoring	MPAFNN	–	Standard MPA	The MPAFNN method is compared with PSO, GSA, PSOGSA and GWO	2021	[208]
72	Heartbeats Classification	MPA-CNN	–	Standard MPA	The MPA-CNN methods is compared with SVM, CNN, KNN, PSO, GA, RF and MRFO-SVM	2021	[200]
73	Image Segmentation using Multilevel Thresholding	MPATII-FE	–	Standard MPA	The MPATII-FE method is compared with PFA, PPA, DE, PSO, and HPFPPA-D	2021	[209]
74	Image Fusion	TSD-MPA	–	Standard MPA	The TSD-MPA method is compared with CSMCA, NSCT, CSR, NSST-PA-PCNN and NSST-MSMG-CNN	2021	[210]
75	Fault diagnosis of rolling bearing	MPA-SVM-TLOE	–	Standard MPA	The MPA-SVM method is compared with ABC-SVM, AFSA-SVM, SA-SVM, SVM, and SSAE	2021	[211]
76	Feature Selection	MPA-KNN	–	Standard MPA	The MPA-KNN method is compared with GWO, MFO, SCA, WOA, SSA. BFO and HHO	2021	[212]
77	Photo Voltaic models	–	–	Standard MPA	The proposed method is compared with PSO, HS, SBMO, SSO and MSSO	2021	[213]
78	PID Controllers for LFC problems	–	–	Standard MPA	The proposed method is compared with GWO and ABC	2021	[214]
79	Hybrid photovoltaic /diesel generator/ battery system	AMPA	–	Standard MPA	The AMPA method is compared with PSO	2021	[215]
80	Heat Power System and Fuel Cell	DMPA	–	Standard MPA	The DMPA method is compared with basic MPA and NSGA-II	2021	[216]
81	Tensile Behavior Prediction	RVFL-MPA	–	Standard MPA	The RVFL-MPA method is compared with many state-of –art methods	2020	[217]
82	Photo Voltaic models	–	–	Standard MPA	The proposed method is compared with SOA, SA, GOA and WOA	2020	[218]
83	Photo Voltaic models	–	–	Standard MPA	The proposed method is compared with MRFO, HHO and PSO	2020	[219]
84	Wind Solar Generation system	–	–	Standard MPA	The proposed method is compared with ALO, HAS, PSO, DE, SGA, BBO, TLABO etc.,	2020	[220]

Table 9 Full Form of the different proposed methods as mentioned in Table 8

S. No	Full Form of the different proposed methods	Abbreviation
1	Artificial Neural Network-Based Marine Predators Algorithm [199]	MPA-ANN
2	Improved Marine Predators Algorithm and Convolution Neural Network [200]	IMPACNN
3	Multi-Group Marine Predator Algorithm-Based Enhanced Recurrent Neural Network [201]	MGMPA-ERNN
4	Marine Predators Algorithm and Maximum Gabor Energy [202]	MPA-MGE
5	Marine Predator Algorithm-Based Maxima Power Point Technique [203]	MPA-MPPT
6	Extended Marine Predator Algorithm based ANN [157][157]	ANN-EMPA
7	Deep Learning and Marine Predators Algorithm [204]	SFD-Hyb-CNN-SVM-MPA
8	Marine Predators Algorithm and Feed forward Neural Networks [208]	MPAFNN
9	Marine Predators Algorithm and Convolution Neural Networks [200]	MPA-CNN
10	Type II Fuzzy Entropy and Marine Predators Algorithm [209]	MPATII-FE
11	Three-Scale image Decomposition and Marine Predators Algorithm [210]	TSD-MPA
12	Marine Predators Algorithm-based Support Vector Machine and Topology Learning and Out-of-Sample Embedding [211]	MPA-SVM-TLOE
13	Random Vector Functional Link integrated with Marine Predators Algorithm [217]	RVFL-MPA
14	Marine Predators Algorithm with Q-Learning [207]	QMPA
15	Adaptive Marine Predators Algorithm [215]	AMPA
16	Developed Marine Predators Algorithm [215]	DMPA

CEC-06 2019 tests and is compared with five state-of-arts methods namely PSO, HHA, DS, JAYA, WOA, LCA, GOA and EO. The experimental result clearly reveals the fact that the MPLW outperforms the other methods mentioned above. The paper further suggest that the proposed method can be further applied to unravel discrete space, binary and multi-objective optimization problems, as well as for solving the problem of transmission sensitivity.

Eid et al. [167] in his work proposed a revised variant of MPA known as Improved Marine Predator Algorithm (IMPA) for the purpose of optimal allocation of active and reactive power resources in distribution networks. The proposed method employs Reactive power control strategy, Predator strategies to lessen the overall system losses and voltage deviations and make the most of the voltage stability further improving the distribution system's total performance. The validation of the performance of IMPA is performed on two standard test systems, 69-bus and 118-bus distribution networks to prove the proposed algorithm's efficiency as well as scalability. Further, the proposed IMPA method is compared with three state-of-arts methods namely such as MPA, AEO and PSO. The experimental result clearly reveals the fact that the IMPA methods is capable of finding optimal solution and outperforms the other methods mentioned above.

Houssein et al. [192] in his paper proposed a new revised variant of MPA known as Opposition-Based Marine Predators Algorithm (MPA-OBL) for the for global optimization and multilevel thresholding image segmentation. The proposed method employs Opposition-Based Learning (OBL) strategy to boost the performance of the traditional MPA basically by improving their search efficiency, enhancing the exploitation phase as well as convergence. The validation of the performance of MPA-OBL is performed to solve IEEE CEC'2020 benchmark problems. Further, the proposed method is compared with seven state-of-arts methods namely LSHADE-SPACMAOBL, CMA_ES-OBL, DE-OBL, HHO-OBL, SCA-OBL, SSA-OBL and MPA. The experimental result clearly reveals the fact that the MPA-OBL methods generates remarkably proficient outcomes in contrast with the other competitor algorithms as mentioned above. Additionally, the proposed method is used for image segmentation by means of two objective functions of Otsu and Kapur's methods over a number of benchmark images at considering different threshold values using three evaluation matrices namely Peak signal-to-noise ratio (PSNR), Structural similarity (SSIM), and Feature similarity (FSIM) indices.

In the work of Dinh [210] a hybridized variant of MPA known as Three-Scale image Decomposition and Marine Predators Algorithm (TSD-MPA) for multi-modal image fusion is proposed. The proposed TSD-MPA employs Three-Scale Decomposition (TSD) technique to achieve the base and detail components; local energy function to preserve significant data and MPA for generating the optimal parameter. The validation of the performance of TSD-MPA is done with the help of the medical images and the proposed method is compared with five state-of-arts methods namely CSMCA, NSCT, CSR, NSST-PA-PCNN and NSST-MSMG-CNN. The experimental results clearly highlights that the TSD-MPA method meaningfully improves the quality of the fused image's and preserves the information in regard to the edge.

6 Conclusion and Potential Future Research Directions

A number of studies projected using MPA has addressed and solved numerous optimization problems though, MPA was originally anticipated to deal with continuous optimization problems. Additionally, although MPA has vigorous parameters, still the issue of obtaining optimal or near optimal solution arises in some of the scenarios because of the local optima stagnation, low convergence speed and discrepancy between exploitation and exploration. Moreover, MPA has some crucial issue in terms of its structure i.e., the phases of algorithm wherein the number of iterations is inadequate to explore the search space and then find the optimal solutions thereby greatly affecting the searching mechanism. On the other hand, MPA suffers from few of the deficiency such as the incapability to yield a varied initial population with high productivity lack of quick escaping of the local optimization which needs to be taken care of.

This has led to the proposal and introduction of several variants of MPA to address the flaws and issues encountered in the standard MPA and convert MPA into a stronger, robust and effective algorithm that would be capable of managing diverse search spaces. In this paper, a comprehensive survey of MPA has been performed according to the revision, hybridizations and applications. The MPA variants i.e., both the revised and the hybridized are elaborated in the previous section. From the study so far, it is clear that MPA algorithm has gained enormous popularity and importance due to which39 revised or modified variants of MPA has been introduced, developed and implemented so far (in two years) to resolve problem from various application areas. Above all standard MPA as well as revised MPA has been integrated with the existing algorithms and strategies generating 35 new hybrid algorithms to resolve the numerous issues from different research domains. Since its development several research papers have been published by several researchers and academicians highlighting its effectiveness and such competitive performance of MPA are due to its effortlessness, superior convergence speed, realistic execution time and most importantly its high potential to blend and strive with new optimization techniques and strategies. No doubt, MPA and its variants have noticeably proved itself as a successful method to unravel vague real-world optimization problems; however, it can still be further investigated. Few of the prospective research directions have been anticipated below that shall expectantly turn out to be constructive for the researcher to exhume and discover MPA in other arena of research.

1. Numerous variants of MPA has been developed so far and all the variants have demonstrated the best of the results in different area of research, however, the mixed-integer variant of MPA (MIMPA), Constrained MPA (CMPA)or even parameter-less MPA (PMPA)could be an interesting area to explore in future. Furthermore, few revised variants of MPA had been explored in the field of robot path planning and navigation, however, more stringent variant of MPA could be devised such as Mobile MPA/Dynamic MPA that would have the capability to tackle and control dynamic trajectory, dynamic obstacles, dynamic goal etc., could definitely be a good work to work in future. The introduced revised variants of MPA utilized in the field of image processing could be utilized to work for color image classification, segmentation [221], enhancement [222] especially for medical images (MRI, CT etc.,) to extract regions containing clinical features.
2. Variety of swarm-based, math-based meta-heuristic algorithm has been hybridized with MPA and its variants to resolve different optimization problem however, in future one can even think of applying or integrating plant-based [119, 127], human-based [8] and even physics/chemistry [47, 68] based meta-heuristic algorithms to identify the potential of MPA and further progress the computational performance and generate quality solution.
3. Numerous problems belonging to wide range of applications areas has been explored using MPA and its variants, however, the researcher can focus on the devising the solution using MPA or its variants as an optimizer to optimize the existing classifier/mechanism and further apply to identify urban sprawl using the series of satellite images available. MPA technology can be further extended to solve different optimization problems in the power system applications, energy storage devices, smart grids, knowledge discovery, fog systems, DNA fragment assembly problem, signal denoising, work

scheduling, parameter optimization and smart home applications.

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