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REVIEW ARTICLE

A Contemporary Systematic Review on Meta-heuristic Optimization Algorithms with Their MATLAB and Python Code Reference

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Abstract
Optimization is a method which is used in every field, such as engineering, space, finance, fashion market, mass communication, travelling, and also in our daily activities. In every field, everyone always wants to minimize or maximize something called the objective function. Traditional and modern optimization techniques or Meta-Heuristic (MH) optimization techniques are used to solve the objective functions. But the traditional optimization techniques fail to solve the complex and real-world optimization problem consisting of non-linear objective functions. So many modern optimization techniques have been proposed exponentially over the last few decades to overcome these challenges. This paper discusses a brief review of the different benchmark test functions (BTFs) related to existing MH optimization algorithms (OA). It discusses the classification of MH algorithms reported in the literature regarding swarm-based, human-based, physics-based, and evolutionary-based methods. Based on the last half-century literature, MH-OAs are tabulated in terms of the proposed year, author, and inspiration agent. Furthermore, this paper presents the MATLAB and python code web-link of MH-OA. After reading this review article, readers will be able to use MH-OA to solve challenges in their field.

1 Introduction

Optimization can be classified into two categories: traditional optimization techniques and meta-heuristic (MH) optimization techniques. The traditional optimization techniques such as linear programming methods (Graphical and Simplex methods), non-linear programming methods (Exhaustive search method, dichotomous search method, Fibonacci search method, golden section method, random search method, pattern search method, and steepest descent search method), and specialized algorithm (Integer programming, and geometric programming) [1] as shown in Fig. 1. Traditional optimization methods are also known as the conventional optimization method. Traditional optimization methods have a rapid convergence rate and may provide more accurate optimum solutions, but they need very strict requirements, such as relatively full constraints and continuously differentiable objective functions. The majority of real-world issues are complicated nonlinear problems, and traditional optimization techniques are prone to achieving local optimum values. Traditional optimization techniques do not possess the optimal answer for optimization problems with large dimensions and complicated search space. The search space will expand as the complexity of optimization challenges increases; hence, traditional optimization techniques are susceptible to gradient disappearance as well as gradient explosion. In comparison with the conventional algorithm, MH-OAs are problem-independent with stochastic operators for solving the optimization problem. In order to overcome the obstacles posed by conventional optimization algorithms, heuristic algorithms are extensively researched. The MH optimization algorithms' two categories (Population and Single solution-based) are recognized. Simulated Annealing (SA) [2, 3], Single Candidate Optimizer (SCO) [4], Vortex Search algorithm (VSA) [5], Tabu Search (TS), and Variable Neighbourhood Search (VNS) [6] are the most important

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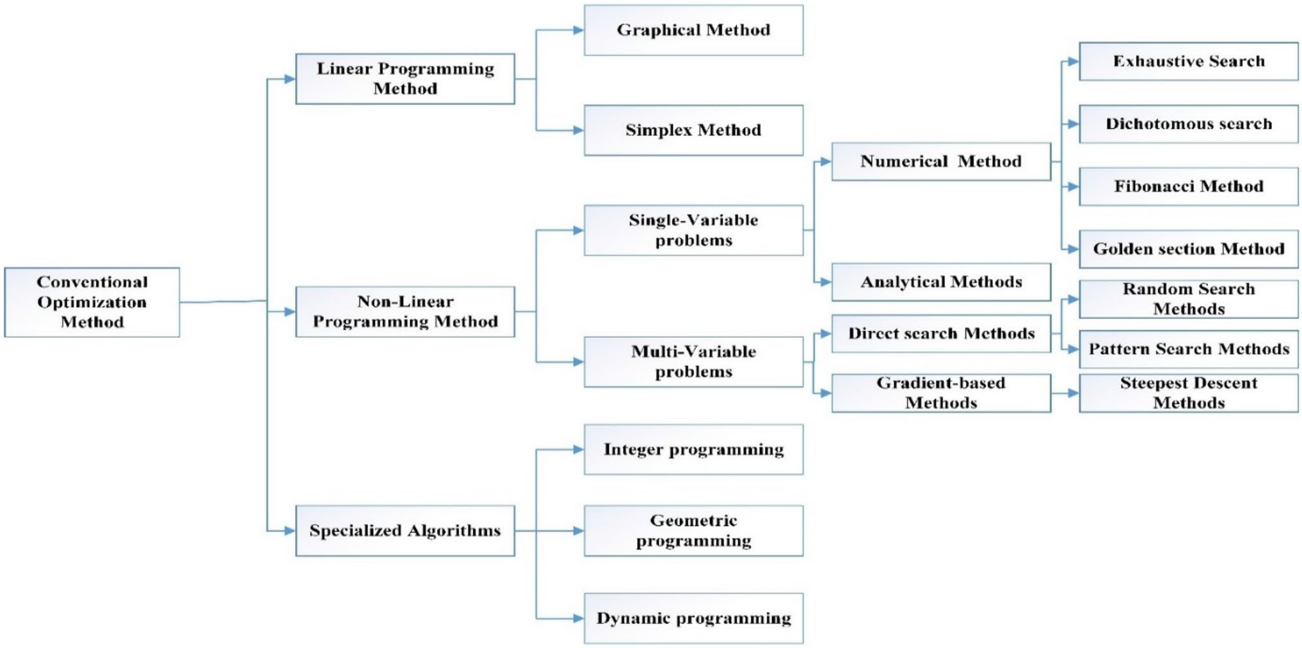


Fig. 1 Conventional optimization techniques

groups of single solution-based algorithms. Teaching Learning Based Optimization (TLBO) [7], Genetic Algorithms (GA) [8], Harmony Search (HS), Artificial Chemical Reaction Optimization Algorithm (ACROA) [9], Particle Swarm Optimization (PSO) [10], Differential Evolution (DE), Ant colony optimization (ACO) [11, 12], Artificial Bee Colony Algorithm (ABC) [13], Honey Bee Mating Optimization (HBMO) [14], Imperialist Competitive Algorithm (ICA), Monkey Search (MS), Biogeography-Based Optimization (BBO) [15], League Championship Algorithm (LCA) [16], Gravitational Search Algorithm (GSA) [17], Cuckoo Search (CS) [18, 19], Bat Algorithm (BA) [20, 21], Charged System Search (CSS) [22], Galaxy-based Search Algorithm (GbSA) [23], Mine blast algorithm(MBA) [24], Water cycle algorithm (WCA) [25, 26], Grey Wolf Optimizer (GWO) [27, 28], Interior search algorithm (ISA) [29], Magnetic Optimization Algorithm (MOA) [30], Ant Lion Optimizer (ALO) [31], Lion Optimization Algorithm (LOA) [32], Football Game Algorithm (FGA) [33], Crow search algorithm (CSA) [34], Salp Swarm Algorithm (SSA) [35], Human Mental Search (HMS), Future search algorithm (FSA) [36], Artificial Electric Field algorithm (AEFA) [37], Poor and Rich Optimization (PRO), Group Teaching Optimization Algorithm (GTOA) [38], Rat Swarm Optimizer (RSO) [39], tiki-taka Algorithm (TTA) [40], Golden Tortoise Beetle Optimizer (GTBO) [41], Arithmetic Optimization Algorithm (ArOA) [42], and Crystal Structure Algorithm (CryStAl) [43] are some most important group of population based optimization algorithm.

There are no optimization techniques (MH algorithms) to solve the problem optimally (No free lunch (NFL) theorem) [44]. So, MH optimization techniques may be beneficial for some problems, and sometimes they may be poorly efficient for others' problems. So that the development of the MH optimization algorithm area is an open problem, and many researchers are trying to propose a new MH-OA [45]. One of the most popular and oldest OA is the GA, which John H. Holland proposed (1975) [46], and John H. Holland was the father of the evolutionary-based algorithm. Later, Scatter Search (SS) was presented by Fred Glover (1977); after that, forgotten for about 20 years, and since its re-introduction (1997) and applied to different problems. S. Kirkpatrick et al. (1983) proposed SA as a single-based solution MH optimization algorithm after that number of MH-OAs presented from 1975-present, which are population or single-based solution optimization algorithms. The performance of the MH-OA was evaluated with some renowned BTFs, as well as the results of the test function were contrasted with the other MH-OA [47]. In 2021, CryStAl was proposed by Siamak T. et al., which was evaluated with two-hundred-thirty-nine illustrious BTFs [43]. In 2017, the HMS algorithm was suggested by Seyed J. M., and Hossein E., and experimented with fifty-seven renowned BTFs [45]. In 2019, the Henry gas solubility optimization (HGSO) algorithm was proposed by Fatma A. Hashim et al., which was evaluated with forty-seven renowned BTFs [48]. In 2020, the Adolescent Identity Search Algorithm (AISA) was proposed by Esref Bogar and Selami Beyhan, which was evaluated with thirty-seven BTFs [49]. Likewise, other MH-OA were assessed with some BTFs which is discussed in benchmarking test functions and MH Optimization Algorithms 1975 to present sections. The main objective of this review article is to present the population-based and single-agent-based MH algorithm from 1975 to the present. The main contributions of this review article are as follows:

- This paper presented a systematic review of different BTFs related to existing MH optimization algorithms.
- It includes a taxonomy review of the MH algorithms in terms of evolutionary, physics, swarm, and human-based algorithms.
- From 1975 to the present, this paper includes a detailed overview and categorization of population-based and single agent-based MH optimization algorithms.
- It presents the comparative study of MH optimization algorithms that are tabulated in terms of the proposed year, author, optimization techniques, and inspiration agent.
- It includes an overview of the Matlab and python code web-link of MH optimization algorithms.
- MH optimization algorithms have been attracting the interest of academic researchers, engineers, students, and professionals for almost 46 years (1975-till present).

The rest of the paper is organized as follows: Sect. 2 introduces the benchmark test functions. Then, the classification of the MH optimization algorithm (evolutionary-based, swarm-based, physics-based, as well as human-based optimization algorithm) is presented in Sect. 3. A comprehensive list of MH optimization algorithms covering authors, inspirations sources, year, and based on is illustrated (1975-till present) in Sect. 4. Section 5 summarizes the MH optimization technique, Matlab code references, and Python code references. Discussion and recommendations are presented in Sect. 6, and the paper is concluded as well as presents some future directions in the last sections of this paper. The outline of the paper is presented in Fig. 2.

2 Benchmarking Test Functions

The most imperative part of the new optimization algorithm (test and validation) is to use BTFs and compare the result of the new optimization algorithm with other optimization algorithms [50]. In other words, BTFs are a group of test functions that can be used to evaluate and validate the performance of the newly proposed optimization algorithm problem (constraints and unconstraint problems, continuous and discrete problems, unimodal and multimodal problems) [51]. To test the validation, efficiency, and reliability of any optimization algorithm is frequently carried out by using a set of BTFs from the literature. In most of the papers, the number of test functions is varied (A few to dozen). Dimensions problem

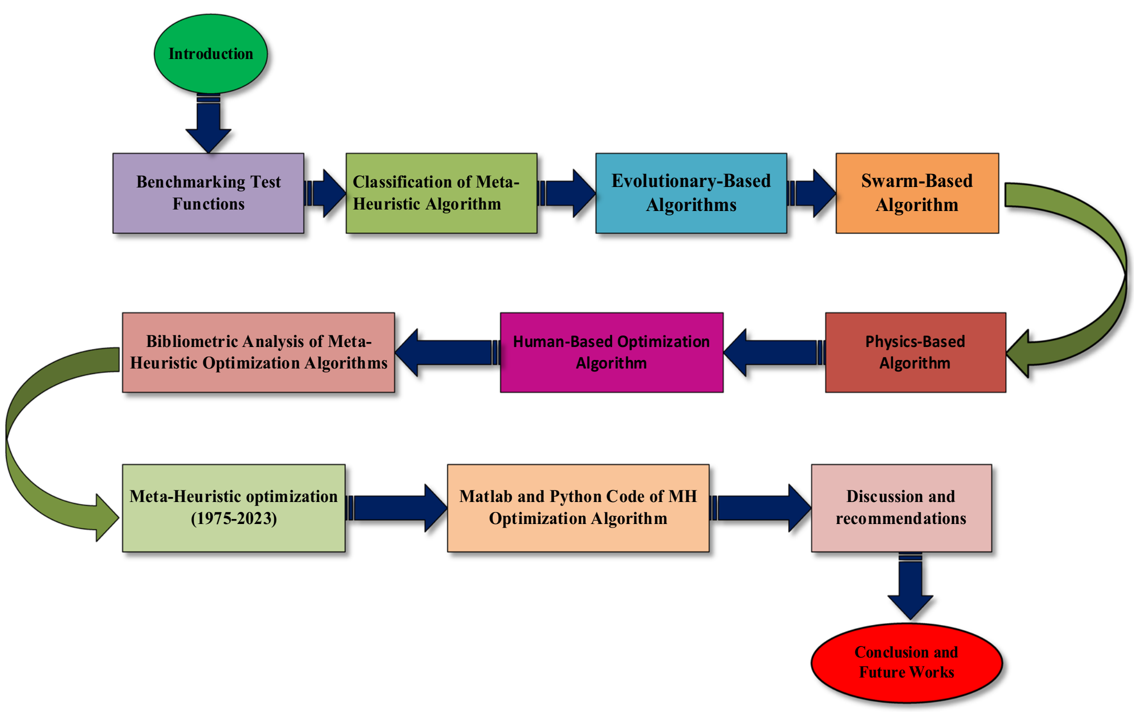


Fig. 2 Outline of the paper

domain size (D), optimal solution($f(x) = f(x_1, x_2, x_3, \ldots, x_n)$), Lb lower bond and Ub upper bond of the variable ($Lb \le x_i \le Ub$) [52]. Test functions which can be used to test and validate the performance of optimizations algorithms such as Ackley_1, Ackley_2, Ackley_3, Ackley_4 or Modified Ackley, Adjiman, Alpine_1, Brad Function, Bartels Conn Function, Beale Function, Biggs EXP_2, Biggs EXP_3, Biggs EXP_4, Biggs EXP_5, Biggs EXP_6, Bird, Bohachevsky_1, Bohachevsky_2, Bohachevsky_3, Booth, Box-Betts Quadratic Sum, Branin RCOS, Branin RCOS_2, Brent, Brown, Bukin_2, Bukin_4, Bukin_6, Camel–Three Hump, Camel–Six Hump, Chen Bird, Chen V, Chichinadze, Chung Reynolds, Cola, Colville, Corana, Cosine Mixture, Cross-in-Tray, Csendes, Cube, Damavandi, Deb_1, Deb_3, Deckkers-Aarts, deVilliers Glasser_1, deVilliers Glasser_2, Dixon & Price, Dolan, Easom, El-Attar-Vidyasagar-Dutta, Egg Crate, Egg Holder, Exponential, EX 1, Freudenstein Roth, Giunta, Goldstein Price, Griewank, Gulf Research Problem, Hansen, Hartman_3, Hartman_6, Helical Valley, Himmelblau, Hosaki, Jennrich-Sampson, Langerman_5, Keane, Leon, Matyas, McCormick, Miele Cantrell, Mishra_1, Parsopoulos, Pen Holder Function, Pathological, Paviani, Pint_er, Periodic, Powell Singular, Powell Singular_2, Powell Sum, Price_1, Price_2, Mishra_5, Price_3, Price_4, Qing, Quadratic, Quartic, Quintic, Rana, Ripple_1, Ripple_25, Rosenbrock_1, Rosenbrock_Modified, Rotated_Ellipse, Rotated Ellipse_2, Rump, Salomon, Mishra_2, Sargan, Scahffer_1, Scahffer_2, Scahffer_3, Scahffer Function_4, Schmidt Vetters Function, Schumer Steiglitz, Schwefel, Shekel_5, Shekel_7, Mishra_3, Schwefel_2.26, Shekel_10, Shubert, Shubert_3, Shubert_4, Mishra_4, Schaffer_F6, Sphere, Step, Schwefel_2.4, Step_2, Mishra_6, Step_3, Stepint, Streched V Sine Wave, Sum Squares, Styblinski-Tang Function, Holder Table_1, Mishra_7, Holder Table_2, Carrom Table, Schwefel_2.22, Testtube Holder, Trecanni, Trid_6, Schwefel_2.23, Mishra_8, Trid_10, Trefethen, Trigonometric_1, Schwefel_2.6, Trigonometric_2, Tripod, Ursem_1, Mishra_9, Schwefel_1.2, Ursem Waves, Venter Sobiezcczanski-Sobieski, Watson, Schwefel_2.36, Wayburn Seader_1, Schwefel_2.21, Ursem_3, Wayburn Seader_2, Ursem_4, Schwefel_2.25, Wayburn Seader_3, W / Wavy, Weierstrass, Whitley, Wolfe, Xin-She Yang_1, Schwefel_2.20, Xin-She Yang_3, Schwefel_2.22, Mishra_10, Xin-She Yang_4, Zakharov Function, Zettl Function, Zirilli or Aluffi-Pentini's, Mishra_11, and Zirilli_2 [43, 52–56]. Different researchers choose different sets of mathematical test functions with different experimental configurations. This may help other researchers to follow the trends and gauge the robustness of the newly proposed MH optimization algorithm.

3 Classification of Meta-heuristic Algorithm

The classification of the MH algorithms is based on the inspiration of swarm, human, physics, and evolutionary-based methods. The classifications of the MH-OA are given in the following section.

3.1 Evolutionary-Based Algorithms

The operators used by the evolutionary-based algorithm are highly motivated by biological behaviour (crossover and mutation). The father of the evolutionary-based algorithm was known as John H. Holland [57]. GA (John H. Holland) inspirited by the Darwinian theory of evolution (1975) [58, 59], Scatter search (SS) (Fred Glover) was based on its sibling TS (1977) [60, 61], Memetic Algorithm (MA) (Moscato) is encouraged by the emulate biological evolution (1989) [62], DE algorithm (Rainer Storn, and Kenneth Price) is stimulated by the natural phenomenon of evolution to solve the real-world problems (1995) [63, 64], BBO algorithm (Dan Simon) inspirited by the Biogeography (2008) [15], Differential Search Algorithm (DSA) (Pinar Civicioglu) is inspirited by brownian-like random walk movement (2012) [65, 66], Stochastic Fractal Search (SFS) algorithm (Hamid Salimi) is encouraged by the natural phenomenon of evolution (2014) [67], Lightning search algorithm (LSA) (Hussain Shareef et al.) is stimulated by natural lightning phenomenon (2015) [68], Bull Optimization Algorithm (BOA) (Oguz FINDIK) is encouraged by the breeding of animals in nature (2015) [69], and GTBO algorithm (Omid Tarkhaneh et al.) is encouraged by the golden tortoise beetle's behaviour, which involves changing colours to attract partners of the opposite sex, as well as its defense mechanism, which employs a type of anal fork to fend off predators (2021) [41].

3.2 Swarm-Based Algorithm

A swarm-based algorithm simulates the animal's behaviour in movement and hunting groups and is usually inspirited by natural patterns (Clusters of birds, colonies, and herds). PSO algorithm (James Kennedy and Russell Eberhart) influenced by fish schooling and bird flocking behavior (1995) [70, 71], ACO (Marco Dorigo et al.) the foraging behavior of several ant species used as inspiration (1996) [11, 72], ABC algorithm (Dervis Karaboga) motivated by the honey bee swarm's brilliant behavior (2005) [13], MS algorithm (Antonio Mucherino and Onur Seref) inspirited by a monkey's habit of mounting trees in search of meals (2008) [73], CS algorithm (Xin-She Y. and Suash D.) was encouraged by the reproduction strategy of cuckoos (2009), KH algorithm (Amir Hossein Gandomi and Amir Hossein Alavi) was influenced by the krills herd each other (2012) [74], GWO (Seyedali Mirjalili et al.) inspirited by the grey wolves (Canis lupus) (2013) [27, 28], Dolphin echolocation (DE) optimization algorithm (A. Kaveh and N. Farhoudi) was influenced by the hunting techniques employed by dolphins (2013) [75], Symbiotic Organisms Search (SOS) optimization algorithm (Min-Yuan Cheng and Doddy Prayogo) is inspirited by strategies for symbiotic interaction employed by organisms in the ecosystem to survive and propagate (2014) [76], Elephant Search Algorithm (ESA) (Suash Deb et al.) is mimicked by the elephant herds behavioral characteristics (2015) [77], ALO algorithm (Seyedali M.) has been inspirited by the natural antlions' hunting techniques (2015) [31], Whale optimization algorithm (WOA) (Seyedali M. and Andrew L.) encouraged by humpback whales' adoption of bubble nets for hunting (2016) [78], SSA (Seyedali M. et al.) was influenced by navigating as well as hunting behavior of salps' swarming in the sea (2017) [35], Spotted hyena optimizer (SHO) (Gaurav Dhiman and Vijay Kumar), inspirited by the behavior of spotted hyenas (2017) [79, 80], Grasshopper Optimisation Algorithm (GOA) (Saremi et al.) is inspirited by the behaviour of grasshopper (2017) [81], Butterfly Optimization Algorithm (BOA) (Sankalap A., and Satvir S.) mimicking the foraging behavior of the butterflies (2018), Harris hawks optimizer (HHO) (Ali Asghar Heidar et al.) influenced by Harris' hawks' natural cooperation attitude as well as chasing behavior (2019) [82], Sandpiper Optimization Algorithm (SOA) (Amandeep Kaur et al.) was motivated by sandpipers' migratory and aggressive nature (2019) [83], Sooty Tern Optimization Algorithm (STOA) (G. Dhiman, and A. Kaur) is inspirited by the sooty tern's natural migration patterns and aggressive behaviors (2019) [84], Sailfish Optimizer (SFO) algorithm (S. Shadravan et al.) is inspirited by the group of hunting sailfish (2019) [85], Seagull optimization algorithm (SOA) (G. Dhiman and V. Kumar) is inspirited by migration as well as attacking behaviors of a seagull in nature (2019) [86], Pathfinder Algorithm (PFA) (H. Yapici and N. Cetinkaya) is inspirited by the influenced with the collaborative animal movement (2019) [87], Red fox optimization algorithm (RFO) (Dawid Połap, and Marcin Woźniak) is inspirited by the model of hunting and eveloping the population of a renowned animal red fox (2020) [88], RSO algorithm (G. Dhiman et al.) was motivated by rats' natural propensity for chasing as well as attacking, (2020) [39], Golden eagle optimizer (GEO) algorithm (Abdolkarim M. et al) was motivated by the golden eagles' ability to adjust their speed for hunting at various points throughout their spiral trajectory (2021) [89], Chameleon Swarm Algorithm (ChSA) (Malik Shehadeh Braik) was influenced by the chameleons' dynamic foraging and navigation behavior in deserts, swamps, and trees (2021) [90], African Vultures Optimization Algorithm (AVOA) (Benyamin A. et al.) is inspirited by the African vultures' foraging as well as navigation behaviors (2021) [91], Artificial lizard search optimization (ALSO) is inspirited by the manner in which red-headed Agama lizards catch their prey (2021) [92], COOT algorithm was influenced by the actions of the Coot, a swarm of birds (2021) [93], Dingo Optimizer (DOX) is inspirited by the action of dingo (2021) [94], Archerfish Hunting Optimizer (AHO) algorithm was influenced by the archerfish's jumping as well as shooting techniques for catching flying insects (2021) [95], Jumping Spider Optimization Algorithm (JSOA) was stimulated by the arachnida salticidade (2021) [96], Northern Goshawk Optimization (NGO) is inspirited by the behaviour of northern goshawk during prey hunting (2021) [97], Orca predation algorithm (OPA) is inspirited by predatory behaviour of orcas (2022) [98], Honey Badger Algorithm (HBA) was motivated by the honey badger's remarkable foraging behaviors (2022) [99], Reptile Search algorithm (RSA) was influenced by crocodiles' hunting activities (2022) [100], Escaping Bird Search (EBS) algorithm is inspirited by the avian life-saving maneuvers(2022) [101], Peafowl (Pavo muticus/cristatus) optimization algorithm (PaOA) was influenced by peafowl swarm's courtship, foraging, as well as chasing behaviors (2022) [102], Golden Jackal Optimization (GJO) is influnced by the golden jackals hunting behaviour (2022) [103], Sea Horse Optimizer (SHO) is encouraged by the sea horses behaviors in nature (2022) [104], Clouded Leopard Optimization (CLO) has been mimicking by the clouded leopards behavior in the wild (2022) [105], Fennec Fox Optimization (FFO) has mimicking by the animal fennec fox behaviors in nature (2022) [106], Zebra Optimization Algorithm (ZOA) has been influenced by the zebras behavior in nature (2022) [107], Gazelle Optimization Algorithm (GOA) is mimicking the survival ability of the gazelles' (2022) [108], Eurasian oystercatcher optimizer (EOO) algorithm has been inspirited by the eurasian oystercatcher (2022) [109], Hermit Crab Shell Exchange (HCSE) algorithm has been inspirited by the different species' natural behavior (2022) [110], Gannet Optimization Algorithm (GaOA) has been the behaviors of gannets during foraging (2022) [111], and Mud Ring Algorithm (MRA) been influenced by bottlenose dolphins' Atlantic region mud ring feeding behavior (2022) [112], American zebra optimization algorithm (AZOA) been influenced by American zebras behaviour (2023) [113], Nutcracker optimization algorithm (NOA) been influenced by the search, cache, and recovery behaviors of nutcrackers (2023) [114], Dynamic Hunting Leadership (DHL) algorithm has been inspirited by the wild animal hunting (2023) [115], Osprey optimization algorithm (OOA) algorithm has been inspirited by the osprey behavior (2023) [116], Termite life cycle optimizer (TLCO) algorithm has been inspirited by the termite colony's life cycle and the modulation of movement methods utilized by many animal species in nature (2023)

[117], and Shrimp and Goby association search algorithm (ShGA) algorithm has been inspirited by the Shrimp and Goby Association behaviour (2023) [118].

3.3 Physics-Based Algorithm

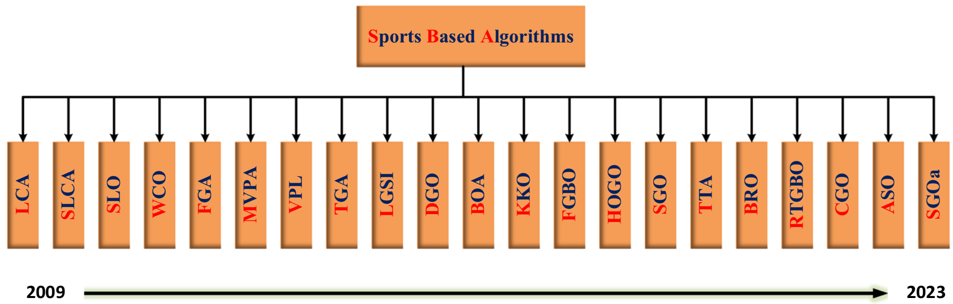
Physics-based algorithms originate from physics law in real life. The SA is inspired by the annealing procedure of the metal working (1983), Big Bang-Big Crunch (BB-BC) was stimulated by the Big Bang as well as Big Crunch Theory (2005) [119], CFO is inspirited by the Analogy to classical particle kinematics in a gravitational field (2007), Intelligent Water Drops (IWD) OA was encouraged by the prominent properties of the natural water drops that flow in the beds of rivers (2007) [120], GSA motivated by the law of gravity as well as the interactions between masses (2009) [17], CSS algorithm was encouraged by the by some principles from physics (2010) [22], ACROA (Bilal Alatas) was influenced by the kinds and patterns of chemical reactions (2011) [9], GbSA (Hamed Shah-Hosseini) was motivated to investigate its surroundings by the spiral arm of spiral galaxies (2011) [23], Black hole (BH) (Abdolreza Hatamlou) is inspirited by the Black hole phenomenon (2012) [121], Ray Optimization (RO) algorithm (Kaveh A., and Khayatazad. M) is inspirited by the Snell's light refraction law (2012) [122], Gases Brownian Motion Optimization (GBMO) (Marjan Abdechiri et al.) was motivated by the turbulent rotating motion and brownian motion of gases (2012) [123], Colliding Bodies Optimization (CBO) (Kaveh A., and Mahdavi V.R.) is inspirited by the collision of two bodies are governed by a physics law (2014) [124], Optics-inspirited optimization (OIO) algorithm (A. H. Kashan) is inspirited by the optical features of concave as well as convex mirrors (Optics) (2014) [125], Kinetic Gas Molecule Optimization (KGMO) (Sara Moein, and Rajasvaran Logeswaran) is inspirited by the kinetic energy of gas molecules (2014) [126], MOA (M. H. Tayarani N., and M. R. Akbarzadeh T.) is inspirited by the magnetic field theory (2014) [30], VSA (Berat Doğan, and Tamer Olmez) was influenced by the vortex pattern formed by the fluids' stirring's vortical flow (2014) [5], Electromagnetic field optimization (EFO) algorithm (Hosein Abedinpourshotorban et al.) is inspirited by the behavior of electro- magnets (2015) [127], Multi-Verse Optimizer (MVO) is inspirited by the 3 thoughts in cosmology (white, black, as well as worm hole) (2015) [128], Heat transfer search (HTS) OA (Vivek K. Patel, Vimal J. Savsani) was stimulated by the law of heat transfer as well as thermodynamics (2015) [129], Sine Cosine Algorithm (SCA) (Seyedali Mirjalili) is inspirited by the proprieties of trigonometric cosine as well as sine functions (2016) [130, 131], Yin-Yang-pair Optimization (YYPO) algorithm (Varun P., and Prakash K.) is inspirited by maintaining a balance among exploration as well as exploitation of the search space (2016) [132], Atom search optimization (ASO) algorithm (Weiguo Zhao et al) was encouraged by the basic molecular dynamics (2018) [133], AEFA (Anita, and Anupam Yadav) was encouraged by the coulomb's law of electrostatic force (2019) [37], HGSO algorithm (Fatma A. H. et al.) is inspirited by the behavior governed by Henry's law (2019) [48], Spring Search Algorithm (SSA) (Mohammad D. et al.) is inspirited by the Hooke's law (2020), Momentum search algorithm (MSA) (Mohammad Dehghani, and Haidar Samet) is inspirited by the Newton's laws: the law of conservation of momentum (2020), Gradient-based optimizer (GBO) algorithm (Iman A. et al.) was influenced by the Gradient-based Newton's method (2020), Plasma Generation Optimization (PGO) algorithm (Ali Kaveh et al) is inspirited by the process of plasma generation (2020), Archimedes optimization algorithm (AOA) (Fatma A. Hashim et al.) is inspirited by the law of physics Archimedes' Principle (2021), Lichtenberg algorithm(LA) (João Luiz JunhoPereira et al.) is inspirited by the Lichtenberg figures patterns (2021), Heat transfer relation-based optimization algorithm (HTOA) (Foad Asef et al.) is inspirited by the heat transfer relationships based on the second law of thermodynamics (2021), Material Generation Algorithm (MGA) (Siamak T. et al.) is inspirited by the material. Material is a mixture of multiple substances comprised of the stuff of the universe with volume and mass (2021). Also, ArOA (Laith Abualigah et al.) was influenced by the behaviour of the basic mathematics arithmetic operators (Addition, Division, Subtraction, as well as Multiplication) (2021), CryStAl (Siamak Talatahar et al.) was influenced by the basic ideas that lead to the formation of crystal structures, namely the inclusion of the basis to the lattice points (2021) [43], Flow Direction Algorithm (FDA) (Hojat Karami et al.) was motivated by the direction of flow to the drainage basin's outlet point with the lowest height (2021), Solar System Algorithm (SSA) (Farouq Zitouni et al.) was encouraged by orbiting behaviour of some objects found in the solar system (2021), Colony Search Optimization Algorithm (CSOA) (Heng Wen et al.) is inspirited by the process by which early people sought out habitable areas (2021). Special Relativity Search (SRS) optimization algorithm was encouraged by an electromagnetic field's particle interaction (2022). Communication-based Optimization Algorithm (COA) has been the power allocation policy to users in non-orthogonal multiple access (NOMA)-based wireless communication networks (2022), Light Spectrum Optimizer (LSO) algorithm has been influenced by the various angles at which light disperses when it passes through raindrops (2022), and Homonuclear Molecules Optimization (HMO) algorithm has been inspirited by the arrangement of electrons surrounding atoms according to the Bohr atomic model, as well as the structure of homonuclear molecules (2022), Energy Valley Optimizer (EVO) has been inspirited by the principles related to stability and different modes of particle decay (2023) [134], Kepler Optimization Algorithm (KOA) has been inspirited by the Kepler's laws of planetary motion (2023) [135], Snow Ablation Optimizer (SAO) has been inspirited by sublimation and melting behavior of snow (2023) [136], Fick's Law Algorithm (FLA) has been inspirited by the Fick's first rule (2023) [137], RIME has been inspirited by the rime-ice physical phenomenon (2023) [138], Young's double-slit experiment optimizer (YDSE) was motivated by the young's double-slit experiment (2023) [139], and Geometric Mean Optimizer (GeMO) was motivated by the unique properties of the geometric mean operator in mathematics (2023) [140].

3.4 Human-Based Optimization Algorithm

Human-based algorithms simulate human behaviour in communities and human cooperation. TS algorithm (Fred Glover and Claude Mcmillan) is inspirited by the mechanics of human memory (1986), HS algorithm (Zong Woo Geem and Joong Hoon Kim) was influenced by the improvisation of the music players (2001), ICA (E. A. Gargari, and C. Lucas) was inspirited by the human socio-political evolution technique (2007), TLBO algorithm (R.V. Rao et al.) was motivated by the effect of a teacher's influence on the performance of childrens in a class (2010), MBA (Ali Sadollah et al.) was based on the idea of a mine bomb blast (2012) [24], ISA (Amir H. Gandomi) was influenced by interior decoration as well as design (2014) [29], Passing Vehicle Search (PVS) algorithm (PoonamSavsani, and VimalSavsani) was influenced by the way an automobile passes another one in a two-lane highway (2016), HMS algorithm (Seyed J. M., and H. E. Komleh) was motivated by the approaches for exploring the bid space in virtual auctions (2017), Human behavior-based optimization (HBBO) algorithm (Seyed A. A.) is inspirited by the human behaviour (2017) [141], FSA (Mahomud Nasr Said Mohamed Elsisi) is inspirited by the person's life (2018) [36], Queuing search (QS) algorithm (Jinhao Zhang et al.) is inspirited by human activities in queuing (2018), Search and rescue optimization algorithm (SAR) (Amir S. et al.) was influenced by human explorations performed during search as well as rescue operations (2019), PRO algorithm (Seyyed Hamid Samareh Moosavi and Vahid Khatibi Bardsiri) was motivated by the efforts of the wealthy and poor to acquire riches and enhance their economic status (2019), GTOA (Yiying Zhang, and Zhigang Jin) is inspirited by the group teaching mechanism (2020), Student psychology based optimization algorithm (SPBO) (Bikash Das et al.) was inspirited by the psychology of childrens who are putting forth greater effort to raise their exam score to the point that they can obtain the class award for top academic achievement (2020), Forensic-Based Investigation (FBI) algorithm (Jui-ShengChou and Ngoc-MaiNguyen) is inspirited by police officers' method of tracking down suspects and investigating them (2020), Learner Performance Based Behavior (LPB) OA (Chnoor M. R., and T. A. Rashid) was motivated by the technique for enrolling high school graduates in various university departments (2020), Ali Baba and the forty thieves (AFT) algorithm (Malik Braik et al.) is inspirited by story of ali baba and the forty thieves (2021), Human Felicity Algorithm (HFA) is inspirited by the human society to become felicity (2022), City Councils Evolution (CCE) is inspirited by the evolution of city councils (2022), Election-Based Optimization Algorithm (EBOA) has been inspirited by the e voting process to select the leader (2022), Boxing Match Algorithm (BMA) has been inspirited by the boxer behaviour (2022), Driving Training-Based Optimization (DTBO) algorithm has been inspirited by the human activity of driving training (2022), Sewing Training-Based Optimization (STBO) algorithm has been inspirited by trainee tailors are being taught the stitching method (2022), Archery Algorithm (AA) has been inspirited by the archer's shooting behavior toward the target panel (2022), Leader–advocate–believer-based optimization algorithm (LAB) has been inspirited by the AI-based competitive behavior (2023) [142], Gold Rush Optimizer (GRO) algorithm has been inspirited by how gold-seekers prospected for gold during the Gold Rush Era (2023) [143], Mountaineering Team-Based Optimization (MTBO) algorithm has been inspirited by the social performance and cooperation of humans (2023) [144], Growth Optimizer (GO) algorithm has been inspirited by the individuals' learning and reflection mechanisms in their social development processes (2023) [145], IbI Logics Algorithm (ILA) algorithm has been inspirited by the IbI logic theory (2023) [146], and Influencer buddy optimization (InBO) has been inspirited by the group of individuals rather than a single person (2023) [147].

Algorithms related to the sports are known as sports-based algorithms as shown in Fig. 3 such as LCA was motivated by the competition between sports teams in a sport league (2009), Soccer league competition algorithm (SLCA) was encouraged by from soccer leagues (2014), Soccer League Optimization (SLO) algorithm was influenced by European nations' football systems (2014), World Cup Optimization (WCO) (Navid Razmjooy et al.) was encouraged by the competitions of FIFA World Cup (2016), FGA (Elyas Fadakar, and Masoud Ebrahimi) is inspirited by the actions of football players throughout a game to locate the best locations to score a goal under the guidance of the team coach (2016) [33], Most Valuable Player Algorithm (MVPA) (Bouchekara) is inspirited by the game where players compete both individually to earn the MVP trophy and together in teams to win the league championship (2017), Volleyball Premier League (VPL) algorithm (Reza Moghdani, and Khodakaram Salimifard) was stimulated by the competition, in addition interaction among volleyball teams during a season (2017), Team game algorithm (TGA) (M.J. Mahmoodabadi) is inspirited by Games involving teams

Fig. 3 Sports-based algorithm



(2018), Ludo Game-based Swarm Intelligence (LGSI) (Prabhat R. S. et al.) was influenced by the Ludo game's regulations, which call for 2 or 4 players to carry out the process of updating various swarm intelligent behaviors (2019), Dice Game Optimizer (DGO) algorithm (Mohammad D. et al) is inspirited by Old game (Dice game) and the searchers are set of players (2019), Darts Game Optimizer (DGO) algorithm (Mohammad D. et al.) was encouraged by the darts game rule (2020), Billiards-inspirited optimization algorithm (BOA) (A. Kaveh et al.) is inspirited by the billiards game (2020), Kho-Kho Optimization (KKO) Algorithm (Abhishek Srivastava, and Dushmanta Kumar Das) is inspirited by the game played in India known as kho kho game (2020), Football game based optimization (FGBO) algorithm (Mohammad D. et al.) is inspirited by the game of football (2020), Hide Objects Game Optimization (HOGO) algorithm (Mohammad D. et al.) is inspirited by the classic game and the searcher agents that attempt to locate a thing concealed in a certain area (2020), Shell Game Optimization (SGO) algorithm (Mohammad D. et al.) was influenced by the guidelines of the shell game to design (2020), TTA (Mohd Fadzil Faisae Ab. Rashid) is inspirited by the football playing style (tiki-taka) (2020), Battle royale optimization (BRO) algorithm (Taymaz R. F.) is inspirited by a type of digital games knowns as ' 'battle royale' (2020), Ring Toss Game-Based Optimization (RTGBO) algorithm (Mohammad D. et al) is inspirited by the behaviour of players and rules of the ring toss game (2021), Chaos Game Optimization (CGO) algorithm (Siamak T. and Mahdi A.) is inspirited by the principle of the chaos game concept (2021), Alpine skiing optimization (ASO) algorithm has been inspirited by the behaviors of skiers competing for the championship (2022), and Squid Game Optimizer Algorithm (SGOa) was proposed (Mahdi Aziz et al.) (2023), is inspirited by the primary rules of a traditional Korean game (2023) [148].

4 Bibliometric Analysis of Meta-heuristic Optimization Algorithms

Optimization is the process of finding the best solution. Optimization is commonly used to solve problems in many fields, including mathematics, engineering design, health, science, economics, and linguistics problems. The optimization algorithm reduces the conventional method's time, error, and effort. Minimize and maximize used as their objective function [149]. So, most of the researchers concentrate their research on finding new optimization algorithms. Glover (1986) first proposed a term called MH, a combination of two-word heuristic and Meta. The term heuristic comes from the word heuristic (an old Greek word) with the meaning of finding (discovering) a new rule in dealing with a different problem, and Meta means some upper-level methodologies [150]. Different types of MH algorithms are used for the optimal tuning of these parameters [36]. Table 1 provides the summarized view of the MH optimization technique, proposed year, inspirational sources, population-based and single-agent-based solutions proposed by the different authors in the field of the MH algorithm from 1975 to the present.

The MH optimization can be classified into five stages: Phase I (1975–1984), Phase II (1985–1995), Phase III (1995–2004), Phase IV (2005–2014), and Phase V (2015-till present). In Fig. 4 presents the timeline of research where the MH-OAs were proposed. Background colors represent different categories of MH-OA. The phases of the MH-OAs are discussed in the following section.

4.1 Phase I (1975–1984)

Phase I consists of 3 MH-OAs (MH-OA), as shown in Fig. 5. GA has been proposed by John H. Holland (1975), that's population-based MH-OA. The Darwinian theory of evolution inspirited GA. In the GA optimization technique, three operators have used selection, crossover, and mutation [8, 59]. SS algorithm has been proposed by Fred Glover (1977) for integer programming, that's population-based MH-OA. The SS is based on its sibling TS [340]. Afterward, it has been almost forgotten for about 20 years, and since its re-introduction (1997) and applied to different problems [60, 153]. The various applications of this OA (Permutation flow shop scheduling problem, data mining, healthcare, 3D image registration problem, the optimal routes that satisfy the demands of customers and suppliers with minimum transportation cost, vehicle routing

Table 1 Meta-Heuristic optimization (1975–2023)

S. no.	Year	Proposed by	Method	Inspirited	Based on	Citation
1	1975	John H. Holland	GA	Darwinian theory of evolution	Population	[58, 59, 82, 151, 152]
2	1977	Fred Glover	SS	Based on its sibling tabu search	Population	[2, 60, 61, 153]
3	1983	S. Kirkpatrick et al	SA	The annealing procedure of the metal working	Single-agent-based solution	[3, 23]
4	1986	Fred Glover, and Claude Mcmillan	TS	Mechanics of human memory	Single-agent-based solution	[154–156]
5	1986	J. Doyne FARMER, and Norman H. PACKARD	Artificial immune system (AIS)	Vertebrate immune system	Population	[157, 158]
6	1989	Moscato	MA	Trying to emulate biological evolution	Population	[62]
7	1995	James Kennedy and Russell Eberhart	PSO	Flocking behaviour in birds and schooling behaviour in fish	Population	[10, 70, 71]
8	1995	Rainer Storn, and Kenneth Price	DE	Natural phenomenon of evolution to solve the real-world problems	Population	[63, 64]
9	1996	Marco Dorigo et al	ACO	Foraging behaviour of some ant species	Population	[11, 12, 72]
10	1997	Mladenović, and Hansen	VNS	Local search heuristic and the neighbourhood structure to meet problem characteristics	Single- agent-based solution	[6]
11	2001	Zong Woo Geem, and Joong Hoon Kim	HS	Improvisation of music players	Population	[159]
12	2003	T. Ray and Liew	Society and Civilization Algorithm (SACA)	Ability to mutually interact	Population	[160]
13	2005	Dervis Karaboga	ABC	Honey bee swarm's brilliant behaviour	Population	[13, 161]
14	2005	Osman Erol and Ibrahim	BB-BC	Big Bang and Big Crunch Theory	Population	[119]
15	2005	Wagner F. Sacco, and Cassiano R.E. de Oliveira	Particle Collision Algorithm (PCA)	Nuclear collision reactions, particularly scattering and absorption	Population	[162]
16	2006	S. He et al	Group Search Optimizer (GSO)	Animal searching behaviour as well as group living theory	Population	[163, 164]
17	2006	Omid Bozorg Haddad et al	HBMO	Process of real honey-bees mating	Population	[14]
18	2006	Ali Reza Mehrabian and Caro Lucas	Invasive Weed Optimization (IWO)	Colonizing weeds	Population	[165]
19	2007	Ali Borji	Parliamentary Optimization Algorithm (POA)	Parliamentary Political Competitions	Population	[166]
20	2007	R. A. Formato	Central Force Optimization (CFO)	Analogy to classical particle kinematics in a gravitational field	Population	[167]
21	2007	Esmaeil Atashpaz-Gargari, and Caro Lucas	ICA	Imperialistic competition	Population	[168]
22	2007	Hamed Shah-Hosseini	IWD	Prominent properties of the natural water drop that flow in the beds of rivers	Population	[120]
23	2008	Xin-She Yang	Firefly Algorithm (FA)	Flashing behaviour of fireflies	Population	[169]
24	2008	Antonio Mucherino and Onur Seref	MS	Monkey's habit of mounting trees in search of meals	Population	[73]

Table 1 (continued)

S. no.	Year	Proposed by	Method	Inspirited	Based on	Citation
25	2008	Timothy C. Havens et al	Roach infestation optimization (RIO)	Social behaviour of cockroaches	Population	[170]
26	2008	Dan Simon	BBO	Biogeography	Population	[15]
27	2009	Ali Husseinzadeh Kashan	LCA	Competition between sports teams in a sport league	Population	[16]
28	2009	Esmat et al	GSA	Law of gravity as well as the interactions between masses	Population	[17]
29	2009	Yang and Suash Deb	CS	Reproduction strategy of cuckoos	Population	[18, 19]
30	2010	Xin-She Yang	BA	Echolocation behaviour of bats	Population	[20, 21]
31	2010	A. Kaveh and S. Talatahari	CSS	Coulomb law and laws of motion	Population	[22]
32	2010	R.V. Rao et al	TLBO	Effect of a teacher's influence on the performance of childrens in a class	Population	[7]
33	2011	Hamed Shah-Hosseini	GbSA	Investigate its surroundings by the spiral arm of spiral galaxies	Population	[23]
34	2011	Kenichi Tamura, and Keiichiro Yasuda	Spiral Optimization (SO)	Logarithmic spiral	Population	[171]
35	2011	Bilal Alatas	ACROA	Types and occurring of chemical reactions	Population	[9]
36	2012	Mohammad Taherdangkoo et al	Stem Cells Algorithm (SCA)	Behaviour of stem cells in reproducing themselves	Population	[172]
37	2012	Gandomi and Alavi	Krill Herd (KH)	Krills herd each other	Population	[74]
38	2012	Ali Sadollah et al	MBA	Mine bomb explosion concept	Population	[24]
39	2012	Pinar Civicioglu	DSA	Brownian-like random walk movement	Population	[65, 66]
40	2012	Xin-She Yang	Flower Pollination Algorithm (FPA)	Pollination process of flowers	Population	[173]
41	2012	Hadi Eskandar et.al	WCA	Rivers as well as streams actually flow into the sea	Population	[25, 26]
42	2012	Abdolreza Hatamlou	BH	Black hole phenomenon	Population	[121]
43	2012	A. Kaveh, and M. Khayatazad	RO	Snell's light refraction law	Population	[122]
44	2012	Marjan et al	GBMO	Turbulent rotating motion and Brownian motion of gases	Population	[123]
45	2013	A. Kaveh and N. Farhoudi	DE	Hunting techniques employed by dolphins	Population	[75]
46	2013	Erik Cuevas et al	States Matter Search (SMS)	Physical principles of the thermal-energy motion mechanism	Population	[174]
47	2013	Seyedali Mirjalili et al	GWO	Grey wolves (Canis lupus)	Population	[27, 28]
48	2013	Pinar Civicioglu	Backtracking Search Optimization Algorithm (BSA)	Social group of living creatures at random intervals to hunting areas that were previously found fruitful for obtaining nourishment	Population	[175]

Table 1 (continued)

S. no.	Year	Proposed by	Method	Inspirited	Based on	Citation
49	2013	Surafel Luleseged Tilahun, and Hong Choon Ong	Prey Predator Algorithm (PPA)	Prey-predator interaction of animals	Population	[176]
50	2013	E. Osaba et al	Golden Ball (GB)	Soccer concepts	Population	[177]
51	2013	SUBRAMANIAN C et al	African Wild Dog algorithm (AWDA)	Communal hunting behaviour of African wild dogs	Population	[178]
52	2014	Xianbing Meng et al	Chicken Swarm Optimization (CSO)	Behaviours of the chicken swarm (roosters, hens and chicks)	Population	[179]
53	2014	Yu-Jun Zheng	Water Wave Optimization (WWO)	Shallow water wave theory	Population	[180]
54	2014	Hamid Salimi	SFS	Natural phenomenon of growth	Population	[67]
55	2014	Min-Yuan Cheng and Doddy Prayogo	SOS	Strategies for symbiotic interaction employed by organisms in the ecosystem to survive and propagate	Population	[76]
56	2014	Erik Cuevas et al	Social Spider Optimization (SSO)	Cooperative behaviour of social-spiders	Population	[181]
57	2014	Haibin Duan, and Peixin Qiao	Pigeon-inspirited optimization (PIO)	Natural pigeon behaviour	Population	[182]
58	2014	Amir H. Gandomi	ISA	Interior design and decoration	Population	[29]
59	2014	A. Kaveh, and V.R. Mahdavi	CBO	One-dimensional collisions between bodies	Population	[124]
60	2014	Sara Moein and Rajasvaran Logeswaran	KGMO	Kinetic energy of gas molecules	Population	[126]
61	2014	A.H. Kashan	OIO	Optical features of concave as well as convex mirrors	Population	[125]
62	2014	NaserMoosavian, and Babak-KasaeeRoodsari	SLCA	Soccer leagues, in addition, based on the competitions among teams as well as players	Population	[183]
63	2014	Tayarani-N., and Akbarzadeh-T	MOA	Ideas in magnetic field theory	Population	[30]
64	2014	Erfan Khaji	SLO	Football System in European Countries	Population	[184]
65	2014	Berat Dogˇan, and Tamer Olmez	VSA	Vortex pattern formed by the fluids' stirring's vortical flow	Single-agent-based solution	[5]
66	2015	Seyedali Mirjalili	ALO	Natural antlions' hunting techniques	Population	[31]
67	2015	Adil Baykasoˇglu and Sener Akpinar	Weighted Superposition Attraction (WSA)	Superposition as well as the attracted movement of agents	Population	[185]
68	2015	Seyedali Mirjalili	Moth-Flame Optimization (MFO)	Navigation method of moths in nature	Population	[186]
69	2015	Seyedali Mirjalili	Dragonfly algorithm (DA)	Static and dynamic dragonflies swarming behaviours	Population	[187]
70	2015	Sait AliUymaz et al	Artificial algae algorithm (AAA)	Microalgae living behaviours	Population	[188]
71	2015	Gai-Ge Wang et al	Elephant Herding Optimization (EHO)	Elephant group herding behaviour	Population	[189]
72	2015	Venkataraman Muthiah-Nakarajan, Mathew Mithra Noel	Galactic Swarm Optimization (GSO)	Motion of stars, galaxies as well as superclusters of galaxies under the effect of gravity	Population	[190]

Table 1 (continued)

S. no.	Year	Proposed by	Method	Inspirited	Based on	Citation
73	2015	Hosein Abedinpourshotorban et al	EFO	Behaviour of electro-magnets	Population	[127]
74	2015	Suash Deb et al	ESA	Elephant herds behavioral characteristics	Population	[77]
75	2015	Maziar Yazdani and Fariborz Jolai	LOA	Life-style of lions and their cooperation characteristics	Population	[32]
76	2015	Hussain Shareef et al	LSA	Natural lightning phenomenon	Population	[68]
77	2015	Zhenyu Meng et al	ebb tide fish algorithm (ETFA)	Small fish in ebb tides	Population	[191]
78	2015	Mu D. L. et al	Virus colony search (VCS)	Virus employs host cell diffusion and infection methods to spread and thrive in the cell environment	Population	[192]
79	2015	Julius BeneoluchiOdili et al	African Buffalo Optimization (ABO)	African buffalo behaviour among the vast forests and savannahs of that continent	Population	[193]
80	2015	Deyu Tang et al	Invasive Tumor Growth Optimization (ITGO)	Principle of invasive tumor growth	Population	[194]
81	2015	Seyedali Mirjalili et al	MVO	The three thoughts in cosmology (white, black, as well as worm hole)	Population	[128]
82	2015	Simon Fong et al	Wolf Search Algorithm (WSA)	Wolf preying behaviour	Population	[195]
83	2015	Hamzeh Beiranvand, and Esmaeel Rokrok	General Relativity Search Algorithm (GRSA)	General Relativity Theory (GRT)	Population	[196]
84	2015	Mustafa Servet Kiran	Tree-Seed Algorithm (TSA)	Relation between trees and their seeds	Population	[197]
85	2015	Oguz Findik	BOA	Breeding of animals in nature	Population	[69]
86	2015	Anthony Brabazon et al	Raven Roosting Optimization (RRO)	Social roosting as well as foraging behaviour of one species of bird, in addition, the common raven	Population	[198]
87	2015	Vivek K. Patel, and Vimal J. Savsani	HTS	Law of heat transfer as well as thermodynamics	Population	[129]
88	2016	Elyas Fadakar, and Masoud Ebrahimi	FGA	Actions of football players throughout a game to locate the best locations to score a goal under the guidance of the team coach	Population	[33]
89	2016	Navid Razmjooy et al	WCO	FIFA World Cup Competitions	Population	[199]
90	2016	Morteza, and Hassan	Virulence Optimization Algorithm (VOA)	Best way for viruses to infiltrate bodily cells	Population	[200]
91	2016	Poonam Savsani, and Vimal Savsani	PVS	Way an automobile passes another one on a two-lane highway	Population	[201]
92	2016	S. Mirjalili and A. Lewis	WOA	Humpback whales' adoption of bubble nets for hunting	Population	[78]
93	2016	A.Ebrahimi and E.Khamehch	Sperm whale algorithm (SWA)	Sperm whale's lifestyle	Population	[202]

Table 1 (continued)

S. no.	Year	Proposed by	Method	Inspirited	Based on	Citation
94	2016	Kaveh and Bakhshpoori	Water Evaporation Optimization (WEO)	Tiny quantity of water molecules evaporating from a solid surface with a varying degree of wettability	Population	[203]
95	2016	Seyedali Mirjalili	SCA	Proprieties of trigonometric cosine as well as sine functions	Population	[130, 131]
96	2016	Yun-Chia Liang & Josue Rodolfo Cuevas Juarez	Virus Optimization (VO)	Viruses attacking a living cell	Population	[204]
97	2016	Ali Osman Topal and Oguz Altun	Dynamic Virtual Bats Algorithm (DVBA)	Skill of a bat to modify the wavelength and frequency of sound waves when hunting	Population	[205]
98	2016	AlirezaAskarzadeh	CSA	Intelligent behaviour of crows	Population	[34]
99	2016	ZhenyuMeng, Jeng-ShyangPan	Monkey King Evolutionary (MKE)	The action of the MonkeyKing	Population	[206]
100	2016	ZhenyuMeng et.al	QUasi-Affine TRansformation Evolutionary (QUATRE)	Quasi-affine transformation approach	Population	[207]
101	2016	Fengji Luo et al	Natural aggregation algorithm (NAA)	Collective decision-making intelligence of social animals	Population	[208]
102	2016	Yousef Sharafi et al	Competitive optimization algorithm (COOA)	Competitive behaviour of various creatures (bees ants as well as cat to survive in nature)	Population	[209]
103	2016	Guang-Yu Zhu and Wei-Bo Zhang	Optimal Foraging Algorithm (OFA)	Animal Behavioral Ecology Theory	Population	[210]
104	2016	Varun Punnathanam, and Prakash Kotecha	YYPO	Maintaining a balance between exploration as well as the exploitation of the search space	Population	[132]
105	2016	A. Kaveh, and A. Zolghadr	Tug of War Optimization (TWO)	Game of tug of war	Population	[211]
106	2016	Qingyang Zhang et al	Collective Decision Optimization Algorithm (CDOA)	Human social behaviour is based on characteristics relating to decision-making	Population	[212]
107	2017	Ahmed T. Sadiq Al-Obaidi	Camel Herds Algorithm (CHA)	Camel's behaviour in the wild	Population	[213]
108	2017	Alexandros Tzanetos, and Georgios Dounias	Sonar Inspirited Optimization (SIO)	Underwater acoustics that war ships use for reckoning targets and obstacles	Population	[214]
109	2017	Osama Abdel Raouf, and Ibrahim M. Hezam	Sperm Motility Algorithm (SMA)	Fertilization process in humans	Population	[215]
110	2017	S. Hr. Aghay Kaboli et al	Rain-fall optimization (RFO)	Behaviour of raindrops	Population	[216]
111	2017	A. Foroughi Nematollahi et al	Lightning Attachment Procedure Optimization (LAPO)	Lightning attachment procedure	Population	[217]
112	2017	A. Kaveh, and A. Dadras	Thermal exchange optimization (TEO)	Newton's law of cooling	Population	[218]

Table 1 (continued)

S. no.	Year	Proposed by	Method	Inspirited	Based on	Citation
113	2017	Bouchekara	MVPA	Game where players compete both individually to earn the MVP trophy and together in teams to win the league championship	Population	[219]
114	2017	Reza Moghdani, and Khodakaram Salimifard	VPL	The competition, in addition to interaction among volleyball teams during a season	Population	[220]
115	2017	Seyedali Mirjalili et al	SSA	Navigating as well as hunting behavior of salps' swarming in the sea	Population	[35]
116	2017	Saremi et al	GOA	Behaviour of grasshopper swarms	Population	[81]
117	2017	Gourav D. and V. Kumar	SHO	Behaviour of spotted hyenas	Population	[79, 80]
118	2017	Seyed-Alireza Ahmadi	HBBO	Human behaviour	Population	[141]
119	2017	Seyed Jalaleddin Mousavirad and Hossein Ebrahimpour-Komleh	HMS	Approaches for exploring the bid space in virtual auctions	Population	[45]
120	2018	Armin Cheraghalipour et al	Tree Growth Algorithm (TGA)	Trees competition for obtaining light as well as foods	Population	[221]
121	2018	WeiguoZhao et.al	ASO	Basic molecular dynamics	Population	[133]
122	2018	Mohit Jain et al	Squirrel search algorithm (SSA)	Southern flying squirrels	Population	[222]
123	2018	GauravDhiman and Vijay Kumara	Emperor penguin optimizer (EPO)	Emperor penguins' huddling behaviour	Population	[223]
124	2018	Jinhao Zhang et al	QS	Human activities in queuing	Population	[224]
125	2018	Nikos Ath.Kallioras et al	Pity beetle algorithm (PBA)	Behaviour of bark beetles	Population	[225]
126	2018	Daniel Zaldivar et al	Yellow Saddle Goatfish Algorithm (YSGA)	Yellow Saddle Goatfish behaviour	Population	[226]
127	2018	Human Shayanfar and Farhad Soleimanian Gharehchopogh	Farmland Fertility (FF)	Farmland fertility in nature	Population	[227]
128	2018	Mahomud Nasr Said Mohamed Elsisi	FSA	Person's life	Population	[36]
129	2018	Sankalap Arora, and Satvir Singh	BOA	Foraging behaviour of the butter_flies	Population	[228]
130	2018	M.J. Mahmoodabadi (et al.)	TGA	Games involving teams	Population	[229]
131	2018	Hisham A. Shehadeh et al	Sperm Swarm Optimization (SSO)	Sperm motility to fertilize the egg	Population	[230]
132	2018	SINA ZANGBARI KOOHI et al	Raccoon Optimization Algorithm (ROA)	Rummaging behaviours of real raccoons for food	Population	[231]
133	2019	Sasan Harifi et al	Emperor Penguins Colony (EPC)	Behaviour of emperor penguins	Population	[232]
134	2019	Amandeep Kaur et al	SOA	Migration and attacking behaviour of sandpipers	Population	[83]
135	2019	Gaurav Dhiman, and Amandeep Kaur	STOA	Migration and attacking behaviours of sea bird sooty tern in nature	Population	[84]
136	2019	Mohammad D. et al	DGO	Dice game	Population	[233]
137	2019	Anita, and Anupam Yadav	AEFA	Coulomb's law of electro_static force	Population	[37]

Table 1 (continued)

S. no.	Year	Proposed by	Method	Inspirited	Based on	Citation
138	2019	Ali Asghar Heidar et al	HHO	Harris' hawks' natural cooperation attitude as well as chasing behaviour	Population	[82]
139	2019	S. Shadravan et al	SFO	Group of hunting sailfish	Population	[85]
140	2019	Zhuoran Zhang et al	Birds Foraging Search (BFS)	The different behaviours of birds during the foraging process	Population	[234]
141	2019	Gaurav Dhiman and Vijay Kumar	SOA	Migration as well as the attacking behaviours of a seagull in nature	Population	[86]
142	2019	Hamza Yapici and Nurettin Cetinkaya	PFA	Collective movement of animal group	Population	[87]
143	2019	Fatma A. et al	HGSO	Henry's law	Population	[48]
144	2019	Mohd Herwan Sulaiman et al	Barnacles Mating Optimizer (BMO)	Nature's barnacles' mating behaviours	Population	[235]
145	2019	Weiguo Zhao et.al	Manta ray foraging optimization (MRFO)	Intelligent behaviours of manta rays	Population	[236]
146	2019	Seyyed Hamid and Vahid Khatibi	PRO	Efforts of the wealthy and poor to acquire riches and enhance their economic status	Population	[237]
147	2019	Prabhat R.Singh et al	Ludo Game-based Swarm Intelligence (LGSI)	Ludo game's regulations, which call for 2 or 4 players to carry out the process of updating various swarm intelligent behaviours	Population	[238]
148	2019	Saeed Balochian and Hossein Baloochian	Social mimic optimization (SMO)	Mimicking the behaviour of people in society	Population	[239]
149	2019	Amir Shabani et al	SAR	Human explorations performed during the search as well as rescue operations	Population	[240]
150	2019	Mohammad D. et al	Group Optimization (GO)	Population updating	Population	[241]
151	2019	Mohammad D. et al	Donkey Theorem Optimization (DTO)	Behaviour of Donkeys	Population	[242]
152	2020	Ali Kaveh et al	PGO	Process of plasma generation	Population	[243]
153	2020	M. Dehghani et al	Following' Optimization Algorithm (FOA)	Physical processes or entities	Population	[244]
154	2020	M. Dehghani et al	Multi Leader Optimizer (MLO)	People moving forward and obediently obeying the leaders	Population	[245]
155	2020	M. Dehghani et al	Doctor and Patient optimization (DPO)	Process of treating patients by a physician	Population	[246]
156	2020	M Kahrizi, and S.Kabudian	Projectiles optimization (PRO)	Projectile motion is in physics as well as governed by its laws	Population	[46]
157	2020	Mohamad M. Fouad et al	Dynamic Group-based Cooperative Optimization (DGCO)	Swarms of individuals act cooperatively to accomplish their collective goals	Population	[247]
158	2020	Amir Mohammad Fathollahi-Fard et al	Red deer algorithm (RDA)	Scottish red deer's mating behaviour during the breading season	Population	[248]

Table 1 (continued)

S. no.	Year	Proposed by	Method	Inspirited	Based on	Citation
159	2020	Esref Bogar and Selami Beyhan	AISA	Process of identity development/search of adolescents	Population	[49]
160	2020	A. Kaveh et al	BOA	Billiards game	Population	[249]
161	2020	Mojtaba Ghasemi et al	Turbulent_Flow of Water_based Optimization (TFWO)	Nature search phenomenon, i.e. whirlpools created in turbulent flow of water	Population	[250]
162	2020	Shafiq-ur-Rehman Massan et al	Dynastic optimization algorithm (DOA)	Human nature and from the social sciences in particular	Population	[251]
163	2020	Satnam Kaur et al	Tunicate Swarm Algorithm (TuSA)	Tunicates' swarm behaviour as well as jet propulsion during foraging and navigation	Population	[252]
164	2020	Shimin Li et al	Slime_Mould Algorithm (SMA)	The way that slime mould oscillates in nature	Population	[253]
165	2020	Kaveh and Dadras Eslamlou	Water strider algorithm (WSA)	Water strider bugs' lifecycle	Population	[254]
166	2020	Khishe and Mosavi	Chimp_Optimization Algorithm (ChOA)	Chimp's individual intelligence as well as sexual motivation in group hunting	Population	[255]
167	2020	Qamar Askari et al	Political_Optimizer (PO)	Multi-stage process of the politics	Population	[256]
168	2020	Afshin Faramarzi et al	Marine Predators Algorithm (MPA)	Lévy and Brownian movements in ocean predators	Population	[257]
169	2020	YiyingZhang, and ZhigangJin	GTOA	Group teaching mechanism	Population	[38]
170	2020	Hazim Nasir and Károly	Dynamic differential annealed optimization (DDAO)	Production process of dual-phase (DP) high-strength steel	Population	[258]
171	2020	Bikash Das et al	Student psychology-based optimization algorithm (SPBO)	Psychology of learners who are putting in extra effort to raise their exam score to the point where they can be considered the best learner in the class	Population	[259]
172	2020	Iman A. et al	GBO	Gradient_based Newton's method	Population	[260]
173	2020	Qamar et al	Heap_Based Optimizer (HBO)	Corporate rank hierarchy	Population	[261]
174	2020	Essam H. Houssein et al	Lévy_Flight Distribution (LFD)	Lévy_flight random walk	Population	[262]
175	2020	Abhishek Srivastava and Dushmanta Kumar Das	KKO	Kho-Kho Game played in India	Population	[263]
176	2020	Jui-ShengChou and Ngoc-MaiNguyen	FBI	Police officers' method of tracking down suspects and investigating them	Population	[264]
177	2020	M. A. Al-Betar et al	Coronavirus_Herd Immunity_Optimizer (CHIO)	Herd immunity idea as a process to tackle COVID-19	Population	[149]
178	2020	Dawid Połap, and Marcin Woźniak	RFO	Model of hunting and eveloping the population of a renowned animal, red fox	Population	[88]
179	2020	Malik Braik et al	Capuchin Search Algorithm (CapSA)	Dynamic behaviour of capuchin monkeys	Population	[265]

Table 1 (continued)

S. no.	Year	Proposed by	Method	Inspirited	Based on	Citation
180	2020	Chnoor M., and Tarik A	LPB	Technique for enrolling high school graduates in various university departments	Population	[266]
181	2020	Gaurav Dhiman et al	RSO	Chasing and attacking behaviours of rats in nature	Population	[39]
182	2020	Mohammad D. et al	SSA	Hooke's law	Population	[267]
183	2020	Mohammad D. et al	DGO	Darts game rule	Population	[268]
184	2020	Mohammad D. et al	FGBO	Game of football	Population	[269]
185	2020	Mohammad D. et al	HOGO	Classic game and the searcher agents that attempt to locate a thing concealed in a certain area	Population	[270]
186	2020	Mohammad D. and Haidar Samet	MSA	Momentum conservation law	Population	[271]
187	2020	Mohammad D. et al	SGO	Guidelines of the shell game to design	Population	[272]
188	2020	Mohd Fadzil Faisae Ab. Rashid	TTA	Football playing style called tiki-taka	Population	[40]
189	2020	Taymaz R. F	BRO	Type of digital games knowns as ''battle royale.''	Population	[273]
190	2020	V.Hayyolalam and A. A. P. Kazem	Black Widow Optimization Algorithm (BWOA)	Black widow spiders unique mating behaviour	Population	[274]
191	2021	Mohammad D. et al	RTGBO	Behaviour of players and rules of the ring toss game	Population	[275]
192	2021	Siamak T. and Mahdi A	CGO	Principle of Chaos Game theory	Population	[150]
193	2021	MahdiAzizi	Atomic Orbital Search (AOS)	Some quantum mechanics concepts as well as the quantum-based atomic model	Population	[276]
194	2021	Fatma A. Hashim et al	AOA	Archimedes' Principle	Population	[277]
195	2021	Abdolkarim Mohammadi-Balani et al	GEO	Golden eagles' ability to adjust their speed for hunting at various points throughout their spiral trajectory	Population	[89]
196	2021	Omid Tarkhaneh et al	GTBO	Golden tortoise beetle's behaviour, which involves changing colours to attract partners of the opposite sex, as well as its defence mechanism, which employs a type of anal fork to fend off predators	Population	[41]
197	2021	Malik Shehadeh Braik	ChSA	Chameleons' dynamic foraging and navigation behaviour in deserts, swamps, and trees	Population	[90]
198	2021	Laith A. et al	Aquila_Optimizer (AO)	Actions are taken by Aquila in the nature when hunting its prey	Population	[278]
199	2021	João Luiz JunhoPereira et al	Lichtenberg algorithm (LA)	Lichtenberg figures patterns	Population	[279]

Table 1 (continued)

S. no.	Year	Proposed by	Method	Inspirited	Based on	Citation
200	2021	Yenny Villuendas-Rey et al	Mexican Axolotl Optimization (MAO)	Nature	Population	[280]
201	2021	Foad Asef et al	HTOA	Heat transfer relationships based on the second law of thermodynamics	Population	[281]
202	2021	Siamak T. et al	MGA	Material	Population	[282]
203	2021	Benyamin Abdollahzadeh et al	AVOA	African vultures' foraging as well as navigation behaviours	Population	[91]
204	2021	Neetesh Kumar et al	ALSO	Manner in which red-headed Agama lizards catch their prey	Population	[92]
205	2021	Laith Abualigah et al	ArOA	Main arithmetic operators in mathematics	Population	[42]
206	2021	Yutao Yang et al	Hunger Games Search (HGS)	Social animals' cooperative behaviour where search activity is proportional to their level of hunger	Population	[283]
207	2021	Jiaze Tu et al	Colony_Predation Algorithm (CPA)	Corporate animal predation in the natural world	Population	[284]
208	2021	Iraj Naruei, and Farshid Keynia	COOT	Actions of the Coot, a swarm of birds	Population	[93]
209	2021	Siamak Talatahar et al	CryStAl	Basic ideas that lead to the formation of crystal structures, namely the inclusion of the basis to the lattice points	Population	[43]
210	2021	Jui-Sheng Chou, and Dinh-Nhat Truong	Jellyfish Search (JS)	Behaviour of jellyfish in the ocean	Population	[285]
211	2021	Mohammad D. et al	Cat and Mouse Based Optimizer (CMBO)	Natural behaviour between cats and mice	Population	[286]
212	2021	Mohammad D. et al	Teamwork Optimization Algorithm (TOA)	Members of a team to attain their target goal	Population	[287]
213	2021	Fatemeh Ahmadi Zeidabadi et al	Mixed Leader Based Optimizer (MLBO)	In order to lead the algorithm population, a new member is generated by combining the best members of the population and a random member	Population	[288]
214	2021	Sajjad Amiri Doumari et al	Two-stage optimization (TSO)	Employ a selective group of moral people from the populace	Population	[289]
215	2021	Amit Kumar Bairwa et al	DOX	Behaviour of dingo	Population	[94]
216	2021	Heming Jia et al	Remora_Optimization Algorithm (ROA)	Parasitic behaviour of remora	Population	[290]
217	2021	HojatKarami et al	FDA	Direction of flow to the drainage basin's outlet point with the lowest height	Population	[291]
218	2021	Siamak T. et al	Social Network Search (SNS)	Social network users' attempts to increase their popularity by simulating their users' emotions when expressing their ideas	Population	[292]
219	2021	Malik Braik et al	AFT	Story of Ali baba and the forty thieves	Population	[293]

Table 1 (continued)

S. no.	Year	Proposed by	Method	Inspirited	Based on	Citation
220	2021	A. Naik and Suresh C. S	Past Present Future (PPF)	Technique by which a person can learn from a successful member of society	Population	[294]
221	2021	Olaide N, and Absalom E	Ebola Optimization Algorithm (EOSA)	Ebola virus disease propagation model	Population	[295]
222	2021	Ahmed T. Salawudeen et al	Smell Agent Optimization (SAO)	Interaction between a biological being that has the ability to smell, leading to the evaporation of a small molecule	Population	[296]
223	2021	Farouq Z. et al	Solar System Algorithm (SSA)	Orbiting behaviour of some objects found in the solar system	Population	[297]
224	2021	Farouq Z. et al	AHO	Archerfish's jumping as well as shooting techniques for catching flying insects	Population	[95]
225	2021	Heng Wen et al	CSOA	Process by which early people sought out habitable areas	Population	[298]
226	2021	Drishti Yadav	Blood Coagulation Algorithm (BCA)	Human body's blood coagulation process	Population	[299]
227	2021	Iraj N. and Farshid K	Wild Horse Optimizer (WHO)	Decency behaviour of the horse	Population	[300]
228	2021	Hernán Peraza-Vázquez et al	JSOA	Arachnida Salticidae hunting behaviour	Population	[96]
229	2021	Mathew Mithra Noel et al	Firebug Swarm Optimization (FSO)	Reproductive swarming behaviour of Firebugs	Population	[301]
230	2021	Mohammad D. et al	NGO	Behaviour of northern goshawk during prey hunting	Population	[97]
231	2021	B. Abdollahzadeh et al	Artificial gorilla troops optimizer (AGTO)	Collective intelligence of natural organisms in nature	Population	[302]
232	2022	Hojjat Emami	Stock_Exchange Trading Optimization (SETO)	Behavior of traders as well as stock prices varies in the stock market	Population	[303]
233	2022	Weiguo Zhao et al	Artificial Hummingbird Algorithm (AHA)	Three foraging techniques as well as three flight movements used by hummingbirds in the environment	Population	[304]
234	2022	Yuxin Jiang et al	OPA	Predatory behaviour of orcas	Population	[98]
235	2022	Fatma A. Hashim et al	HBA	Honey badger's remarkable foraging behaviours	Population	[99]
236	2022	LaithAbualigah et al	RSA	Crocodiles' hunting activities	Population	[100]
237	2022	Mohsen Shahrouzi and Ali Kaveh	EBS	Aerial escaping strategies of a bird	Population	[101]
238	2022	Jingbo Wang et al	PaOA	Courtship, foraging, as well as chasing behaviours of peafowls swarm	Population	[102]
239	2022	Deepak Panwar et al	Human Eye Vision Algorithm (HEVA)	Power of human eye vision	Population	[305]
240	2022	MohammadVerij kazemi and ElhamFazeli Veysari	HFA	Efforts of human society to become felicity	Population	[306]

Table 1 (continued)

S. no.	Year	Proposed by	Method	Inspirited	Based on	Citation
241	2022	Fatma A. Hashim and Abdelazim G. Hussien	Snake Optimizer (SO)	Unique mating behaviour of snakes	Population	[307]
242	2022	Pavel Trojovský and Mohammad Dehghani	Pelican Optimization Algorithm (POA)	Pelican hunting behaviour	Population	[308]
243	2022	Abdesslem Layeb	Tangent Search Algorithm (TSA)	Mathematical tangent function	Population	[309]
244	2022	Jeffrey O. Agushaka et al	Dwarf Mongoose Optimization (DMO)	Dwarf mongoose foraging behaviour	Population	[310]
245	2022	Mahdi Esmailnia Kivi and Vahid Majid-nezhad	Sheep Flock Optimization (ShFO)	Shepherd and sheep behaviours in the pasture	Population	[311]
246	2022	Behnam Mohammad Hasani Zade & Najme Mansouri	Predator–Prey Optimization (PPO)	Prey–predator interaction of animals	Population	[312]
247	2022	Amir Masoud Rahmani, and Iman AliAbdi	Plant competition optimization (PCO)	Plant competition processes	Population	[313]
248	2022	Malik Braik et al	White Shark Optimizer (WSO)	Great white shark's behaviours	Population	[314]
249	2022	Hoda Zamani et al	Starling Murmuration Optimizer (SMO)	Starlings' behaviours	Population	[315]
250	2022	Ali E. Takieldeen et al	Dipper Throated Optimization Algo-rithm (DTOA)	Dipper throated bird	Population	[316]
251	2022	Einollah Pira	CCE	City Council	Population	[317]
252	2022	Peng Chen et al	Termite Queen Algorithm (TQA)	Division of labour in termite populations	Population	[318]
253	2022	Na Lin et al	Nomad Algorithm (NA)	Migratory behavior of nomadic tribes on the prairie	Population	[319]
254	2022	DebaoChen et al	Poplar Optimization Algorithm (POA)	Sexual and asexual propagation mechanism	Population	[320]
255	2022	Nitish Chopra and Muhammad Mohsin Ansari	GJO	Hunting behaviour of the golden jackals	Population	[103]
256	2022	V.Goodarzimehr et al	SRS	Electromagnetic field's particle interaction	Population	[321]
257	2022	Masoomeh Mirrashid and HoseinNad-erpour	Transit Search (TrS)	Exoplanet exploration method	Population	[322]
258	2022	Shijie Zhao et al	SHO	Movement, predation and breeding behav-iours of sea horses in nature	Population	[104]
259	2022	Tareq M. Shami	SCO	Single candidate solution	Single-solution-based	[4]
260	2022	Jeffrey O. Agushaka et al	GOA	Gazelles' survival	Population	[108]
261	2022	Asmaa M. Khalid et al	Coronavirus Disease Optimization Algorithm (COVIDOA)	Mechanism of coronavirus when hijacking human cells	Population	[323]
262	2022	Yongliang Yuan et al	ASO	Behaviours of skiers competing for the championship	Population	[324]
263	2022	Pavel Trojovský and Moham-mad Dehghani	EBOA	Voting process to select the leader	Population	[325]

Table 1 (continued)

S. no.	Year	Proposed by	Method	Inspirited	Based on	Citation
264	2022	EVA TROJOVSKÁ and Mohammad Dehghani	CLO	Behavior of clouded leopards in the wild	Population	[105]
265	2022	EVA TROJOVSKÁ et al	FFO	Fennec's digging ability as well as escape strategy from wild predators	Population	[106]
266	2022	EVA TROJOVSKÁ et al	ZOA	Behavior of zebras in nature	Population	[107]
267	2022	Mohammad D. et al	DTBO	Human activity of driving training	Population	[326]
268	2022	Mohammad D. et al	STBO	Trainee tailors are being taught the stitching method	Population	[327]
269	2022	Fatemeh Ahmadi Zeidabadi et al	AA	Archer's shooting behaviour toward the target panel	Population	[328]
270	2022	Ahmad Salim et al	EOO	Food behaviour of Eurasian	Population	[109]
271	2022	Ajay Sharma et al	HCSE	Different species' natural behaviour	Population	[110]
272	2022	Petr Coufal et al	Snow Leopard Optimization Algorithm (SLOA)	Behaviours of snow leopards	Population	[329]
273	2022	M. Tanhaeean et al	BMA	Boxer's behaviour	Population	[330]
274	2022	Jeng-ShyangPan et al	GaOA	Behaviours of gannets during foraging	Population	[111]
275	2022	Majid Hadi, and Reza Ghazizadeh	COA	Power allocation policy to users in non-orthogonal multiple access (NOMA)-based wireless communication networks	Population	[331]
276	2022	Mohamed Abdel-Basset et al	LSO	Light dispersions with various angles while traveling through rain droplets	Population	[332]
277	2022	Hojjat Emami	Anti-coronavirus optimization (ACVO)	Measures recommended mitigating the spread of COVID-19	Population	[333]
278	2022	ABEER S. DESUKY	MRA	Bottlenose dolphins in Florida's Atlantic coast exhibit mud ring feeding behaviour	Population	[112]
279	2022	Amin Mahdavi-Meymand and Mohammad Zounemat-Kermani	HMO	Arrangement of electrons surrounding atoms according to the Bohr atomic model, as well as the structure of homo-nuclear molecules	Population	[334]
280	2022	BAbdollahzadeh et al	Mountain Gazelle Optimizer	Mountain gazelles life	Population	[335]
281	2023	Mahdi Azizi et al	SGOa	Traditional Korean game rule	Population	[148]
282	2023	Sarada Mohapatra and Prabhujit Mohapatra	AZOA	American zebras' social behaviour	Population	[113]
283	2023	Mahdi Azizi et al	EVO	Principles related to stability and different modes of particle decay	Population	[134]
284	2023	Mohamed Abdel-Basset et al	KOA	Kepler's laws of planetary motion	Population	[135]

Table 1 (continued)

S. no.	Year	Proposed by	Method	Inspirited	Based on	Citation
285	2023	Lingyun D, and Sanyang L	SAO	Sublimation and melting behavior of snow	Population	[136]
286	2023	Fatma A. H. et al	FLA	Fick's first rule	Population	[137]
287	2023	Ruturaj Reddy et al	LAB	AI-based competitive behaviour	Population	[142]
288	2023	Hang Su et al	RIME	Rime-ice physical phenomenon	Population	[138]
289	2023	Mohamed Abdel-Basset et al	NOA	Search, cache, and recovery behaviors of nutcrackers	Population	[114]
290	2023	Mohamed Abdel-Basset et al	YDSE	Young's double-slit experiment	Population	[139]
291	2023	Kamran Zolf	GRO	How gold-seekers prospected for gold during the Gold Rush Era	Population	[143]
292	2023	Bahman Ahmadi et al	DHL	Wild animal hunting	Population	[115]
293	2023	Pavel T. and M. Dehghani	Subtraction-Average-Based Optimizer (SABO)	The searcher agent subtraction average is used to update the location of population members in the search space	Population	[336]
294	2023	Seyed Muhammad H. M	Victoria Amazonica Optimization (VAO)	Victoria Amazonica plant	Population	[337]
295	2023	Iman F. et al	MTBO	Social performance and cooperation of humans	Population	[144]
296	2023	Mohammad D. and P. Trojovský	OOA	Ospreys hunting fish from the seas	Population	[116]
297	2023	Qingke Zhang et al	GO	Individuals' learning and reflection mechanisms in their social development processes	Population	[145]
298	2023	Hoang-Le Minh	TLCO	The termite colony's life cycle and the modulation of movement methods utilized by many animal species in nature	Population	[117]
299	2023	Farshad Rezaei et al	GeMO	Unique properties of the geometric mean operator in mathematics	Population	[140]
300	2023	Masoomeh Mirrashid, and Hosein Naderpour	ILA	IbI logic theory	Population	[146]
301	2023	El-Sayed M. El-kenawy et al	Al-Biruni Earth Radius (BER)	Swarm members in achieving their global goals	Population	[338]
302	2023	Shuyin Xia et al	Granular-ball optimization algorithm (GrBO)	Granularball computing	Population	[339]
303	2023	Thanh Sang-To et al	ShGA	Shrimps and Goby fishes	Population	[118]
304	2023	Rahul Kottath and Priyanka Singh	InBO	Social environments behavior	Population	[147]

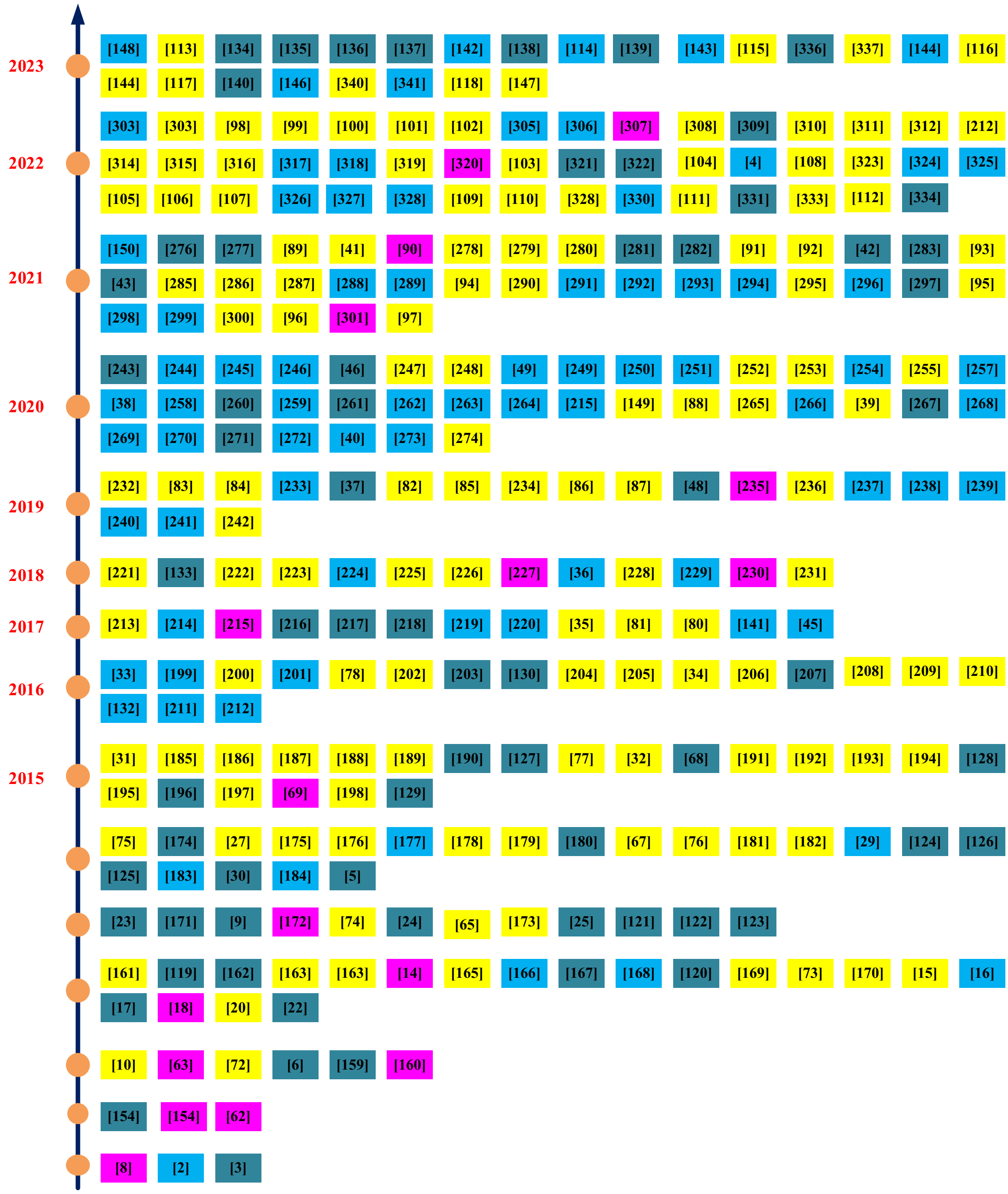


Fig. 4 Timeline of research where MH-optimization Algorithms were proposed; Background colours represent different categories of MH-optimization Algorithms: Evolutionary, Swarm Intelligence, Physics Based, and Human Based optimization algorithms

problem (VRP) with time windows, as well as split deliveries, forecast the correlation between input and output of power load, DNA sequencing problem, Chinese postman problem, design the automatic test generators, design the optimal schedule for flexible manufacturing systems, to increase the number of tolls and maintain the optimal traffic flow for the transportation network, to solve the linear ordering problem, to minimize the reduced-ordered binary decision diagrams, etc.) [340]. SA has been proposed by S. Kirkpatrick et al. (1983), that's Single- agent-based solution MH-OA. This OA was encouraged by the annealing procedure of the metal working [341]. The performance of this OA has been evaluated with Traveling Salesmen problems (TSP) [3].

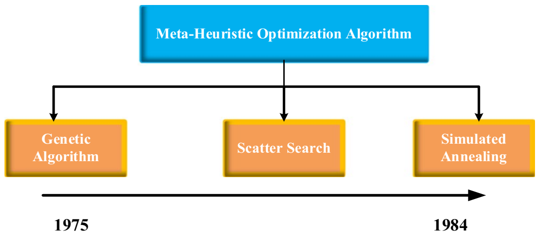


Fig. 5 Optimization_algorithms from 1975 to 1984

4.2 Phase II (1985–1994)

Phase II consists of 3 MH-OAs, as shown in Fig. 6. Fred Glover and Claude Mcmillan proposed the TS algorithm (1986), formulated in 1989 [33], a Single agent-based solution MH-OA. The algorithm is inspirited by the mechanics of human memory [154]. This OA solved various problems (Employee scheduling (1986), Maximum satisfiability problems (1987), Character recognition (1987), Machine scheduling (1989), Maximum stable set problems (1989), Vehicle routing Problem (1999), Open vehicle routing problem (2004), Container loading problem (2002), Optimal PMU placement (2005), and Job shop problem (2005)) [156, 342]. AIS has been proposed by J. Doyne Farmer, And Norman H. Packard (1986), that's population-based MH-OA. This OA has been inspirited by the vertebrate immune system [157]. However, the immune system was contrasted with the classifier system [158]. This OA has been applied to the data mining problem (1993), but lately, the application of this OA has been rapidly increasing to optimization problems [343]. MA has been proposed by Pablo Moscato (1989), that's population-based MH-OA. This OA is inspirited by the trying to emulate biological evolution. This OA was evaluated with the TSP. The MA outcomes have been contrasted with GA and SA [62].

4.3 Phase III (1995–2004)

Phase III consists of 6 MH-OAs, as shown in Fig. 7. James K. and Russell E. have proposed the PSO algorithm (1995) [10], that's population-based MH-OA. PSO is inspirited by the birds' flocking behaviour and the fish' schooling behaviour. This OA was evaluated with renowned mathematical BTFs. The result of the PSO algorithm has been assessed with GA [71]. DE algorithm was proposed by (1995), that's population-based MH-OA. This OA inspirited the natural phenomenon of evolution to solve real-world problems [63]. This OA has been evaluated with nine illustrious mathematical BTF (Sphere, Rosenbrock's Saddle, Step, Quartic, Shekel's Foxholes, Corana's Parabola, Griewangk's, Zimmermann's, And Polynomial Fitting Problem). The results of the DE were contrasted with GA, and SA [64]. ACO algorithm was proposed by Marco Dorigo et al. in the early 1990s, that's population-based MH-OA. Marco Dorigo initially proposed this OA in his Ph.D. thesis. Aiming to solve the optimal path problem in a graph [344]. ACO algorithm is a stochastic local search method that has been inspirited by the foraging behaviour of some ant species [11]. This OA consists of three steps (Construct Ants Solutions, Evaporate Pheromone, and Deamon Actions). These three steps are repeated until the optimization problem has converged [345]. The first application of ACO in structural engineering (25-bar space truss) was proposed by Bland (2001) [47]. VNS has been presented by N. Mladenović, and P. Hansen (1997), that's single agent-based solution MH-OA. This OA is inspirited by the local search heuristic and the neighbourhood structure to meet problem characteristics. This OA was evaluated with TSP problems with backhauls and without backhauls [6, 346].

HS algorithm has been proposed by Zong Woo Geem, and Joong Hoon Kim (2001), that's population-based MH-OA. The improvisation of music players inspirited this OA. This OA was evaluated with the TSP and a least-cost pipe network design problem. The HS algorithm's outcomes

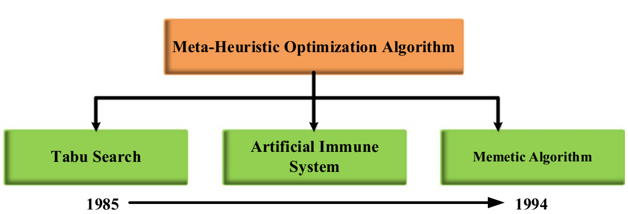


Fig. 6 MH-Optimization Algorithms from 1985 to 1994

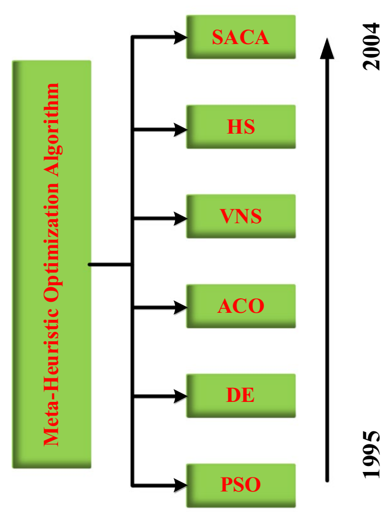


Fig. 7 MH-Optimization Algorithms from 1995 to 2004

have been contrasted with GA and SA [159]. T. Ray and K. M. Liew have proposed SACA (2003), that's population-based MH-OA. This OA is inspirited by the ability to interact mutually. This OA was evaluated with four engineering design challenges (Spring design (SD), 3-Bar Truss Design (BTD), Welded Beam Design (WBD), and Speed Reducer Design (SRD)) [160].

4.4 Phase IV (2005–2014)

Phase IV is also divided into parts (parts I and II). Part I (2005–2010), and Part II (2011–2014). Phase IV consists of 53 MH optimization techniques. Sub-sections of Phase-IV are discussed as following parts:

4.4.1 Part I (2005–2010)

Phase IV consists of 20 MH-OA, as shown in Fig. 8. Dervis Karaboga (2005) proposed the ABC technique, that's population-based MH-OA. The intelligent behaviour of the honey bee swarm inspires the ABC techniques [347]. The performance of this OA was checked with renowned BTF(Sphere, Rosenbrock valley, as well as Rastrigin) [161]. Latter (2007), this OA was evaluated with five high-dimension BTF (Griewank, Rastrigin, Rosenbrock, Ackley, as well as Schwefel). In addition, the outcomes of the ABC OA were contrasted with PSO and GA [13]. BB-BC algorithm proposed by Osman K. and Ibrahim E. (2005), that's population-based MH-OA. This OA is inspirited by Big Bang as well as Big Crunch Theory. The performance of BB-BC optimization techniques was evaluated with BTFs (Ackley, Rastrigin, Ellipsoid, Step, Rosenbrock, and Sphere). The outcomes of the BB-BC were contrasted with the combat genetic algorithm (C-GA) OAss [119]. The PCA was proposed by Wagner F. Sacco, and Cassiano R.E. de Oliveira (2005), that's population-based MH-OA. This OA is inspirited by nuclear reactions, particularly scattering as well as absorption. The performance of the PCA algorithm has been evaluated with three renowned BTFs (Easom's, Shekel's Foxholes, and Rosenbrock's valley) and real-life engineering problems

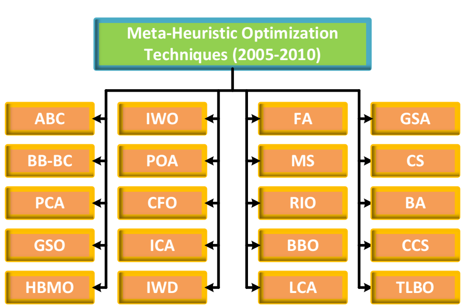


Fig. 8 Meta-heuristic optimization_algorithm from 2005 to 2010

(Nuclear engineering). The findings of the PCA algorithm were contrasted with GA [162]. The GSO has been proposed by S. He et al. (2006), that's a nature-inspirited population-based MH-OA. The animal searching behaviour as well as group living theory inspire this OA. This OA was evaluated with five illustrious BTFs (Ackley's, Generalized Rastrigin's, Schwefel's_2.26, Rosenbrock's, and Sphere). The outcomes of the GSO algorithm were contrasted with other MH-OA (HS, PSO, and Evolutionary Programming) [164]. HBMO technique has been proposed by Omid Bozorg Haddad et al. (2006), that's population-based MH-OA. The process of actual honey-bees mating inspirited this OA. This OA was verified with renowned mathematical BTFs. In addition, HBMO has been evaluated by a real-world optimization problem (Single Reservoir Operation Optimization). The outcomes of the HBMO algorithm were contrasted with GA [14]. The IWO was proposed by A.R. Mehrabian and C. Luca (2006), a stochastic population-based MH-OA. The IWO algorithm is inspirited by colonizing weeds. The IWO algorithm was contrasted with four other evolutionary OA like GA, SFL, MA, and PSO [165]. POA has been proposed by Ali Borji (2007), that's population-based MH-OA. Parliamentary political competitions inspire this OA. This OA was evaluated with three illustrious BTFs (Rastrigin, Sphere, and Ackley). The outcomes of the POA algorithm were evaluated with GA [166]. R. A. Formato (2007) proposed the CFO technique, that's population-based MH-OA. The analogy inspires this OA to classical particle kinematics in a gravitational field. The effectiveness of this OA was evaluated by synthesizing a 32-element linear array with three specific design criteria and designing a 3-element equalizer for the canonical Fano load. This OA was also evaluated with various BTF (Mod Colville, Mod Rosenbrock, 2D sine, Mod Sphere, Mod Step, Mod Rastrigin, Mod Ackleyís, Mod Griewank, Schwefel 2.26, Mod Camel-Back, Branin, Shekelís, Modulated R2 Function, Three Cylinders, and Mod Keaneís). The findings of the BB-BC were contrasted with PSO and ACO [167]. The ICA has been proposed by Esmaeil A. G., and Caro L. (2007), that's population-based MH-OA. This OA is stimulated by imperialistic competition. Four renowned standard BTFs were employed to evaluate this OA. The outcomes of the ICA were contrasted with GA, and PSO [168]. The IWD algorithm was proposed by H. S. Hosseini (2007), that's population-based MH-OA. This OA is inspirited by the prominent properties of the natural water drops that flow in the beds of rivers [348]. This OA was evaluated with renowned BTFs and solved the TSP [120]. FA was proposed by Xin-S. Y. (2008), that's population-based MH-OA for global optimization. The flashing behaviour of fireflies inspirited this OA. This OA has been evaluated with tension and compression spring (T/CSD) optimization problems [169]. Later, Xin-She Yang (2009) contrasted this OA with PSO and GA. The comparison of these OAs was evaluated with some illustrious BTFs (Yang's, Shubert's, Griewank's, Easom, Rastrigin, Ackley, Schwefel, De Jong, Rosenbrock, and Michalewicz) [349].

The MS has been proposed by Antonio Mucherino, and Onur Seref (2008), that's population-based MH-OA for global optimization. This OA is inspirited by the monkey's habit of mounting trees in search of meals. The effectiveness of this OA method was also checked with two sets of biomedical problems (Lennard–Jones and Morse clusters, and tube model). The outcomes of the ICA were contrasted with SA, and HS [73]. The RIO has been proposed by Timothy C. H. et al. (2008), that's population-based MH-OA. The social behaviour of cockroaches inspirited this OA. Eight renowned standard benchmark functions were employed to evaluate this OA (Sphere, Hump, Easom, Michalewicz, Griewank, Ackley, Rosenbrock, and Rastrigin Functions). The findings of the RIO algorithm were contrasted with PSO [170]. BBO algorithm proposed by Dan Simon (2008), that's population-based MH-OA. This OA is inspirited by biogeography (the study of the geographical distribution of biological organisms). Fourteen illustrious standard benchmark functions were employed to evaluate this OA (Ackley, Step, Sphere, Fletcher, Griewank, Quartic, Rastrigin, Rosenbrock, Penalty #1, Penalty #2, Schwefel 1.2, Schwefel 2.21, and Schwefel 2.26), and actual real-world problem (sensor selection problem for aircraft engine health estimation). The results of this OA were contrasted with other MH-OAs (ACO, DE, ES, GA, PSO, and SGA) [15]. The LCA was proposed by Ali Husseinzadeh Kashan (2009), that's population-based MH-OA for numerical function optimization. This OA was encouraged by the competition between sports teams in a sports league. Five illustrious standard benchmark functions were employed to evaluate this OA (Schwefel, Ackley, Rastrigin, Rosenbrock, as well as Sphere). The outcomes of the LCA were contrasted with PSO [16]. GSA has been proposed by Esmat R. et al. (2009), that's population-based MH-OA. The law of gravity and mass interactions inspires this OA. In this OA, each agent (mass) has 4-specifications (passive gravitational mass, position, active gravitational mass, as well as inertial mass). Twenty-three illustrious standard benchmark functions were employed to evaluate this OA. The outcomes of the GSA were contrasted with other MH-OAs (PSO, CFO, and RGA) [17]. CS algorithm was proposed by Xin-She Y., and Suash D. (2009), that's population-based MH-OA. This OA was encouraged by the reproduction strategy of cuckoos[18, 350]. A set of renowned standard BTFs were employed to evaluate this OA (Michaelwicz, Multiple Peaks, Rosenbrock's, Shubert's (18 minima), Griewank's, Easom's, Rastrigin's, Ackley's, Schwefel's, and De Jong's). The outcomes of the CS were contrasted with GA, and PSO [19]. The BA was proposed by Xin-S.Y. (2010), a population-based MH-OA. This OA is inspirited by the echolocation behaviour of bats [20]. This OA was evaluated with the renowned Rosenbrock's benchmark function. The outcomes of the BA were contrasted with GA, and PSO [21]. CSS, proposed by A. Kaveh, and S. Talatahari (2010), that's population-based MH-OA. This OA was stimulated by some principles from physics (Coulomb law from electrostatics, as well as laws of motion from Newtonian mechanics). In this OA, three concepts were considered (Self-adaptation step, cooperation step, and competition step). This OA was evaluated with BTFs (rosenbrock, rastrigin, hartman_6, hartman_3, griewank, goldstein and price, exponential, de joung, cosine mixture, cb_3, camel, branin, aluffi-pentiny, becker and lago, bohachevsky_1, and bohachevsky_2) and engineering problem (WBD, T/CSD, and Pressure Vessel Design (PVD)) [22]. TLBO has been proposed by R.V. Rao et al. (2010), that's nature-inspirited population-based MH-OA for constrained mechanical design optimization problems. This OA has been influenced by effect of a teacher's influence on the performance of childrens in a class. This OA has been evaluated with five different constrained benchmark functions and mechanical engineering problems (WBD, T/CSD, PVD, GTD, Multiple Disc Clutch Brake Design (MDCBD), Step Cone Pulley Design (SCPD), Belleville-SD, Robot gripper, Hydrodynamic thrust bearing, as well as Rolling element bearing Design (REBD) problem). The outcomes of TLBO were contrasted with other MH-OA (ABC, PSO, GA, and HS) [7].

4.4.2 Part II (2011–2014)

Part II of phase IV consists of 33 MH-OAs, as shown in Figs. 9 and 10. GbSA has been proposed by Hamed Shah-Hosseini (2011), that's population-based MH-OA. This OA simulated the spiral arm of spiral galaxies to explore its surroundings. This OA was two renowned datasets (Iris and E.coli) were employed for testing the PCA (principal components analysis)-estimation capability of the GbSA-PCA [23]. The SO algorithm has been proposed by Kenichi Tamura, and Keiichiro Yasuda (2011), that's population-based MH-OA. The logarithmic spiral phenomena inspirited this OA. This OA was evaluated with two-dimensional

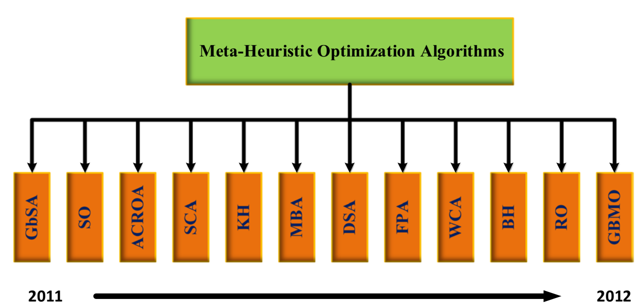


Fig. 9 MH-Optimization Algorithms from 2011–2012

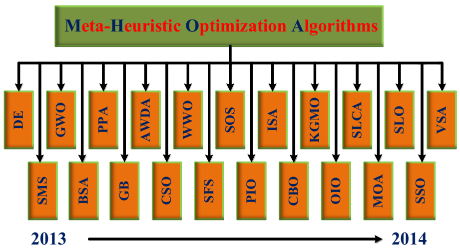


Fig. 10 MH-Optimization Algorithms from 2013–2014

benchmark problems (Rosenbrock, 2^n minima, and Rastrigin). The outcomes of the SO algorithm were contrasted with PSO [171]. ACROA has been proposed by Bilal Alatas (2011), that's population-based physics-based MH-OA. The occurrence of chemical reactions stimulated this OA. Three illustrious standard benchmark functions were employed to evaluate this OA. (griewangk, rastrigin, as well as rosenbrock). The outcomes of the ACROA algorithm were contrasted with ABC, and BBO [9]. Mohammad Taherdangkoo et al. (2012) proposed SCA, that's population-based MH-OA. The behaviour of stem cells in reproducing themselves inspirited this OA. Four illustrious standard benchmark functions were employed to evaluate this OA with 30 runs, 5000 iterations, and 100 population sizes. The outcomes of the SCA algorithm were contrasted with the different MH-OA (PSO, GA, ABC, and ACO) [172]. The KH algorithm has been proposed by Amir Hossein G. and Amir H. A. (2012), that's bio-inspirited population-based MH-OA. The krills herd each other inspirited this OA. For more precise modelling of this OA, two genetic operators (Crossover and Mutation) were used. This OA was evaluated with twenty renowned BTFs (Sphere, Schwefel_1.2, Schwefel_2.22, Rosenbrock, Rastrigin, Quartic, Griewank, Ackley, Branin, Shekel_1, Shekel 2, Shekel_3, Kowalik Hartman_1, Schwefel_2.21, Hartman_2, Goldstein And Price, Schwefel_2.26, De Joung (Shekel's Foxholes), and Camel Back_6 Hump). The findings of KH were contrasted with other MH-OAs (GA, PSO, ES, BBO, DE, and ACO) [74]. MBA has been proposed by Ali S. et al. (2012), that's population-based MH-OA for solving constrained engineering optimization problems. The mine bomb explosion concept inspires MBA. This OA was evaluated with eight constrained BTFs and eight engineering problems (3-BTD, REBD, Belleville-SD, GTD, SRD, WBD, SD, and PVD). The outcomes of the MBA were contrasted with other MH-OAs (PSO, GA, DE, ABC, TLBO, and FSA) [24]. DSA has been proposed by Pinar Civicioglu (2012), that's a population-based MH-OA. The Brownian-like random walk movement inspires this OA. Fifty-two renowned standard benchmark functions were employed to evaluate this OA: 40 BTFs (Goldsteinprice, Zakharov, Trid, Sumsquares, Stepint, Step_2, Sphere_2, Camelback, Shubert, Shekel_10, Shekel_5, Shekel_7, Trid, Schwefel_1_2, Schwefel, Schwefel_2_22, Schaffer, Rosenbrock, Rastrigin, Quartic, Powersum, Powell, Perm, Michalewics D_10, Michalewicsd_5, Michalewicsd_2, Matyas, Langermann, Hartman_3, Griewank, Fletcher, Easom, Colville, Branin, Booth, Bohachecsky_1, Bohachecsky_2, Bohachecsky_3, Beale, And Ackley), and twelve test function (Shifted_Sphere, Schwefel's_2.13, Shifted_Rotated_Weierstrass, Shifted_Rotated_Rastrigin's, Shifted_Rastrigin's, Shifted_Rotated_Ackley's With Global Optimum On Bounds, Shifted_Rotated_Griewank's Without Bounds, Shifted_Rosenbrock's, Schwefel's_2.6 With Global Optimum On Bounds, Shifted_Schwefel's_1.2 With Noise In Fitness, Shifted_Rotated High Conditioned Elliptic, And Shifted_Schwefel's Problem). The findings of DSA were contrasted with other MH-OAs (PSO, ABC, and GSA) [66].

The FPA has been proposed by Xin S. Y. (2012), that's population-based MH-OA. The pollination process of flowers inspirited this OA. Ten illustrious standard benchmark functions were employed to evaluate this OA (Ackley, De Jong's, Easom's, Griewangk's, Michaelwicz's, Rastrigin's, Rosenbrock's, Schwefel's, Yang's forest-like, as well as Shubert's function) and were contrasted with other MH-OAs (GA, and PSO) [173]. WCA was proposed by Hadi Eskandar et al. (2012), that's population-based MH-OA applied to several constrained optimization as well as engineering design problems. WCA was motivated by nature and how rivers as well as streams actually flow into the sea. This OA was evaluated with 4 constraint benchmark problems and seven engineering design problems (3-BTD, SRD, PVD, T/CSD, WBD, REBD, and MDCBD). The outcomes of this OA were contrasted with other MH-OA (PSO, GA, TLBO, ABC, and DE) [25]. The BH algorithm was proposed by Abdolreza Hatamlou (2012), that's a population-based MH optimization approach for data clustering. The Blackhole phenomenon inspirited the BH algorithm. This OA was evaluated by six benchmark data sets and was contrasted with PSO, and GSA [121]. RO algorithm was proposed by A. Kaveh, and M. Khayatazad (2012), that's population-based MH-OA. This OA was based on snell's light refraction law. This OA was evaluated with BTFs (Rastrigin, Griewank, Goldstein And Price, Exponential, De Joung, Cosine Mixture, Cb3, Camel, Branin, Becker And Lago, Bohachevsky_1, Bohachevsky_2, And Aluffi-Pentiny), some mathematical optimization problem (Shekel_10, Shekel_5, Shekel_7, Goldstein And Price, Rastrigin, Griewank, Exp_16, Exp_2, Exp_4, Exp_8, De Joung, Ap, Cm, Cb_3, Bf_1, Bf_2, Branin Camel, And Bl)and three mechanical engineering design problem (T/CSD, WBD, and 25-Bar Spatial Truss (BST)). The outcomes of the RO were contrasted with other MH-OA (PSO, GA, and HS) [122]. GBMO algorithm has been proposed by Marjan Abdechiri et al. (2012), that's population-based MH-OA. The turbulent rotating motion and Brownian motion of gases inspire this OA. This OA was evaluated with seven standard BTFs (Zakharov, Booth, Sphere Ackley, Rastrigin, Griewank, And Rosenbrock), and real-world optimization challenges (Lennard–Jones potential, and Tersoff Potential Function Minimization Problem). The outcomes of the GBMO were contrasted with other MH-OAs (GA, PSO, GSA, and ICA) [123].

The DE has been proposed by A. Kaveh, and N. Farhoudi (2013), that's population-based MH-OA. This OA simulated the approaches used by hunting techniques employed by dolphins. Dolphins produce a sound (Sonar) to trace the target. Input parameter for this OA (Loops number, Effective radius, Convergence curve formula, Number of locations, and less than any possible fitness). This OA was verified with the mathematical function optimization problem, Structural optimization (minimize the weight of the structure), 3 truss structures (582-bar tower truss, 25-BST, and 72-BST), and 2 Frame structures (3-bay 24-story planar frame, as well as 3-bay 15-story planar frame). The outcomes of the DE were contrasted with other MH-OAs (PSO, GA, SA, HS, BB, ACO, and CSS) [75]. The SMS has been proposed by Erik C. et al. (2013), that's population-based MH-OA. The physical principles of the thermal-energy motion mechanism inspire this OA. Twenty-four renowned standard benchmark functions were employed to evaluate this OA. And a set of GECCO functions (GECCO-2010 Discus function, GECCO-2010 Different Powers function, GECCO-2010 Schwefel function, GECCO-2005 Shifted Sphere Function, GECCO-2005 Shifted Schwefel's Problem, GECCO-2005 Shifted Schwefel's Problem 1.2 with Noise in Fitness, GECCO-2005 Schwefel's Problem 2.6 with Global Optimum on Bounds, GECCO-2005 Shifted Rosenbrock's, GECCO-2005 Schwefel's Problem, and GECCO-2005 Rotated Version of Hybrid Composition Function). The findings of the SMS OA were contrasted with other MH-OAs (PSO, GSA, and DE) [174]. GWO has been proposed by Seyedali M. et al. (2013), that's population-based MH-OA. GWO OA is inspirited by grey wolves (Canis lupus). GWO algorithm simulates the Canis lupus behaviour. This OA was evaluated with twenty-nine illustrious test functions, solved engineering design optimization problems (T/CSD, WBD, and PVD), and was applied in optical engineering (optical buffer design). The outcomes of GWO were contrasted with other MH-OAs (PSO, GSA, DE, EP, and ES) [27]. BSA was proposed by Pinar Civicioglu (2013), that's population-based stochastic OA, evolutionary computing-based global search OA. This OA was evaluated in three-set first test includes 50 widely used standard benchmark problems, the second test includes twenty-five benchmark test problems used in CEC2005, as well as the third test set includes three real-world problems used in CEC2011. The findings of the BSA were contrasted with PSO, and ABC [175]. PPA was proposed by Surafel Luleseged Tilahun, and Hong Choon Ong (2013), that's a population-based bio-inspirited MH-OA. This OA is inspirited by the prey-predator interaction of animals where the predator runs after the prey. Five illustrious standard BTFs were employed to evaluate this OA (Easom's, stochastic, step, Shubert's, and Michalewicz function). The findings of PPA were contrasted with other MH-OAs (PSO, and GA) [176]. GB algorithm was proposed by E. Osaba et al. (2013), that's a population-based game-based MH-OA to solve combinatorial optimization problems. Soccer concepts inspirited this OA. This OA was evaluated with a set of mathematical BTFs (TSP, and Capacitated VRP). The outcomes of the GB algorithm were contrasted with GA, and Distributed GA [177]. AWDA has been proposed by C. Subramanian et al. (2013), that's population-based MH-OA. The cooperative hunting behaviour of African wild dogs inspires this OA. This OA was evaluated with illustrious BTFs, and real-world engineering problems (PVD, WBD, and T/CSD). The outcomes of the AWDA were contrasted with GA, and HS [178]. The CSO has been proposed by Xianbing Meng et al. (2014), that's population MH-OA. The behaviours of the chicken swarm (roosters, hens, and chicks) inspirited this OA. This OA was evaluated with twelve illustrious BTFs (Exponential, Brown, Bent Cigar, Axis Parallel Hyper-Ellipsoid, Rastrigin, Powell Sum, Step, Sphere, Griewank, Ackley, Discus, as well as High Conditioned Elliptic), along with engineering design challenges (SRD). The outcomes of the CSO were contrasted with other MH-OAs (PSO, BA, and DE) [179]. The WWO has been proposed by Yu-Jun Zheng (2014), that's nature-inspirited population-based MH-OA. The shallow water wave theory inspires this OA. This OA was evaluated with thirty renowned BTFs and high-speed train scheduling problems. The outcomes of the WWO were contrasted with other MH-OAs (BA, BBO, IWO, and GSA) [180]. The SFS algorithm was proposed by Hamid Salimi (2014), that's population-based MH-OA. The SFS algorithm is encouraged by the natural phenomenon of growth. SFS algorithms can solve both constrained and unconstrained global optimization problems with a continuous variable. SFS algorithms include two main processes one is the diffusion process, and another one is the update process [67]. The SOS algorithm was proposed by Min-Yuan Cheng and Doddy Prayogo (2014), that's population-based MH-OA. The SOS is inspirited by the strategies for symbiotic interaction employed by organisms in the ecosystem to survive and propagate. Twenty-three unconstrained mathematical problems evaluated this OA, four structural engineering design challenges (Cantilever Beam Design (CBD), Minimize I-beam vertical deflection, 15 and 52-bar planar truss structure) and were contrasted with different optimization techniques (GA, DE, PSO, BA, PBA, and CS) [76]. The SSO has been proposed by Erik Cuevas et al. (2014), that's population-based MH swarm OA. The cooperative behaviour of social spiders inspires this OA. This OA consisted of two different agents (Male, and Female collective operators). This OA was evaluated with nineteen illustrious BTFs (Sphere, Salomon, Powell, Griewank, Ackley, Rastrigin, Schwefel, Penalized, Penalized_2, Zakharov, Sum of Squares, Levy, Dixon & Price, Quartic, Step, Rosenbrock, Schwefel_1.2, and Schwefel_2.22). The outcomes of the SSO were contrasted with PSO, and ABC [181]. The PIO algorithm was proposed by Haibin Duan and Peixin Qiao (2014), that's a population-based MH-OA for a feasible and effective algorithm for air robot path planning. The natural pigeon behaviour inspirited this OA. Two operators (Map and compass operator, and Landmark operator) were designed by using some rules. This OA was evaluated with the number of experiments conducted, and the findings of the PIO were contrasted with the DE algorithm [182]. ISA has been proposed by Amir H. Gandomi (2014), that's a population-based MH-OA. Interior design and decoration inspirited this OA. This OA was evaluated with fourteen renowned classical BTFs (Dekkers and Aarts, Wood, Kowalik, Hartman_3, Hartman_6, Goldstein and Price, Easom, Ackley, Sphere, Rosenbrock, Rastrigin, Levy and Montalvo_1, Levy and Montalvo_2, and Griewank), and engineering design problem (Gear Train Design (GTD), 72 bar space truss, T/CSD, PVD, and WBD). The outcomes of the ISA were contrasted with other MH-OA (PSO, DE, GSO, and GA) [29]. The CBO proposed by Kaveh A., and Mahdavi V.R. (2014), that's population-based MH-OA. This OA was based on one-dimensional collisions between bodies. The collision of two bodies is governed by a physics law (laws of momentum and energy). This OA's efficiency was evaluated using three real-world engineering design problems (PVD, WBD, and T/CSD) and 2 structural design problems (Design of Forth truss bridge and Weight minimization of the 120-bar truss dome). The outcomes of the CBO were contrasted with other optimization_algorithms (PSO, HS, RO, and BB-BC) [124].

The KGMO was proposed by Sara Moein, and Rajasvaran Logeswaran (2014), that's population-based MH-OA. The kinetic energy of gas molecules inspirited this OA. The twenty-three BTFs were employed to evaluate this OA. The function grouped into the set first set consists of an unimodal (1–7), the second set consists of a multimodal high dimensional (8–13), and the third set consists of a multimodal with fixed dimension (14–23). The result of the KGMO was GSA, and PSO [126]. The OIO algorithm has been proposed by A. H. Kashan (2014), that's population-based MH-OA. This OA is inspirited by the optical features of concave as well as convex mirrors. This OA was evaluated with five experiments, the first experiment consisted of twenty-three classic test functions, the second experiment consisted of three numerical functions, the third experiment consisted of fifty functions, the fourth experiment optimized all BTFof IEEE CEC 2005, and the fifth experiment consist of a real-world engineering design problem (Centrifugal pump). The outcomes of the OIO were contrasted with other MH-OAs (ABC, TLBO, DE, and PSO) [125]. SLCA was proposed by Naser Moosavian, and Babak KasaeeRoodsari (2014), that's population-based game-based MH-OA. This OA was motivated by Soccer leagues, in addition, based on the competitions among teams as well as players. This OA used two operators(Mutation operator, and Substitution operator) [351]. This OA was evaluated with three benchmark pipe networks (Two-loop network, New York City water supply tunnels network, and Hanoi network). The outcomes of the SLCA were contrasted with other MH-OA (PSO, GA, DE, SA, SS, and HS) [183]. The MOA has been proposed by Tayarani M.H., and Akbarzadeh M.R. (2014), that's a physics-inspirited population-based MH-OA. The principles of magnetic field theory inspirited this OA. Twenty-one BTFs have been used to evaluate this OA (Sphere, Schwefel's_2.22, Schwefel's_2.21, Rosenbrock, Elliptic, Rotated elliptic, Single-group shifted and m-rotated elliptic, Single-group shifted m-dimensional Schwefelsproblem1.2, Schwefel's_1.2, Generalized Schwefel's_2.26, Generalized Rastrigin's, Ackley's, Generalized Griewank, Generalized Penalized_1, Generalized penalized_2, Michalewicz, Goldberg & Richardson, Dejong_4, Single-group shifted, and m-rotated Rastrigin's, Single-group shifted and m-rotated_Ackley's and Single-group shifted m-dimensional Rosenbrock's). The findings of the MOA were contrasted with other MH-OAs (PSO, GA, DE, ES, FEP, and EP) [30]. SLO algorithm has been proposed by Erfan Khaji (2014), that's population-based game-based MH-OA. The football system in European countries inspirited this OA. This OA started with initial populations including 3 groups (Wealthiest, regular, and poorest). This OA was evaluated with four renowned BTFs. The findings of the SLO were contrasted with GA, and PSO [184]. VSA was proposed by Berat Dog˘an, and Tamer Olmez (2014) that's single solution-based MH-OA to perform numerical function optimization. This OA is inspirited by the vortex pattern created by the vortical flow of the stirred fluids. This OA was evaluated with fifty illustrious BTFs (Rosenbrock, Schwefel_1.2, Schwefel_2.22, Powell, Zakharov, Trid_10, Trid_6, Fletcher Powell_2, Colville, Matyas, Easom, Beale, Quartic, SumSquares, Langerman_10, Sphere, Step, Stepint, Bohachevsky_2, Fletcher Powell_5, Bohachevsky_3, Six Hump Camel Back, Schaffer, Michalewicz_2, Michalewicz_5, Michalewicz_10, Schwefel, Rastrigin, Booth, Bohachevsky_1, Branin, Foxholes, Dixon–Price, Kowalik, Gold Stein-Price, Shubert, Shekel_5, Shekel_7, Shekel_10, Langerman_2, Penalized, Penalized_2, Ackley, Griewank, Hartman3, Hartman_6, PowerSum, Perm, Langerman_5, and Fletcher Powell_10). The findings of the VSA algorithm were contrasted with a single solution-based (SA, and PS) and population-based MH-OA (PSO, and ABC) [5].

4.5 Phase V (2015-Till Present)

Phase V is also divided into eight-part (part I, part II, part III, part IV, part V, part VI, and Part VII). Part I (2015), Part II (2016), Part III (2017), Part IV (2018), Part V (2019), Part VI (2020), Part VII (2021) and Part VIII (2022). Subsections of Phase V are discussed as follows:

4.5.1 Part 1 (2015)

Part I of phase V consists of 22 MH-OA, as shown in Fig. 11. The ALO algorithm was proposed by Seyedali Mirjalili (2015), a nature-inspired population-based MH-OA. The hunting mechanism of antlions in nature, inspirited this OA. This OA was evaluated with fifteen renowned test functions divided into three groups: unimodal (1–7), multimodal (8–13), and composite (14–19), engineering problems (CBD, and 3-BTD), and shapes of two ship propellers are optimized. The findings of the ALO were contrasted with other MH-OA (PSO, SMS, BA, CS, GA, FA, and FPA) [31]. The WSA algorithm was proposed by Adil Baykasoˇglu, and Sener Akpinar (2015), that's population-based MH-OA. This OA is based on two mechanisms (superposition as well as the attracted movement of agents). This OA was evaluated with seventy-one illustrious BTFs (Ackley's, Wood's, Shekel_5, Storn's Tchebychev, Sinusoidal, Shekel's Foxholes, Shekel_7, Schwefel, Shubert, Schaffer_1, Schaffer_2, Salomon, Rosenbrock, Rastrigin, Price's Transistor Modelling, Powell's Quadratic, Periodic, Paviani's, Odd Square, Neumaier_2, Neumaier 3, Multi-Gaussian, Modified_Rosenbrock, Modified_Langerman, Miele and Cantrell, Meyer and Roth, McCormick, Levy and Montalvo_2, Levy and Montalvo_1, Kowalik, Hosaki, Helical Valley, Hartman_6, Hartman_3, Gulf Research, Griewank, Shekel_10, Goldstein and Price, Exponential, Epistatic_Michalewicz, Easom, Dekkers and Aarts, Cosine Mixture, Camel Back-6 Six Hump, Camel Back-3 Three Hump, Branin, Bohachevsky_2, Bohachevsky_1, Becker and Lago, Schwefel's P1.2, Rosenbrock, Schwefel's P2.21, Schwefel's P2.22, Zakharov, Elliptic, Rastrigin, Ackley, Griewank Schwefel, Noncontinuous Rastrigin, Weierstrass, Levy, Composition (64–71) and Aluffi-Pentini's). The outcomes of the WSA were contrasted with other MH-OAs (SA, TS, and BPA) [185]. The MFO was proposed by Seyedali Mirjalili (2015), that's a nature-inspirited population-based MH-OA. This OA is inspirited by the navigation method of moths. Twenty-Nine BTFs have been used to evaluate this OA, in addition to Marine propeller design, and nine engineering challenges (WBD, GTD, 3-BTD, PVD, CBD, I-beam design, T/CSD, 15-BTD, and 52-BTD). The outcomes of the MFO were contrasted with other MH-OAs (PSO, GSA, BA, FA, and GA) [186]. DA was proposed by Seyedali Mirjalili (2015), that's population-based MH swarm intelligence OA for solving single-objective, discrete, and multi-objective problems. The static and dynamic dragonflies swarming behaviours inspire this OA. This OA was evaluated with illustrious BTFs divided into 3 groups: unimodal test functions (1–7), multi-modal test functions (8–13), and composite test functions (14–19). The findings of the DA were contrasted with other MH-OA (PSO, and GA) [187]. AAA has been proposed by Sait Ali Uymaz (2015), that's MH-OA, and highly effective population-based evolutionary. Microalgae living behaviours in nature inspires the AAA optimization technique. In the AAA optimization technique, two operators have been used one is an adaptation, and another one is the evolutionary process [188]. The EHO was proposed by Gai G. W. et al. (2015), a swarm-based MH optimization technique used for solving global optimization tasks. The herding behaviour of the elephant group stimulates the EHO algorithm. In EHO algorithms, two operators are used one is clan updating and separating operators [189]. The GSO has been proposed by Venkataraman Muthiah-Nakarajan, and Mathew Mithra Noel (2015), that's population-based MH-OA. This OA was encouraged by the motion of stars, galaxies as well as

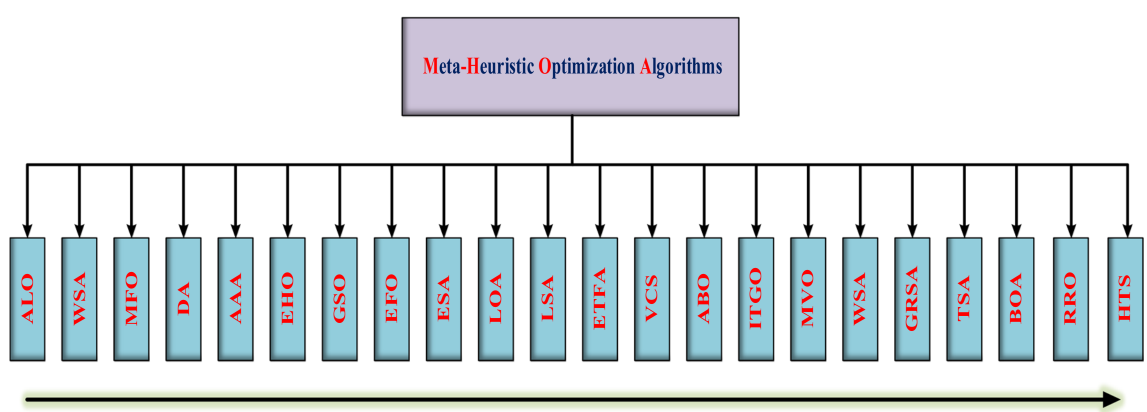


Fig. 11 MH-Optimization Algorithm (2015)

superclusters of galaxies under the effect of gravity. This OA was evaluated with fifteen renowned BTFs (Sphere, Rotated Ackley, Ackley, Rotated Griewangk, Griewangk, Rotated Rastrigin, Rastrigin, Rosenbrock, Weierstrass, Shifted-Rotated Weierstrass, Zakharov, Shifted-Rotated Ackley, Shifted-Rotated Rastrigin, Noisy Sphere, and Non-Continuous Rastrigin). The findings of the GSO were contrasted with PSO variants algorithms [190]. The EFO has been proposed by Hosein Abedinpourshotorban et al. (2015), that's physics-inspirited population-based MH-OA. This OA was based on electro-magnet behaviour and took advantage of the golden ratio. This OA was evaluated over 30 high dimensional CEC 2014 optimization functions. The findings of the EFO were contrasted with other MH-OA (ABC, GSO, and GSA) [127]. ESA has been proposed by Suash Deb et al. (2015), that's bio-inspirited MH-OA. The ESO algorithm is encouraged by the elephant herd's behavioural characteristics. ESO algorithm divides the agent into two groups: male elephant and female elephant as search agents in doing the dual task of exploration and exploitation [77]. LOA was proposed by Maziar Y., and Fariborz J. (2015), that's population-based MH-OA. LOA was stimulated by the special lifestyle of lions and their cooperation characteristics. This OA was evaluated by a set of thirty BTFs of the congress on evolutionary computation (CEC) 2015 as well as contrasted with different optimization techniques (BBO, GSA, BA, and WWO) [32]. LSA was proposed by Hussain Shareef et al. (2015), that's population-based MH-OA to solve constraint optimization problems. The natural phenomenon of lightning inspirited this OA. Twenty-Four BTFs have been used to evaluate this OA (Rosenbrock, Sphere, Step, Quartic, Schwefel_2.21, Branin, Foxholes, Rastrigin, Schwefel, Shekel_5, Hartman_3, Schwefel_1.2, Goldstein–Price, Shekel_7, 6-Hump Camel Back, Kowalik, Penalized_2, Schwefel_2.22, Penalized, Griewank, Shekel_10, Ackley, Hartman_6, and TSP). The outcomes of the LSA were contrasted with other MH-OAs (DSA, BSA, FFA, HSA, and PSO) [68]. The ETFA was proposed by Zhenyu M. et al. (2015), a bio-inspirited MH optimization technique to solve the tough optimization problem. The small fish in ebb tides inspirited this OA. ETFA was contrasted with different optimization techniques such as PSO, CSO, BA, and HSO algorithms [191]. VCS algorithm proposed by Mu Dong Li et al. (2015), that's population-based nature-inspirited MH-OA. This OA was based on the virus employing host cell diffusion and infection methods to spread and thrive in the cell environment. This OA was employed 3 main behaviour (viruses diffusion, host cell Infection, and immune response). This OA was evaluated with unconstrained, CEC 2014-BTFs and constraint engineering design problems (T/CSD, PVD, and WBD). The result of the VCS was contrasted with other MH-OA (WCA, MBA, DE, ABC, GSA, CS, CMA, and AMO) [192]. The ABO has been proposed by Julius Beneoluchi Odili et al. (2015), that's population-based MH-OA. This OA was encouraged by the African buffalo behaviour among the vast forests and savannahs of that continent. Thirteen BTFs as well as TSP have been used to evaluate this OA. The findings of the ABO were contrasted with other MH-OAs (PSO, GA, ACO, SA, and GA) [193]. The ITGO has been proposed by Deyu Tang et al. (2015), that's population-based MH-OA. This OA was stimulated by the principle of invasive tumor growth. The ITGO, tumor cell was separated into 4 categories (Proliferative, quiescent, dying, as well as invasive cells). This OA was evaluated with fifty functions from CEC 2005, CEC 2008, and CEC 2010. The outcomes of the ITGO were contrasted with other MH-OA (PSO, BBO, TLBO, GSA, CS, GWO, and DE) [194].

The MVO has been proposed by Seyedali M. et al. (2015), that's nature-inspirited population-based MH-OA for global optimization. The three perceptions in cosmology (white, black, and worm hole) inspirited this OA. This OA was evaluated with nineteen illustrious BTFs divided into three sets (unimodal, multimodal, as well as composite), and five engineering designs (WBD, CBD, 3-BTD, PVD, and CBD). The findings of the MVO were contrasted with other MH-OAs (PSO, GWO, GA, and GSA) [128]. The WSA was proposed by Simon Fong et al. (2015), a population-based bio-inspirited MH-OA. The preying wolf behaviour inspirited this OA. This OA has copied how wolves search for meals and survive by avoiding their enemies. This OA was evaluated with renowned BTFs (Rosenbrock's, Michalewicz's, Bohachevsky's, Moved axis parallel, Griewangk's, Schaffer's F6, Sphere model, and Rastrigrin's). The outcomes of the WSA were contrasted with another MH-OA (PSO, and GA) [195]. The GRSA was proposed by Hamzeh Beiranvand and Esmaeel Rokrok (2015), a population-based MH-OA. The General Relativity Theory inspirited this OA. Twenty-Three BTFs, and real-world electrical engineering applications (Optimal Power System Stabilizers design in a multi-machine power system) have been used to evaluate this OA. The findings of the GRSA were contrasted with GA, and PSO [196]. The TSA was proposed by Mustafa Servet Kiran (2015), that's a population-based MH-OA. This OA is inspirited by the relation between trees and their seeds. Twenty-Three BTFs have been used to evaluate this OA (Dixon&Price, Michalewicz, Himmelblau, Schaffer, Weierstrass, Levy, Alpine, Penalized_1, Penalized_2, Ackley, Schwefel_2.26, Griewank, Non-Continuous Rastrigin, Rastrigin, Rosenbrock, QuarticWN, Quartic, Step, Schwefel_2.21, Schwefel_2.22, SumPower, SumSquares, Elliptic, and Sphere). The outcomes of the TSA algorithm were contrasted with another MH-OA (PSO, ABC, FA, BA, and HS) [197]. BOA was proposed by O_guz Findik (2015), that's population-based MH-OA. The breeding of animals in nature inspires this OA. This OA was evaluated with fifty renowned BTFs (Fletcherpowell_10, Fletcherpowell_2, Fletcherpowell_5, Langerman_2, Langerman_5, Langerman_10, Penalized_2, Penalized, Ackley, Griewank, Hartman_6, Hartman_3, Powersum, Perm, Shekel_5, Shekel_7, Shekel10, Kowalik, Schaffer, Six Hump Camel Back, Bohacevsky2, Bohacevsky3, Shubert, Gold Stein Price, Michalewichz10, Michalewichz5, Michalewichz2, Schwefel, Rastrigin, Booth, Bohacevsky1, Branin, Foxholes, Dixon-Price, Rosenbrock, Schewefel 1.2, Schwefel 2.22, Powell, Zakharov, Trid6, Trid10, Colville, Matyas, Easom, Beale, Stepint, Step, Sphere, and Sumsquares, Quartic). The findings of the BOA were contrasted with another MH-OA (GA, PSO, DE, and ABC) [69]. The RRO was proposed by Anthony B. et al. (2015), that's population-based MH-OA. This OA was encouraged by the social roosting as well as foraging behaviour of one species of bird, in addition the common raven. Four BTFs have been used to evaluate this OA (Rosenbrock, Rastrigin, Griewank, and DeJong). The outcomes of the RRO were contrasted with PSO [198]. The HTS algorithm was proposed by Vivek K. Patel, and Vimal J. Savsani (2015), that's a population-based physics-inspirited MH-OA. The law of thermodynamics and heat transfer inspires this OA. Twenty-Three BTFs of CEC 2006 have been used to evaluate this OA. The findings of the HTS were contrasted with other MH-OAs (BBO, ABC, PSO, DE, and TLBO) [129].

4.5.2 Part II (2016)

Part II of Phase V consists of 19 MH-OAs, as shown in Fig. 12. FGA was proposed by Elyas Fadakar, and Masoud Ebrahimi (2016), that's a population-based game-based MH-OA. The actions of football players throughout a game to locate the best locations to score a goal under the guidance of the team coach inspire this OA. This OA was evaluated with twelve illustrious BTFs (unimodal as well as multimodal). The findings of the FGA were contrasted with BA, and PSO [33]. WCO algorithm has been proposed by Navid R. et al. (2016), that's a population-based game-based MH-OA. This OA has been based on the FIFA World Cup Competitions. This OA was evaluated with renowned BTF (Rastrigin, Rosenbrock, Booth, Cubic, and Beale), and engineering problems (optimized design of PID controller to the AVR control system with uncertainties). The outcomes of the WCO were contrasted with another MH-OA (PSO, GA, and ICA) [199]. The VOA proposed by Morteza Jaderyan, and Hassan Khotanlou (2016), that's population-based MH-OA to solve continuous as well as non-linear optimization problems. This OA was encouraged by the best way for viruses to infiltrate bodily cells. This OA simulated three major mechanisms in the virus life (reproduction and mutation mechanism, cloning mechanism to generate the best viruses for rapid and excessive infection of the host environment, and mechanism of escaping from the infected region). This OA was evaluated with eleven BTFs. The findings of the VOA were contrasted with other MH-OAs (COA, PSO, and GA) [200]. The PVS was proposed by Poonam Savsani, and VimalSavsani (2016), that's population-based MH-OA. This OA is inspirited by the mechanism of the vehicle passing on a two-lane highway. PVS algorithm can be distinguished as a human-based algorithm. This OA was verified with thirteen challenging constraints BTFs, and thirteen engineering design challenges. The outcomes of the PVS were contrasted with other MH-OA (TLBO, ABC, BA, CSA, FFA, ISA, GA, WCA, MBA, and BBO) [201]. The WO was proposed by Seyedali M. and Andrew L. (2016), a nature-inspirited MH-OA that simulates the humpback whale's social behaviour. WO algorithm has been evaluated with six structural design problems and twenty-nine other optimization problems. This OA has three operators to mimic the search for prey, encircling prey, and bubble-net foraging [78]. SWA has been proposed by A. Ebrahimi, and E. Khamehchi (2016), that's population-based MH-OA. This OA was motivated by the sperm whale's lifestyle. This OA was verified with twenty-six BTF (Ackley, DixonePrice, Zakharov, Michalewicz_5, Colville, Shubert, Boachevsky_3, Boachevsky_2,

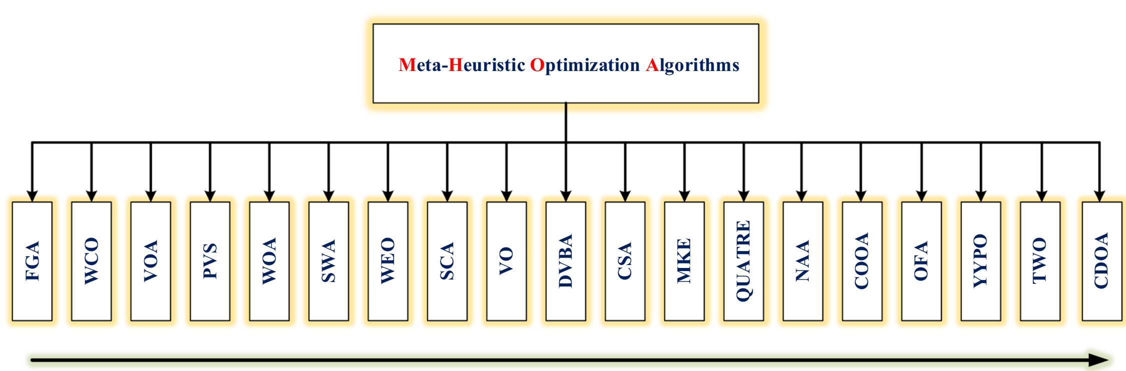


Fig. 12 MH-Optimization Algorithms (2016)

Rosenbrock, Schwefel_2.22, Schwefel_1.2, Quartic, SumSquares, Step, Michalewicz_10, Camel Back, Six Hump, Schaffer, Michalewicz_2, Booth, Bohachevsky_1, Matyas, Easom, Beale, Griewank, De Jong, and Rastrigin), three benchmarks in serval direction as well as one production optimization challenges. The findings of the SWA were contrasted with other MH-OA (GA, PSO, DE, PBA, and BA) [202]. The WEO proposed by Kaveh A. and Bakhshpoori T. (2016), that's population-based MH-OA. This OA was encouraged by tiny amount of water molecules evaporating from a solid surface with a varying degree of wettability. This OA was evaluated with forty illustrious BTFs: seventeen unconstrained BTFs, thirteen classical constrained test functions, and three engineering design challenges (PVD, T/CSD, and WBD). The outcomes of the WEO were contrasted with other MH-OAs (BA, PSO, CSS, and GA) [203]. SCA has been proposed by Seyedali M. (2016), that's population-based MH-OA. This OA is inspirited by the proprieties of trigonometric sine and cosine functions [131]. This OA was evaluated in 3 stages: the first stage (Unimodal, multi-modal, as well as composite) was employed to verify (exploration, local optima avoidance, exploitation, as well as convergence), the second stage was two-dimensional versions of some of the test functions were chosen and resolved, and the third stage the cross-section of an aircraft' swing was optimized. The outcomes of the SCA were contrasted with other MH-OA (PSO, GA, GSA, FA, FPA, and BA) [130]. The VO has been proposed by Yun-Chia Liang & Josue Rodolfo Cuevas Juarez (2016), that's population-based MH-OA. This OA is inspirited by the behaviour of viruses attacking a living cell. Eight BTFs have been used to evaluate this OA (Sphere, Weierstrass, Generalized Griewank, Rosenbrock, Generalized Schwefel_2.26, Schwefel_2.22, and Ackley). The outcomes of the VO algorithm were contrasted with other MH-OA (GA, PSO, HS, IWO, and ABC) [204]. The DVBA has been proposed by Ali Osman Topal, and Oguz Altun (2016), that's nature-inspirited population-based MH-OA. This OA is inspirited by the skill of a bat to modify the wavelength as well as the frequency of sound waves when hunting. This OA was evaluated with thirty renowned mathematical test functions with constrained optimization problems from CEC 2014, and divided into 4 clusters (Unimodal, multimodal, hybrid, and composite functions). The findings of the DVBA were contrasted with other MH-OA (GA, PSO, BA, and SA) [205]. CSA has been proposed by Alireza Askarzadeh (2016), that's a population-based MH-OA. This OA was encouraged by the intelligent crow's behaviour. This OA was evaluated with five illustrious BTFs (Griewank, Ackley, Sphere, Schwefel, and Rosenbrock), and six constrained engineering design problems (3-BTD, PVD, T/CSD, WBD, CBD, and Belleville-SD). The findings of the CSA have been contrasted with other MH-OA (PSO, GA, ABC, MBA, TLBO, and GA) [34]. The MKE algorithm has been proposed by Zhenyu Meng, and Jeng-ShyangPan (2016), that's population-based MH-OA. The action of the Monkey King stimulated this OA. Twenty-Eight BTFs from BBOB 2009, and CEC 2008, in addition to routing and fuel consumption in grid networks, have been used to evaluate this OA. The outcomes of the MKE have been contrasted with other PSO variants [206]. The QUATRE was proposed by Zhenyu Meng et al. (2016), that's population-based MH-OA. The quasi-affine transformation approach inspires this OA. This OA was evaluated with renowned BTFs from CEC 2008 and CEC 2013 suites. The outcomes of the QUATRE were contrasted with PSO variants and GA variants [207]. The NAA was proposed by Fengji L. et al. (2016), that's population-based MH-OA for real-parameter optimization. This OA was mimics by the collective decision-making intelligence of social animals. Seven BTFs have been used to evaluate this OA (Rotated_Griewank's, De_Jong, Ackley's, Rastrigin's, Rotated_Ackley's, Griewank's, and Rotated_Rastrigin's). The findings of the EPO were contrasted with other MH-OA (PSO, and DE) [208]. The COOA has been proposed by YousefSharafi et al. (2016), that's population-based MH-OA. This OA is stimulated by the competitive behaviour of various creatures (Birds, cats, bees, as well as ants to survive in nature). Fifteen BTFs have been used to evaluate this OA (NoncontinuousRastrigin, Quintic, Pathological, Ellipse, Brown, Alpine, Schwefel problem   3, Schwefel   2, Schwefel problem   1, Cigar, Weierstrass, Ackley, Rosenbrock, Rastrigin, and Sphere). The outcomes of the COOA were contrasted with other MH-OA (PSO, ACO, ABC, ICA, and CSO) [209]. The OFA proposed by Guang-Yu Zhu, and Wei-Bo Zhang (2016), that's population-based MH-OA. This OA is inspirited by the animal behavioural ecology theory (Optimal Foraging Theory). Twenty-Six BTFs have been used to evaluate this OA and the outcomes of this OA have been contrasted with other MH-OA (PSO, DE, BA, BFO, and SFLA) [210].

The YYPO algorithm has been proposed by Varun Punnathanam, and Prakash Kotecha (2016), that's a physical-based population-based MH-OA. This OA was based on maintaining stability between exploration as well as exploitation of the search space. This OA was evaluated with twenty-eight renowned BTFs, IEEE CEC 2013 test suites, and engineering problems (PVD, T/CSD, and WBD). The outcomes of the YYPO algorithm were contrasted with other MH-OA (ABC, GWO, PS, ALO, and PSO) [132]. The TWO has been proposed by Kaveh A. and Zolghadr A. (2016) that's population-based MH-OA. The tug-of-war game stimulated this OA. This OA was evaluated with a renowned set of mathematical BTFs (Camel, Branin, Becker and Lago, Bohachevsky_2, Bohachevsky_1, Aluffi-Pentiny, Hartman_3, Griewank, Goldstein and price, Exponential, DeJoung, Cosine mixture, Cb_3, and Hartman_6), and engineering design challenges (T/CSD, WBD, planar 10-bar truss structure subject to frequency constraints, 25-BST, 72-BST, and 120-bar dome truss). The findings of the TWO algorithms were contrasted with other MH-OA (GA, PSO, HS, and RO) [211]. The CDOA has been proposed by Qingyang Zhang et al. (2016), that's population-based MH-OA. This OA is inspirited by human social behaviour based on characteristics relating to decision-making. Twenty-One BTFs have been used to evaluate this OA (Shifted_Rotated Ackley's with Global Optimum on Bounds, Generalized Penalized, Shifted_Rastrigin's, Shifted_Rotated Rastrigin's, Ackley's, Shifted_Rotated Weierstrass, Schwefel's_2.13, Generalized Rastrigin's, Quartic i.e. Noise, Generalized Rosenbrock's, Schwefel's_2.21, Sphere, Shifted_Sphere, Shifted_Schwefel's_1.2, Shifted_Rotated Griewank's without Bounds, Shifted_Rotated High Conditioned Elliptic, Shifted_Schwefel's_1.2 with Noise in Fitness, Schwefel's_2.6 with Global Optimum on Bounds, Shifted_Rosenbrock's, Shifted_Expanded Griewank's plus Rosenbrock's (F8F2), and Shifted_Rotated Expanded Scaffers F6 Function (F8F2)) and 2 nonlinear functions without noise and with noise (SISO, and MISO). The findings of the CDOA were contrasted with MH-OAs (GSA, PSO, ABC, FPA, CS, and CSA) [212].

4.5.3 Part III (2017)

Part III of phase V consists of 13 MH-OA, as shown in Fig. 13. CHA has been proposed by Ahmed T. Sadiq Al-Obaidi (2017), that's a population-based MH-OA. This OA is stimulated by the camel's behaviour in the wild. This OA was evaluated with the Flexible Job Shop Scheduling Problem. The CHA outcomes were contrasted with other MH-OA (TS, GA, and CS) [213]. The SIO algorithm proposed by Alexandros Tzanetos, and Georgios Dounias (2017), is population-based MH-OA. The underwater acoustics stimulated this OA that warships use for reckoning targets and obstacles. Twelve BTFs have been used to evaluate this OA (Schaffer_N. 2, Schaffer_N. 4, Cross-In-Tray, Easom, Three-Hump Camel, Lévi _N. 13, Matyas, Bukin_N. 6, Booth's, Goldstein_Price, Beale's, and Ackley's). The findings of the SIO were verified with BA [214]. SMA was proposed by Osama Abdel Raouf and Ibrahim M. Hezam (2017), that's population-based MH-OA. The fertilization process inspires this OA in humans. Eleven BTFs have been used to evaluate this OA (Sphere, De-Jong, Unbounded domains, Styblinski-Tang, Sine Envelope, Shekel, Schaffer, Powell, Pathological, Hezam, and Drop-wave function) and real-world engineering problems (Corrugated bulkhead design, and GTD problem). The findings of the SMA algorithm were contrasted with other MH-OA (PSO, FA, and CS) [215]. The RFO algorithm has been proposed by S. Hr. Aghay Kaboli et al. (2017), that's population-based MH-OA for solving constrained optimization challenges. The raindrop's behaviour mimicked this OA. Nine BTFs have been used to evaluate this OA. (Six-Hump Camel-Back, Shekel, Hartman, Goldstein-Price, Kowalik, Griewank, Ackley, Rosenbrock, and Sphere), and real-word applications (Economic dispatch in power system). The outcomes of the RFO algorithm were contrasted with other MH-OA (GA, PSO, and EP) [216]. The LAPO algorithm proposed by A. Foroughi Nematollahi et al. (2017), that's population-based physical-based MH-OA. The Lightning attachment procedure inspires this OA. Twenty-Nine BTFs have been used to evaluate this OA, which contains four different groups of functions (Unimodal, multimodal, fixed-dimension multimodal, as well as composite functions), and real-world engineering challenges (WBD, T/CSD, PVD, optimal power flow, GTD and CBD problem). The outcomes of the LAPO algorithm were contrasted with other MH-OAs (ABC, PSO, DE, GWO, ALO, CSA, ICA, and Firefly) [217]. The TEO algorithm was proposed by A. Kaveh and A. Dadras (2017), that's population-based MH-OA. This OA was evaluated with thirteen renowned BTFs, and engineering problems (WBD, Stepped-CBD, T/CSD, and PVD). The outcomes of the TEO were contrasted with other MH-OA (PSO, BA, CSS, WEO, WCA, SCM, and CBO) [218]. MVPA was proposed by Bouchekara H. R. E. H. (2017), that's a population-based game-based MH-OA. This OA is inspirited by the game where players compete both individually to earn the MVP trophy and together in teams to win the league championship. This OA was evaluated with one-hundred renowned mathematical BTF(Zirilli, Zettl, ZeroSum, Zacharov, YaoLiu_04, XinSheYang_02, Wolfe, Sphere, Sodp, Shubert, Shekel_05, Schwefel_36, Schwefel_26, Schwefel_22, Schwefel06, Schaffer, Rosenbrock, Rastrigin, Wavy, Vincent, UrsemWaves, Ursem4, Ursem_1, Ursem_3, Trid, Trefethen, Treccani, Three-HumpCamel, TestTubeHolder, StyblinskiTang, StretchedV, Stochastic, Rana, Quintic, Price1, Price2, Price4, Power, Powell, Plateau, Perm_01, PenHolder, Paviani, Pathological, NewFunction03, NewFunction02, NewFunction01, NeedleEye, MultiModal, Mishra_02, Mishra_01, Michalewicz, McCormick, Matyas, Levy_13, Levy, Leon, Langermann, Kowalik, Infinity, Hosaki, Holzman, HolderTable,

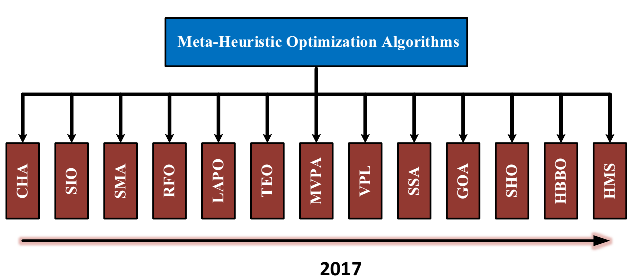


Fig. 13 MH-Optimization Algorithms (2017)

HimmelBlau, HelicalValley, Hartmann6, Hartmann_3, Hansen, Gulf Griewank, GoldsteinPrice, Giunta, Gear, FreudensteinRoth, Exp_2, EggHolder, Easom, DropWave, Cigar, Colville, Corana, CrossInTray, DixonPrice, DCS, Decanomial, CrownedCross, CrossLegTable, Chichinadze, Ackley, Adjiman, Alpine, AMGM, Beale, Bird, CarromTable Bukin_4, Bukin_6, Branin, BoxBetts, and Bohachevsky) via 4 experiment. The outcomes of the MVPA were contrasted with other MH-OA (SA, GA, DE, PSO, HS, ABC, FA, GSA, TLBO, LCA, DSA, and BH) [219]. The VPL algorithm proposed by Reza Moghdani, and Khodakaram Salimifard (2017), that's game-based population-based MH-OA. This OA was based on the competition, in addition to interaction among volleyball teams during a season. William G. Morgan (1895) presented a new game called Mintonette, and later (1896), this sport changed its name to volleyball because of the volleying nature of the game. Twenty-Three BTFs have been used to evaluate this OA consisting of unimodal (1–7), multimodal (8–13) and fixed-dimension multimodal (14–23), and three-classical engineering design challenges (T/CSD, WBD, and PVD). The findings of the VPL were contrasted with other MH-OAs (GA, DE, PSO, ABC, FA, HS, SLC, and LCA) [220].

The SSA, and multi-objective SSA (MSSA), proposed by Seyedali M. et al. (2017), that's bio-inspirited population-based MH-OA for solving optimization challenges with single and multiple objectives. SSA and MSSA were influenced by the navigating as well as hunting behavior of salps' swarming in the sea. This OA was evaluated with BTFs and engineering design challenges (WBD, I-beam design, T/CSD, 3-BTD, CBD, Two-dimensional airfoil design, and Marine propeller design using MSSA). The outcomes of the SSA and MSSA have been contrasted with other MH-OAs (GSA, PSO, FA, GA, BA, GSA, HS, and FPA) [35]. GOA has been proposed by Shahrzad Saremi et al. (2017), that's population-based MH-OA. This OA is inspirited by the behaviour of grasshopper swarms in nature for solving optimization challenges. This OA was verified with twenty-five illustrious BTFs taken from CEC- 2005 and engineering optimization problems (CBD, 3-BTD, and 52-BTD). The outcomes of the GOA were contrasted with other MH-OAs (PSO, GA, DE, FA, BA, GSA, and FPA) [81]. The SHO algorithm proposed by Gaurav Dhiman and Vijay Kumar (2017) is a bio-inspirited population-based MH-OA. The behaviour of spotted hyenas inspires this OA [352]. This OA was evaluated with twenty-nine renowned BTFs to investigate the exploration, local optima avoidance, exploitation, and convergence behaviour, five real-life constraints, and unconstrained engineering design challenges (T/CSD, WBD, PVD, REBD, and SRD). The outcomes of the SHO were contrasted with other MH-OAs (MFO, MVO, GA, SA, GSA, PSO, GWO, SCA, and HS) [79]. The HBBO has been proposed by Seyed-Alireza Ahmadi (2017), that's a population-based MH-OA to solve complex optimization challenges. This OA is inspirited by human behaviour. Fourteen BTFs have been used to evaluate this OA consisting of unimodal (1–7), and low and high dimensional multimodal (8–14). The findings of the HBBO were contrasted with the GA, and PSO [141]. The HMS algorithm has been proposed by Seyed Jalaleddin Mousavirad, Hossein Ebrahimpour-Komleh (2017), that's population-based MH-OA. The exploration strategies of the bid space in online auctions inspire this OA. Fifty-Seven BTFs have been used to evaluate this OA (unimodal, multimodal, fix-dimension, high dimensional, composite, shifted, and rotated test functions), and engineering problems (PVD, WBD, and 3-BTD problem). The findings of the HMS algorithm were contrasted to the other MH-OAs (PSO, ABC, BBO, FA, HS, GWO, WOA, and ICA) [45].

4.5.4 Part IV (2018)

Part IV of phase V consists of 13 MH-OAs, as shown in Fig. 14. The TGA proposed by Armin C. et al. (2018) is a population-based MH-OA. This OA is inspirited by the tree's competition for acquiring light and food. Thirty BTFs have been used to evaluate this OA in low and high-dimension problems, three engineering challenges (T/CSD, PVD, and WBD), and two industrial engineering optimization challenges (Single-machine scheduling and Transportation). The findings of the TGA were contrasted with other MH-OA (PSO, WSA, SA, GA, and TS) [221]. The ASO proposed by Weiguo Zhao et al. (2018) is a physics-inspirited population-based MH-OA. Basic molecular dynamics inspire this OA. This OA was verified with thirty-seven test functions separated into five various categories (unimodal, multimodal, low-dimensional, hybrid, as well as composite functions). The findings of the ASO were contrasted with other MH-OA (PSO, SA, GA, GSA, and WDO) [133]. The SSA proposed by Mohit J. et al. (2018) is a population-based nature-inspirited MH-OA. This OA was encouraged by the dynamic foraging behaviour of Southern flying squirrels. Serval BTFs have been used to evaluate this OA, including IEEE CEC-2014, and 2D-OFPI control scheme for the

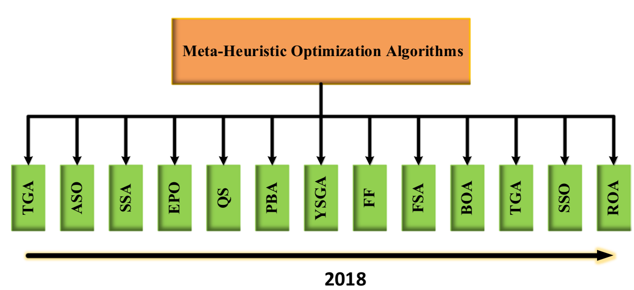


Fig. 14 MH-Optimization Algorithm 2018

Heat Flow Experiment. The outcomes of the SSA were contrasted with other MH-OAs (PSO, FF, BA, and ABC) [222]. The EPO algorithm was proposed by Gaurav Dhiman and Vijay Kumar (2018), that bio-inspirited MH-OA. This OA simulated the emperor penguins huddling behaviour. The scientific name of the emperor penguins is Aptenodytes forsteri. Forty-Four BTFs have been used to evaluate this OA and six real-life constraints (Displacement of loaded structure, 25-BTD, T/CSD, WBD, SRD, and PVD) and one unconstraint (REBD) engineering design challenge. The findings of the EPO were contrasted with other MH-OAs (SHO, PSO, GSA, GA, HS, GWO, MVO, and SCA) [223]. The QS has been proposed by Jinhao Zhang et al. (2018), that's a population-based MH-OA for solving engineering optimization problems. Human activities in queuing mimicked this OA. Thirty constraints BTFs evaluated this OA from CEC-2014, five constraint mechanical design problems (WBD, SRD, PVD, T/CSD, Bearing design), and four engineering constraint problems (MDCBD, Belleville-SD, Planetary-CBD, and Stiffened welded shell design optimization). The outcomes of the QS were contrasted with other MH-OA (PSO, GA, ABC, and BBO) [224]. PBA has been proposed by Nikos A. Kallioras et al. (2018), that's nature-inspirited population-based MH-OA. The bark beetles' behaviour mimicked this OA. The Pityogenes chalcographus is a common bark beetle species. This OA was evaluated with thirteen unimodal, multi-modal, separable, as well as non-separable BTFs (Rotated_Rastrigin's, Rotated_Griewank's, Rotated_Ackley's, Step, Quadric, Weierstrass, Sphere, Schwefel, Griewank, Rastrigin, Rosenbrock, Ackley and Shifted_Rotated Rastrigin's function), thirty BTFs using CEC-2014. The outcomes of the QS were contrasted with other MH-OAs (PSO, and Adaptive Differential Evolution) [225]. YSGA has been proposed by Daniel Zaldivar (2018), that's bio-inspirited MH-OA. The yellow saddle goatfish behaviour inspires this OA. Twenty-Seven BTFs have been used to evaluate this OA and evaluated in engineering optimization challenges (GTD, T/CSD, FM synthesizer, and 3-BTD). The outcomes of the YSGA were contrasted with other MH-OAs (PSO, GWO, CSA, WOA, and ABC) [226].

The FF optimization_algorithm has been proposed by Human Shayanfar and Farhad Soleimanian Gharehchopogh (2018), that's a population-based MH-OA for solving continuous optimization problems. The farmland fertility in nature stimulated this OA, which is divided into serval parts of farmland and divided into two type's: internal and external memory [353]. This OA was evaluated with twenty BTFs (Sum Of Different Powers, Griewank, Levy, Rastrigin, Styblinski-Tang, Rotated Hyper-Ellipsoid, Matyas, Sphere, Ackley, Rosenbrock, Dixon-Price, Beale, Powell, Michalewicz, Camel, Zakharov, Schwefel, Alpine, Bohachevsky, and Bent Cigar). The outcomes of the FF optimization-algorithm were contrasted with other MH-OAs (PSO, HS, ABC, DE, BA, and FA) [227]. The FSA has been proposed by Mahomud Nasr Said Mohamed Elsisi (2018), that's a population-based MH-OA. The person's life inspires this OA. In this world, people search for a good life. If a person's life is not good, he tries to change their lifestyle and simulate a successful person. Twenty-Three BTFs have been used to evaluate this OA. The findings of the FSA algorithm were contrasted with other MH-OAs (PSO, GA GSA, FFA, and LSA) [36]. The BOA has been proposed by Sankalap A. and Satvir S. (2018), that's population-based nature-inspirited MH-OA for global optimization. This OA was based on the butterfly's foraging behaviour. Thirty BTFs have been used to evaluate this OA (Leon, Zettl, Trid, Sum squares, Shekel_4.5, Power sum, Powell, Matyas, Goldstein price, Booth, Schwefel_2.26, Schwefel_2.22, Schwefel_1.2, Shubert, Schwefel_2.21, Easom, Rosenbrock, Schaffer, Sphere, Alpine, Rastrigin, Beale, Step, Cigar, Michalewiz, Levy, Griewank, Ackley, Bohachevsky, and Quartic function with noise) with different characteristics (Multimodality, separability, regularity, and dimensionality) and 3 engineering challenges (welded beam, SD and CBD problem) which have different natures of objective functions, constraints, and decision variables. The outcomes of the BOA algorithm were contrasted with other MH-OA (ABC, CS, DE, MBO, GA, HS, GSA, and PSO) [228]. TGA was proposed by M.J. Mahmoodabadi et al. (2018), that's population-based game-inspirited MH-OA. This OA was encouraged by games involving teams. This OA involves three operators (passing a ball, making mistakes, and substitution operators). This OA was evaluated with ten renowned BTFs: unimodal (Sphere, Quadric noise, Step, Rosenbrock, Quadric, Schwefel_2.22, and Schwefel_2.21), and multimodal (Griewank, Ackley, and Rastrigin). The findings of the TGA were contrasted with GA, and GSA [229]. The SSO has been proposed by Hisham A. Shehadeh et al. (2018), that's population-based MH-OA. This OA was stimulated by sperm motility to fertilize the egg. This OA was evaluated with illustrious BTFs that represent wireless sensor networks (End-to-End Latency Model, Network Throughput Model End-to-End Delay Model, and Energy Efficiency Model) [230]. ROA was proposed by Sina Zangbari Koohi et al. (2018) that's population-based game-based MH-OA. This OA was encouraged by rummaging behaviours of real raccoons for food. This OA was verified with four illustrious BTFs (Rotated Hyper-Ellipsoid, Grienwank, Ackley, and Rastrigin). The findings of the ROA algorithm were contrasted with other MH-OA (TLBO, IWO, FA, ABC, PSO, GA, ICA, CA, and ACO) [231].

4.5.5 Part V (2019)

Part V of phase V consists of 19 MH-OAs, as shown in Fig. 15. Sasan Harifi et al. (2019) proposed an EPC optimization algorithm that's population-based MH-OA. The emperor penguin's behaviour inspires this OA. This OA was evaluated with eight renowned BTFs (Rastrigin, Rosenbrock, Sphere, Griewank, Ackley, Bukin, Bohachevsky, Zakharov, Booth, and Michalewicz function). The outcomes of the EPC algorithm were contrasted with other MH-OAs (IWO, GWO, PSO, ABC, GA, ICA, DE, and HS) [232]. The SOA was proposed by Amandeep Kaur et al. (2019), that's a population-based bio-inspirited MH-OA for solving real-life engineering problems. This OA was based on the migration as well as the attacking behaviour of sandpipers. Forty-Four BTFs have been used to evaluate this OA, as well as real-world engineering design challenges (5.5 WBD, SRD, Optical buffer design, PVD, T/CSD, 25-BTD, and REBD). Machine-learning algorithms were hybridized with this OA to solve various software engineering challenges. The findings of the SOA algorithm were contrasted with other MH-OA (SHO, GWO, PSO, GA, MFO, SCA, MVO, GSA, and DE) [83]. STOA was proposed by Dhiman G., and Kaur A. (2019), that's a population-based bio-inspirited MH-OA for industrial engineering challenges. This OA was mimicked by the migration and attacking behaviours of sea bird sooty tern in nature. Forty-Four BTFs have been used to evaluate this OA, including unimodal, multimodal, fixed-dimension multimodal, CEC 2005 and CEC 2015, and six constrained engineering challenges (WBD, PVD, SRD, T/CSD, REBD, and 25-BTD). The outcomes of the STOA were contrasted with nine other bio-inspirited MH-OAs (PSO, SHO, GWO, MFO, GA, MVO, SCA, GSA, and DE) [84]. DGO algorithm has been proposed by Mohammad D. et al. (2019), that's a game-based population-based MH-OA. This OA was based on the old game (Dice game), and the searchers are a set of players. This OA was evaluated with twenty-three illustrious BTFs, and a real-life engineering challenge (PVD). The outcomes of the DGO were contrasted with other MH-OA (PSO, GA, ABC, CS, ALO, GOA, and EPO) [233]. AEFA was proposed by Anita, and Anupam Yadav (2019), that's physics-inspirited population-based MH-OA for global optimization. This OA was based on Coulomb's law of electrostatic force. Fifteen BTFs with IEEE CEC-2015 suite: unimodal (1–2), multimodal (3–5), hybrid (6–9), as well as composite (9–15) have been used to evaluate this OA. The findings of the AEFA algorithm were contrasted with other MH-OAs (MOA, PSO, GSA, ABC, and CCS) [37]. The HHO algorithm has been proposed by Ali Asghar Heidari et al. (2019), that's a nature-inspirited population-based MH-OA. This OA mimics the cooperative behaviour as well as the chasing style of Harris' hawks in nature (surprise pounce) [354]. Twenty-Nine BTFhave been used to evaluate this OA and real-world engineering challenges (Three-BTD, T/CSD design, PVD, WBD, MDCB, and REBD). This benchmark function is divided into three categories unimodal, multimodal, and composition. The findings of the HHO algorithm were contrasted with other MH-OAs (PSO, DE, TLBO, GWO, BA, BBO, FA, and FPA) [82]. SFO proposed by S. Shadravan et al. (2019) is a nature-inspirited population-based MH-OA for solving constrained engineering optimization challenges. This OA was encouraged by a group of hunting sailfish. Twenty-Four BTFs have been used to evaluate this OA, and five engineering optimization challenges (Circular antenna array design, 3-BTD, CBD, WBD, and I-beam design challenges). The findings of the SFO algorithm were contrasted with other MH-OA (SBO, GA, MBA, MFO, SOS, PSO, SBO, GWO, ALO, and WCA) [85]. BFS optimization_algorithm proposed by Zhuoran Zhang et al. (2019) is a population-based MH-OA or global optimization. The different behaviours of birds inspire this OA during the foraging process. The overall framework of BFS involves three steps (flying search, territorial, and cognitive behaviour). This OA was evaluated with thirteen classical and thirty modern CEC-2014 BTFs. The findings of the BFS algorithm were contrasted with other MH-OA (TLBO, SMO, GWO, MFO, CSA, SBO, and WOA) [234]. SOA has been proposed by Gaurav Dhiman and Vijay Kumar (2019), that's a bio-inspirited population-based MH-OA for solving computationally expensive problems. This OA is inspirited by the migration and attacking behaviours of a seagull in nature. Forty-Nine BTFs have been used to evaluate this OA, and 7 constrained real-life industrial applications (PVD, SRD, 25-BTD, T/CSD, optical buffer

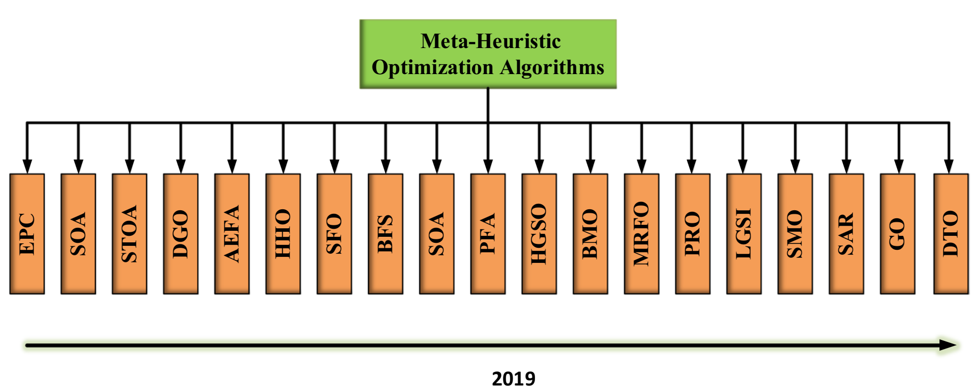


Fig. 15 MH-Optimization Algorithm (2019)

design, REBD, and WBD problem). The outcomes of the SOA algorithm were contrasted with other MH-OA (GWO, PSO, GA, DE, SCA, GSA, GWO, and MFO) [86]. PFA and multi-objective-PFA were proposed by Hamza Yapici and Nurettin Cetinkaya (2019), that's swarm-based MH-OA. PFA is inspirited by the collective moment of animal groups. Two operators were proposed according to the performance of the algorithms, like the mutation operator and binary version. Twenty-Seven BTFs have been used to evaluate this OA, and seventeen benchmark functions are unimodal and multimodal classical benchmarks (Chung Reynolds, Schwefel _2, Step_2, Sheke_l 5, Shekel_7, Rosenbrock, Schwefel_2.22, Sum Squares, Goldstein Price, Schwefel, Zakharov, Six-hump Camel, Trid_6, Griewank Branin RCOS, Hartman_3, and Ackley), other last ten benchmark functions are composite functions handled in CEC2017 and real-world optimization problem (PVD, WBD, T/CSD, CBD, and constraint processing method). The outcomes of the PFA were contrasted with other MH-OAs (PSO, SSO, GWO, and TSA) [87]. The HGSO algorithm proposed by Fatma A. Hashim et al. (2019) is a physics-based MH-OA. This OA is inspirited by the behaviour governed by Henry's law. This OA was evaluated with the CEC-17 test suite, forty-seven BTFs (Venter, Trecanni, Stenger, Schaffer_6, Scahffer_1, Sawtoothxy, Rotated Ellipse, Rump, Periodic, Matyas, Hartman, Egg Crate, ScCrossLegTable, Cross-in-Tray, Chichinadze, Camel-Three Hump, Bohachevsky_3, Bohachevsky_2, Bohachevsky_1, Bartels Conn, Ackley_2, Zakharov, Xin-She Yang_3, Ackley, Xin-She Yang_2, Schwefel_2.25, Rastrigin, Quartic, Mishra_11, Schwefel_2.23, Mishra_2, Schwefel_2.20, Mishra_1, Griewank, Exponential, Cigar, Brown, Alpine, Ackley, Sum Squares, Step_1, Schwefel_2.21, Schwefel_2.22, Powell Singular_1, Powell Singular_2, Powell Sum, Sphere, and Chung Reynolds), and three real-world optimization problem (SRD, T/CSD, and WBD). The findings of the MRFO were contrasted with other MH-OA (GSA, PSO, CS, WOA, GWO, EHO, and SA) [48].

The BMO was proposed by Mohd. Herwan Sulaiman et al. (2019) is a bio-inspirited population-based MH-OA for solving engineering optimization problems. BMO algorithm mimics the mating behaviour of barnacles in nature. This OA was evaluated by twenty-three mathematical test functions to verify the characteristics of BMO in finding the optimal solutions and was contrasted with many other MH-OAs (SSA, MFO, DA, ALO, GOA, SCA, and WOA along with GA and PSO) [235]. The MRFO was proposed by Weiguo Zhao et al. (2019), that's a population-based bio-inspirited MH-OA. This OA mimics the manta rays intelligent behaviours. This OA simulates three unique foraging approaches of manta rays, such as chain, cyclone, as well as somersault foraging. This OA was evaluated with thirty-one BTFs and eight engineering problems (PVD, SRD, MDCBD, Hydrostatic thrust bearing design, Belleville-SD, REBD, WBD, and T/CSD). The outcomes of the MRFO were contrasted with other MH-OAs (PSO, DE, CS, GA, ABC, and GSA) [236]. The PRO algorithm proposed by Seyyed Hamid Samareh Moosavi and Vahid Khatibi Bardsiri (2019) is a population-based MH-OA. PRO algorithm is inspirited by the efforts of the poor and the rich groups to achieve wealth and improve their economic situation. This OA was verified with thirty-three BTFs (Unimodal, multi-modal, fixed-dimension multimodal, and hybrid test functions), a software effort estimation problem, and engineering design problems (PVD, 3-BTD, CBD, and T/CSD). The findings of the PRO were contrasted with other MH-OA (PSO, SCA, SSA, MFO, ALO, WOA, DA, and ABC) [237]. The LGSI proposed by Prabhat R. Singh et al. (2019) is a population-based MH-OA. This OA is inspirited by the ludo game's regulations, which call for 2 or 4 players to update various swarm intelligent behaviours. This OA was evaluated with twenty-three CEC BTFs and seven engineering design challenges (SRD, PVD, SD, WBD, MDCBD, REBD, and 3-BTD). The outcomes of the LGSI algorithm were contrasted with other MH-OA (GOA, MFO, PSO, BBO, GWO, and SCA) [238]. SMO algorithm has been proposed by Saeed Balochian and Hossein Baloochian (2019), that's population-based MH-OA. This OA imitator the behaviour of people in society. This OA was evaluated with twenty-three BTFs and engineering design challenges (PVD, as well as CBD). The findings of the SMO algorithm were contrasted with other MH-OAs (PSO, WOA, GWO, GOA, ABC, HS, BBO, TLBO, BA, LCA, OIO, and SFS) [239]. SAR optimization_algorithm was proposed by Amir Shabani et al. (2019), that's a population-based MH-OA for solving single-objective continuous optimization challenges. This OA is inspirited by the explorations carried out by humans during search and rescue operations. This OA was verified with fifty-five renowned BTFs test suites (IEEE CEC 2015), and engineering challenges (I-Beam Design, CBD, and 25-BST). The result of the SAR algorithm was evaluated with other MH-OA (PSO, GA, DE, ABC, TLBO, and GWO) [240]. GO was proposed by Mohammad D. et al. (2019), that's population-based MH-OA. This OA is inspirited by all agents to update the population of the algorithm. This OA was evaluated with twenty-three renowned BTFs, and a PVD problem. The findings of the GO were contrasted with other MH-OAs (PSO, SHO, GWO, TLBO, GSA, GA, GOA, and EPO) [241]. The DTO was proposed by Mohammad D. et al. (2019), that's population-based MH-OA. This OA was encouraged by the donkey's behaviour. This OA was evaluated with twenty-three illustrious constraints BTS. The outcomes of the DTO were contrasted with other MH-OA

(PSO, GA, GSA, TLBO, GOA, GWO, WCA, and EPO) [242].

4.5.6 Part VI (2020)

Part VI of phase V consists of 39 MH-OA, as shown in Fig. 16. The PGO has been proposed by Ali Kaveh et al. (2020), that's physics-inspirited population-based MH-OA for solving constrained optimization challenges. This OA was based on the process of plasma generation. This OA was evaluated with thirteen renowned constraints, BTFs, as well as engineering challenges (120-bar dome truss, 10-bar planar truss, 25-BST, 272-bar transmission tower, 72-BST, and 582-bar tower truss). The findings of the PGO were contrasted with other MH-OAs (PSO, GA, ABC, DE, CSS, and HTS) [243]. The FOA, proposed by M. Dehghani (2020), that's a population-based MH-OA for solving power engineering optimization challenges. Physical processes or entities inspire this OA. Twenty-three BTFs have been used to evaluate this OA, and a power system application (placement of distributed generation). The findings of the FOA were contrasted with other MH-OAs (GA, GSA, PSO, TLBO, GWO, GOA, WOA, and EPO) [244]. MLO algorithm was proposed by M. Dehghani (2020), that's a population-based MH-OA for solving power engineering optimization challenges This OA is inspirited by the people moving forward and obediently obeying the leaders. This OA was evaluated with illustrious BTFs. The findings of the MLO were contrasted with other MH-OAs (GA, TLBO, PSO, EPO, GOA, GWO, SGO, and HOGO) [245]. The DPO algorithm was proposed by M. Dehghani et al. (2020), that's population-based MH-OA for global optimization. This OA mimics the process of treating patients by a physician. This OA was evaluated with twenty-three renowned BTFs. This OA was also evaluated with the energy commitment problem in a power system with twenty-six power plants and various energy sectors (transportation, residential, public, industrial, commercial, and agriculture sectors. The result of the DPO algorithm was evaluated with other MH-OAs (MPA, WOA, PSO, GA, GWO, GOA, TLBO, and GSA) [246]. PRO algorithm was proposed by Kahrizi M. R., and Kabudian S. J. (2020), that's population-based physics-inspirited MH-OA for Global Optimization. This OA is inspired by the projectile motion in physics and is governed by kinematics models. Thirty BTFs have been used to evaluate this OA with IEEE CEC 2017. The outcomes of the PRO were contrasted with the PSO and DE [46]. The DGCO was proposed by Mohamad M. et al. (2020), that's population-based MH-OA. This OA was stimulated by the swarms of individuals acting cooperatively to accomplish their collective goals. Twenty-three BTFs have been used to evaluate this OA: unimodal (1-7) and multimodal (8-23), and real-world constrained engineering challenges (SRD, himmel blau's nonlinear, T/CSD, PVD, and WBD). The findings of the DGCO were contrasted with other MH-OA (PSO, GA, DE, GWO, and WOA) [247]. RDA was proposed by Amir Mohammad Fathollahi-Fard et al. (2020), that's nature-inspirited population-based MH-OA. This OA mimicked the unusual mating behaviour of Scottish red deer in a breeding season. This OA was evaluated with twelve renowned BTFs (Penalized_1, Penalized_2, Ackley, Rastrigin, Greiwank, Quratic, Step, Rosenbrock, Sphere, Schwefel_1.2, Schwefel_2.21, and Schewfel_2.22), and engineering problems (Single-machine scheduling problem, TSP, Fixed-charge transportation, and VRP). The findings of the RDA were contrasted with other MH-OAs (GA, SA, PSO, ICA, ABC, and FA) [248]. AISA has been proposed by Esref Bogar and Selami Beyhan (2020), that's population-based MH-OA. This OA is inspired by the process of identity development/search of adolescents. This OA was evaluated with thirty-nine BTFs, IIR system identification, and inverse kinematics problem of seven degrees of freedom (7-DOF)

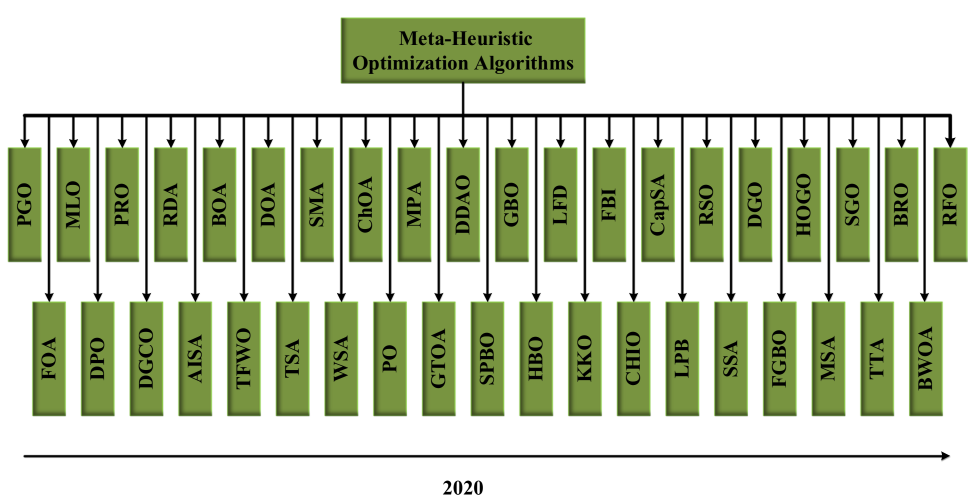


Fig. 16 MH-Optimization Algorithm 2020

robot manipulator consider as an engineering problem. The outcomes of the AISA algorithm were contrasted with other MH-OA (PSO, GWO, BA, GSA, MFO, ABC, SCA, SSA, TSA, and DE) [49]. BOA proposed by A. Kaveh et al. (2020), that's population-based MH-OA. This OA is inspirited by the billiards game. Twenty-Three BTFs have been used to evaluate this OA and engineering design problems (planar 200-bar truss structure, special 72-bar truss, cylindrical_PVD, T/CSD, WBD, CBD, and 120-bar dome-shaped truss structure). The findings of the BOA algorithm were contrasted with other MH-OA (PSO, GA, GSA, GOA, WSA, and FEP) [249]. The TFWO algorithm proposed by Mojtaba Ghasemi et al. (2020), that's population-based MH-OA. This OA was encouraged by the nature search phenomenon, i.e. whirlpools created in a turbulent flow of water. This OA was evaluated with real parameter benchmark function (Schwefel's_2.1, Shifted Rotated_Weierstrass, Shifted Rotated_Rastrigin's, Shifted Rastrigin's, Shifted Rotated_Ackley's with Global Optimum on Bounds, Shifted Rotated_Griewank's without Bounds, Shifted Rosenbrock's, Shifted Schwefel's_1.2 with Noise in Fitness, Shifted Rotated High Conditioned Elliptic, Shifted Sphere, Schwefel_1_2, Weierstras, Ackley, Penalized_1, Shifted Schwefel's_1.2, Griewank, Noncontinuous Rastrigin, Rastrigin, Rosenbrock, Schwefel's_2.6 with Global Optimum on Bounds, and Sphere), and real-world optimization problem (Economic load dispatch, and Reliability–Redundancy Allocation Optimization (RRAO) for the Overspeed protection system of a gas turbine). The findings of the BOA were contrasted with other MH_OAs (ABC, BBO, DE, and GWO) [250].

DOA has been proposed by Shafiq-ur-Rehman Massan et al. (2020), that's population-based MH-OA. This OA was encouraged by human nature as well as the social sciences in particular. This OA was verified with the wind turbine micrositing (WTM) problem. The findings of the DOA algorithm were contrasted with other MH-OA (GA, and DEA) [251]. The TuSA has been proposed by Satnam Kaur et al. (2020), a bio-inspirited based population-based MH paradigm for global optimization. TuSA is inspirited by Tunicates' swarm behaviour as well as jet propulsion during foraging and navigation [355]. Seventy-four BTFs have been used to evaluate this OA with CEC 2015 and CEC 2017 and were contrasted with many other MH-OAs PSO, GA, GSA, SCA, SHO, EPO, and GWO). TuSA is also executed with six constrained and one unconstrained engineering design problem [252]. Shimin Li et al. (2020) proposed SMA, that's population-based MH-OA. The oscillation mode of slime mould inspires this OA in nature [356]. Twenty-three BTFs have been used to evaluate this OA with CEC 2014, and engineering design problems (PVD, WBD, I-beam structure, and CBD). The results of the SMA were contrasted with other MH-OA (SSA, WOA, GWO, PSO, SCA, ALO, DA, GOA, and DE) [253]. The WSA proposed by A. Kaveh, and A. Dadras (2020) is a population-based nature-inspirited MH-OA. This OA was stimulated by the water strider bugs' life cycle. This OA simulated intelligent ripple communication, territorial behaviour, mating style, feeding mechanisms, and succession of water striders. Forty-Four BTFs have been used to evaluate this OA (shifted, unimodal, multimodal, composite, as well as biased), and solve engineering optimization problems (384-Bar double-layer barrel vault, 910-bar double-layer braced barrel vault, CBD, compound gear design, 3-BTD, and WBD). The findings of the WSA were contrasted with other MH-OA (PSO, MFO, ICA, GA, SCA, SSA, and CBO) [254]. The ChOA has been proposed by Khishe M. and Mosavi M.R. (2020), that is population-based MH-OA. ChOA is inspirited by the chimp's individual intelligence as well as sexual inspiration in cluster hunting. ChGO proposed several operators, such as diverse intelligence and sexual motivation operators. This OA was evaluated in three main stages; the first set of thirty mathematical BTFs, the second thirteen high-dimensional test problems, and the third ten real-world optimization problems, and were contrasted with many other optimization_algorithms (GA, GSA, PSO, BH, CS, and GWO) [255]. The PO was proposed by Qamar Askari et al. (2020) is a population-based socio-inspirited MH-OA. This OA mimicked the multi-phased process of politics. This OA was verified with fifty BTFs, and four engineering optimization problems (SRD, T/CSD, PVD, and WBD). The outcomes of the PO were contrasted with other MH-OA (HHO, BOA, PSO, DE, BBO, TLBO, GSA, CS, SCA, WOA, SLC, and GWO) [256]. The MPA was proposed by Afshin Faramarzi et al. (2020), that's a population-based nature-inspirited MH-OA. The Lévy as well as Brownian movements in sea predators inspire this OA. Twenty-nine BTFs have been used to evaluate this OA of CEC-BC-2017, three engineering challenges (WBD, PVD, and T/CSD), and two real-world engineering design challenges in the field of ventilation as well as building energy (Operating fan schedule for demand-controlled ventilation, and building energy performance). The outcomes of the MPA were contrasted with other MH-OA (GA, PSO, SSA, GSA, and CS) [257]. GTOA was proposed by Yiying Zhang and Zhigang Jin (2020), that's a population-based MH-OA for solving global optimization challenges. The group teaching mechanism inspirited the GTOA. Twenty-eight renowned unconstrained BTFs evaluated this OA and, solved four constrained engineering design optimization challenges, and contrasted with many other MH-OAs (SCA, PSO, WOA, GWO, CS, and DE). GTOA requires only 2 control parameters (Population size as well as the stopping criterion) [38]. The DDAO algorithm was proposed by Hazim Nasir Ghafil and Károly Jármai (2020), that's a population-based MH-OA for engineering applications. DDAO algorithm is inspirited by the dual-phase (DP) high-strength steel production process. This OA was evaluated by thirty

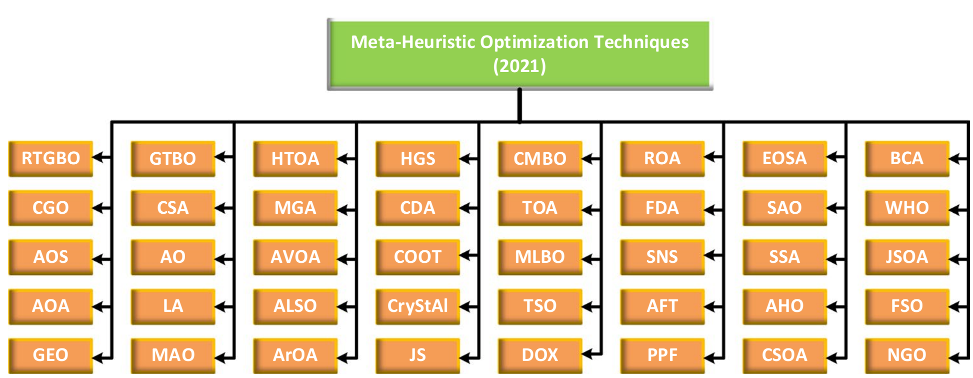
50-dimensional test functions and was contrasted with many other MH-OAs [258]. SPBO algorithm was proposed by Bikash Das (2020), that's population-based MH-OA. This OA was based on the psychology of learners who are putting in extra effort to raise their exam scores to the point where they can be considered the best learner in the class. The SPBO was evaluated by twenty-eight mathematical test functions and 15 CEC 2015 problems. The outcomes of the SPBO were contrasted with other MH-OA (PSO, TLBO, CSA, SOS, DE, GWO, and BOA) [259]. The GBO has been proposed by Iman A. et al. (2020), that's population-based MH-OA. This OA was stimulated by the gradient-based Newton's method. This OA utilizes 2 operators (gradient search rule as well as local escaping operator). The GBO was evaluated by twenty-eight mathematical test functions (unimodal, multimodal, hybrid, and composite) and six engineering challenges (SRD, 3-BTD, I-beam design, CBD, REBD, and T/CSD). The outcomes of the GBO were contrasted with other MH-OAs (GWO, CS, ABC, WOA, and ISA) [260]. The HBO was proposed by QamarAskari et al. (2020), that's population-based MH-OA. The corporate rank hierarchy for global optimization inspirited HBO. The HBO algorithm was evaluated with ninety-seven diverse functions, including twenty-nine CEC-BC-2017, and three constrained mechanical engineering challenges (REBD, MDCBD, and SRD). HBO's exploitative and explorative behaviour is evaluated using twenty-four unimodal as well as forty-four multimodal functions. The findings of the HBO were contrasted with other MH-OA (GA, PSO, SCA, MFO, MVO, and CS) [261]. Essam H.Houssei et al. (2020) proposed an algorithm called Lévy flight distribution (LFD), that's population-based MH-OA for solving engineering optimization challenges. Lévy_flight random walk inspirited this OA. The LFD algorithm was evaluated by the CEC-2017 test suite, three engineering optimization challenges (PVD, WBD, and T/CSD), and the deployment problem in WSNs (wireless sensor networks). The findings of the LFD were contrasted with other MH-OAs (PSO, GA, WOA, SA, MFO, GOA, EHO, HHO, and DE) [262]. The KKO algorithm proposed by Abhishek Srivastava and Dushmanta Kumar Das (2020) is a population-based MH-OA. KKO algorithm is inspirited by the game played in India known as kho kho game. In this game, two teams are playing, one is the running team, and another one is the chasing team. KKO simulates the planning used by the chasing team to touch the runner of the running team(global best solution) [263]. The FBI algorithm was proposed by Jui-Sheng Chou and Ngoc-Mai Nguyen (2020), a population-based MH-OA. FBI is inspirited by the police officers' method of tracking down suspects and investigating them. Four experiments evaluated the performance of this OA, firstly by using fifty renowned multidimensional benchmark problems, secondly to solve resource-constrained scheduling challenges associated with a highway construction project, thirdly to solve thirty benchmark functions by IEEE CEC 2017, and finally by increasing the number of dimensions of benchmark functions to 1000. The outcomes of FBI were contrasted with other MH-OAs (PSO, EFO, WCA, GA, TLBO, FA, WOA, SOS, ABC,and GSA) [264]. The CHIO algorithm was proposed by M. A. Al-Betar et al. (2020), that's population base MH-OA. The herd immunity concept as a way to deal with the COVID-19 pandemic inspirited this OA. This OA was verified with twenty-three BTFs as well as real-world engineering optimization challenges (Bifunctional catalyst blend optimal control problem, frequency-modulated sound waves, and transmission network expansion planning) extracted from IEEE CEC 2011. The outcomes of CHIO were contrasted with other MH-OAs (ABC, FPA, HHO, SCA, SSA, and Jaya) [149]. The RFO algorithm proposed by Dawid Połap and Marcin Woźniak (2020) is a population-based MH-OA. This OA is inspirited by the model of hunting and developing the population of a renowned animal (red fox). This OA was evaluated with twenty-two BTFs and seven real-life engineering problems (GTD, CBD, WBD, 3-BTD, CSD, PVD, and MDCBD). The outcomes of CHIO were contrasted with other MH-OAs (BA, GSA, FA, DA, WWO, FPA, MFO, and RFO) [88]. CapSA was proposed by Malik Braik et al. (2020), a population-based MH-OA used to solve various problems in science, finance, business, and engineering. The dynamic behaviour of capuchin monkeys stimulated this OA. This OA was evaluated with twenty-three BTFs as well as engineering challenges (PVD, SRD, WBD, and T/CSD). The outcomes of the CapSA were contrasted with other MH-OA (PSO, GA, HS, SCA, GSA, ACO, ABC, CS, MVO, and MFO) [265]. The LPB was proposed by Chnoor M. R. and T. A. Rashid (2020) is a population-based MH-OA. This OA was encouraged by the technique for enrolling high school graduates in various university departments. This OA was evaluated with nineteen illustrious BTFs and CEC C06-2019 test functions. The outcomes of LPB were contrasted with other MH-OAs (PSO, GA, and DA) [266].

The RSO algorithm was proposed by Gaurav Dhiman et al. (2020), that is bio-inspirited population-based MH-OA. This OA was stimulated by chasing as well as attacking the behaviours of rats in nature. This OA was evaluated with thirty-eight illustrious BTFs, CEC15 (CEC1-CEC15), and six real-life constrained engineering design challenges (REBD, 25-BTD, SRD, PVD, WBD, and T/CSD). The outcomes of the RSO algorithm have been contrasted with eight other MH-OAs (GA, GSA, SCA, MVO, MFO, PSO, GWO, and SHO) [39]. SSA was proposed by Mohammad D. et al. (2020), that's a physics-based population-based MH-OA to solve single-objective constrained optimization problems. Hooke's law inspirited this OA. This OA was evaluated with twenty-three renowned BTFs CEC 2015 (CEC1-CEC15), as well as engineering problems (WBD, SRD, PVD, T/CSD, and REBD). The outcomes of SSA were contrasted with other MH-OAs (GSA, GA, EPO, TLBO, GOA, GWO, SHO, and PSO) [267]. The DGO algorithm Mohammad D. et al. (2020) proposed is a game-based population-based MH-OA. The rules of the Darts game inspire this OA. Lack of control parameters and simplicity equations are the main features of this OA. This OA was evaluated with twenty-three renowned BTFs. The outcomes of DGO were contrasted with other MH-OA (GSA, GA, WOA, TLBO, PSO, GWO, GOA, and MPA) [268]. The FGBO was proposed by Mohammad D. et al. (2020), that's a population-based game-based MH-OA. The game of football inspires this OA. This OA had four steps (league holding, player transfer, practice, as well as promotion, and relegation). This OA was evaluated with twenty-three renowned BTFs, and energy commitment to solving the problem. The findings of the FGBO algorithm were contrasted with other MH-OAs (PSO, TLBO, GA, GWO, SGO, GOA, EPO, and HOGO) [269]. The HOGO algorithm proposed by Mohammad D. et al. (2020) is a game-based population-based MH-OA. This OA is inspirited by the classic game and the searcher agents that attempt to locate a thing concealed in a certain area. This OA was evaluated with twenty-three renowned BTFs. The findings of the HOGO were contrasted with other MH-OAs (PSO, GSA, TLBO, GWO, GOA, SHO, GA, and EPO) [270]. The MSA was proposed by Mohammad D., and Haidar Samet (2020), that's a population-based physics-based MH-OA. This OA is inspirited by Newton's laws: the law of conservation of momentum. This OA was evaluated with twenty-three illustrious BTFs. The outcomes of the MSA have been contrasted with other MH-OAs (PSO, GSA, GWO, TLBO, GOA, GA, SHO, and EPO) [271]. The SGO algorithm was proposed by Mohammad D. et al. (2020), that's population-based game-based MH-OA. This OA is inspirited by the rules of a game known as a shell game to design. This OA was evaluated with twenty-three renowned BTFs, and real-life engineering challenges (PVD). The findings of the SGO were contrasted with other MH-OAs (PSO, GSA, TLBO, GWO, GOA, GA, SHO, and EPO) [272]. Mohd Fadzil Faisae Ab proposed TTA (2020), that's a population-based game-based MH-OA. This OA is inspirited by the football playing style (tiki-taka). This OA was evaluated with nineteen renowned BTFs, and five engineering challenges (WBD, T/CSD, PVD, 3-BTD, and CBD). The outcomes of the TTA were contrasted with other MH-OAs (SLO, LCA, GB, PSO, ASO, MFO, BOA, HHO, and PFA) [40]. Taymaz R. (2020) proposed the BRO algorithm as a game-inspirited population-based MH-OA. A type of digital games knowns as ''battle royale' inspirited this OA. This OA was evaluated with thirteen illustrious BTFs (Quartic, Step, Rosenbrock, Schwefel_2.21, Rotated hyper-ellipsoids, Schwefel_2.20, Sphere, Levi, Penalized, Griewank, Ackley, Rstrigin, and Schwefel), and engineering problem (Inverse kinematics of robot arms). The outcomes of the BRO algorithm were contrasted with other MH-OA (PSO, SCA, GOA, MVO, MFO, DA, and ALO) [273].

4.5.7 Part VII (2021)

Part VII of phase V consists of 41 MH-OAs, as shown in Fig. 17. The RTGBO algorithm proposed by M. Dehghani et al. (2021) is population-based, game-based MH-OA. This OA is inspirited by players' behaviour and the ring toss game rules. This OA was evaluated with twenty-three renowned BTFs. The outcomes of the RTGBO were contrasted with other MH-OA (PSO, GA, GSA, TLBO, GWO, HOGO, SGO, and EPO) [275]. The CGO algorithm proposed by Siamak T. and Mahdi A. (2021) is an MH-OA. The principle of the chaos game concept inspires the CGO. This OA was evaluated with two hundred thirty-nine test functions divided into four groups, and the outcomes of the CGO were contrasted with some other MH-OAs (FA, TLBO, ICA, ICA, and GWO) [150]. AOS algorithm was proposed by Mahdi A. (2021), that's population-based MH-OA. This OA has been stimulated by Some quantum mechanics concepts as well as the quantum-based atomic model. This OA was evaluated with twenty unconstrained mathematical test functions and five constrained engineering design problems (MDCB, TCSD, WBD, PVD, and SRD) considered alongside two of the most important CEC as CEC 2017 and CEC

Fig. 17 MH- Optimization Algorithm 2021



2020. The outcomes of the AOS were contrasted with other MH-OA (GA, SCA, CSA, ASO, CSS, and BIA) [276]. AOA proposed by Fatma A. Hashim et al. (2021) is a population-based MH-OA. This OA has been stimulated by the law of physics Archimedes' Principle. This OA was evaluated by the CEC 17 test suite as well as four engineering design challenges, contrasted with many other MH-OAs (GA, PSO, SCA, HHO, and EO) [277]. The GEO was proposed by Abdolkarim M. et al. (2021), that's nature-inspired population-based swarm-based MH-OA for solving global optimization challenges. The scientific name of the golden eagle is Aquila chrysaetos, and it belongs to the Accipitridae family. GEO is inspirited by the intelligence of golden eagles in tuning speed at different phases of their spiral trajectory for hunting. Thirty-three mathematical BTFs have been used to evaluate this OA with CEC 2017, and were contrasted with many other MH-OAs (GA, PSO, HS, DA, GWO, and CSA). The multi-objective-GEO algorithm is also proposed to solve multi-objective challenges. The MOGEO algorithm was evaluated with CEC 2009 and DTLZ test suite, and the outcomes of MOGEO were contrasted with other multi-objective algorithms (MOGEO, MOPSO, NSGA-II, and MOSSA) [89]. GTBO algorithm was proposed by Omid Tarkhaneh et al. (2021), that's population-based MH-OA. GTBO is inspirited by the golden tortoise beetle's behaviour, which involves changing colours to attract partners of the opposite sex, as well as its defense mechanism, which employs a type of anal fork to fend off predators. Golden tortoise beetle can be found in Florida, and eastern North America. GTBO is also an evolutionary algorithm. Twenty-four BTFs have been used to evaluate this OA and were contrasted with many other MH-OAs (GA, ALO, PSO, ABC, and BWO) [41]. The ChSA proposed by Malik Shehadeh Braik (2021) is a population-based bio-inspirited MH-OA solving engineering design problems. This OA has been mimicking the chameleons' dynamic foraging and navigation behaviour in deserts, swamps, and trees. This OA was verified by sixty-seven BTFs with CEC 2015 and CEC 2017, and was contrasted with many other MH-OAs (CSA, SSA, PSO, GA, HS, GWO, and EO). Twenty-three BTFs have been used to evaluate this OA, a CEC-2015 test suite with fifteen test functions and a CEC-2017 test suite with twenty-nine functions. In addition, this OA has also been evaluated with five real-world classical engineering design challenges (WBD, PVD, T/CSD, SRD, and REBD) [90]. The AO algorithm proposed by Laith A. et al. (2021) is a population-based MH-OA. This OA has been motivated by the actions taken by Aquila in nature when hunting its prey. This OA was evaluated by the CEC 2017 test suite with thirty test functions and the CEC 2019 test suite with ten test functions, contrasted with many others (PSO, GOA, TLBO, ALO, SSA WOA, and SCA). In addition, this OA was also evaluated with seven real-world classical engineering design problems (PVD, WBD, 3-BTD, SRD, CBD, MDCBD, and T/CSD) [278]. The LA has been proposed by João Luiz JunhoPereira et al. (2021), that's a hybrid physics-based MH-OA. The Lichtenberg figures patterns encouraged this OA. This OA was evaluated by ten non-linear as well as unconstrained functions as well as real-world engineering challenges (WBD). The outcomes of the LA were contrasted with other MH-OAs (ACO, SFC, and GA) [279]. The MAO algorithm proposed by Yenny Villuendas-Rey et al. (2021) is a bio-inspirited population-based MH-OA. This OA is inspirited by nature because plants and animals tend to optimize many of their life processes. This OA was evaluated using four BTFs: unimodal, multimodal, composite, and competition. The MAO outcomes were contrasted with other MH-OAs (CS, DE, WOA, ABC, FA, MBO, SMA, and FDO) [280]. The HTOA proposed by Foad Asef et al. (2021) is a population-based MH-OA. The challenging objective was to find a better solution in a shorter computation time. This OA was encouraged by the heat transfer relationships based on the thermodynamics second law. This OA was evaluated with twenty-six BTFs such as, first twenty functions were classical test functions (Drop Wave, Goldstein Price, six-hump camel, Ackley N._2, Salomon, Ackley, Schwefel, Alpine, Schwefel_2.21, Sphere, Brown, Quartic, Rastrigin, Griewank, Xin-She Yang, Kowalik, Schwefel _1.2, Branin's RCOS No.01, Schwefel_2.22, and Hartman_3), six composite benchmark functions CEC 2005, and solve the real-world problem (PID controller and regression). The findings of the HTOA were contrasted with other MH-OAs (PSO, GWO, WOA, BBO, CA, GA, DE, HOA, and BOA) [281]. MGA has been proposed by Siamak T. et al. (2021), that's population-based MH-OA for the optimization of engineering Problems. The material inspirited this OA. Material is a mixture of multiple substances comprised of the stuff of the universe with volume and mass. This OA considers three main concepts of material chemistry: compounds, reactions, and stability to formulate an MH-OA. This OA was evaluated with ten constraint BTFs with CEC 2017 suites, and fifteen engineering problems (CBD, steel I-Shaped beam, rolling-element bearing, hydrostatic thrust bearing, planetary-GTD, 3-BTD, PVD, SRD, T/CSD, WBD, MDCB, SCPD, 10-BTD, GTD, and piston lever). The outcomes of the MGA were contrasted with other MH-OAs (PSO, ABC, TLBO, WCA, MBA, WOA, and CSA) [282]. AVOA was proposed by Benyamin A. et al. (2021), that's a population-based nature-inspirited MH-OA for global optimization problems. African vultures' lifestyles inspirited this OA [357]. This OA has copied the behaviour of African vultures' foraging and navigation behaviours. This OA was evaluated with thirty-six mathematical illustrious BTFs; unimodal (1–7), multi-modal (8–13), multi-modal fixed-dimension (14–23), and hybrid composition (24–36), and eleven engineering design problems (T/CSD, Lennard–Jones potential problem, WBD, PVD, 3-BTD, Static economic load dispatch problem, Cassini 2: Spacecraft trajectory optimization problem, MPDCB, IIR digital filtering systems modelling problem, REBD, and Messenger: Spacecraft trajectory). The findings of the AVOA were contrasted with other MH-OAs (TLBO, DE, GWO, BBO, PSO, GSA, SSA, WOA, MFO, FFA, DE, and IPO) [91]. The ALSO was proposed by Neetesh Kumar et al. (2021), that's population-based nature-inspired MH-OA. This OA mimics the manner in which red-headed Agama lizards catch their prey. This OA was evaluated with twenty-five renowned BTF (Ackley, Griewankt, Rosenbrock, Shubert, Boachevsky_3, Boachevsky_2, Six Hump Camel Back, Schaffer, Michalewicz_10, Michalewicz_5, Michalewicz_2, Booth1, Bohachevsky_1, Dixon-Price, Schwefel_1.2, Schwefel_2.22, Zakharov, Colville, Matyas, Easom, Beale, Quartic, Sum Squares Sphere, and Step), and seven CEC 2014 benchmark functions. The outcomes of the ALSO were contrasted with other MH-OAs (PSO, GWO, MVMO, SSA, and GA) [92]. The ArOA was proposed by Laith Abualigah et al. (2021), that's a population-based nature-inspirited MH-OA. This OA is inspirited by the behaviour of the mathematics basics arithmetic operators (Addition, Division, Subtraction, and Multiplication). The performance of this OA was evaluated with twenty-three illustrious BTFs, and five real-world engineering design problem (T/CSD, 3-BTD, WBD, PVD, and SRD). The findings of the AOA were contrasted with 11 MH-OAs (PSO, GA, BBO, BA, FA, FPA, CS, MFO, GWO, GSA, and DE) [42]. The HGS algorithm was proposed by Yutao Yang et al. (2021), a population-based MH-OA. This OA is inspirited by Social animals' cooperative behaviour, where search activity is proportional to their hunger level. The performance of this OA was evaluated with twenty-three illustrious BTF, IEEE CEC 2014, and engineering design challenges (I-beam design, MDCBD, and WBD). The outcomes of the HGS algorithm were contrasted with other MH-OA (PSO, GSA, GA, BBO, DE, FA, BA, SSA, SCA, GWO, WOA, MVO, ALO, DA, GOA, and MFO) [283]. The CPA proposed by Jiaze Tu et al. (2021) is a population-based MH-OA. This OA was evaluated with fifty-three test functions, among which twenty-three mathematical BTFs, thirty CEC 2014 functions, as well as five engineering design challenges (PVD, T/CSD, I-beam design, WBD, and MDCBD). The CPA outcomes were contrasted with other MH-OAs (PSO, SCA, SSA, WOA, GWO, MFO, ABC, GSA, BA, FA, and DE) [284]. The COOT algorithm proposed by Iraj Naruei and Farshid Keynia (2021) is a population-based MH-OA. This OA was evaluated with thirteen renowned BTFs consisting of seven-unimodal as well as five-multimodal, and CEC 2017 consists of three-unimodal, seven-multimodal, ten-hybrid test functions, and ten-composite test functions. The COOT algorithm was evaluated with an eight-engineering design challenge (REBD, SRD, SCPD, CBD, MDCBD, WBD, PVD, and T/CSD). The outcomes of the COOT were contrasted with other MH-OAs (PSO, MVO, GA, SSA, GSA, and FDO) [93].

The CryStAl was proposed by Siamak T. et al. (2021), that's population-based MH-OA. This OA was stimulated by the main ideas that lead to the formation of crystal structures, namely the inclusion of the basis to the lattice points. This OA was evaluated with two-hundred-thirty-nine illustrious BTFs with four different groups: first group one hundrend sevetten functions with 2–10 dimensions from 1 to 117 test functions (Ackley_2, Ackley_3, Adjiman, Quardratic, Price_1, Price_2, Price_3, Price_4, Periodic, Pen Holder, Parsopoulos, Mishra_3, Mishra_4, Mishra_5, Mishra_6, Mishra_8, Mishra_10, Michaelewicz, Mexican hat, McCormick, Matyas, Levy_5, Levy_3, Leon, Keane, Jennrich-Sampson, Hosaki, Himmelblan, Hansen, Goldstein Price, Giunta, Freudenstein Roth, Exp 2, Egg Crate, El-Attar-Vidyasagar-Dutta, Easom, Deckker-Aarts, Damavandi, Cube, Cross-in-Tray, Chichinadze, Chen V, Chen Bird, Carrom table, Camel_3 Hump, Camel_6 Hump, Bukin_4, Bukin_6, Brent, Branin RCOS, Branin RCOS_2, Booth, Bohachevsky_1, Bohachevsky_2, Bohachevsky_3, Bird, Biggs EXP_2, Becker-Lago, Beale, Bartels Conn, Trid_10, Paviani, Ann-XOR, Trid_6, Hartman_6, Biggs EXP_6, Langerman_5, Dolan, DeVillers Glasser_2, Biggs EXP_5, Shekel_5, Shekel_7, Shekel_10, Miele Cantrell, Kowalik, Gear, DeVilliers Glasser_1, Corana, Colville, Biggs EXP_4, Wolfe, Mishra_9, Meyer-Roth, Helical Valley, Hartman_3, Gulf Research Problem, Biggs EXP_3, Zirilli 2, Zirilli or Aluffi-Pentini, Zettl, Wayburn Seader_1, Wayburn Seader_2, Wayburn Seader_3, Sobieski, Venter Sobiezcczanski-Sobieski, Ursem Waves, Ursem_1, Ursem_3, Ursem_4, Tripod, Trefethen, Trecanni, Test Tube Holder, Holder Table_1, Holder Table_2, Carrom table, Schwefel_2.6, Schwefel_2.36, Scahffer_1, Scahffer_2, Scahffer_3, Scahffer_4, Rump, Rotated Ellipse, Rotated Ellipse_2, Rosenbrock Modified, Ripple_1 and Ripple_25), the second group fifty-eight functions with 50 dimensions from 118 to 175 (Zakharov, Xin-She Yang_1, Schwefel_1.2, Xin-She Yang_2, Schwefel_2.23, Xin-She Yang_3, Xin-She Yang_4, Xin-She Yang_5, Xin-She Yang_6 W/Wavy, Trigonometric_1, Schwefel_2.26, Trigonometric_2, Schwefel_2.4, Trid, Styblinski-Tang, Sum Squares, Stretched V Sine Waves, Stepint, Step, Step_2, Step_3, Sphere, Schwefel, Schwefel_2.21, Schumer Steiglitz, Salomon, Rosenbrock Quintic, Qing, Rastrigin, Powell Sum, Powell Singular, Powell Singular_2, Pint'er, Pathological, Mishra_11, Schwefel_2.22, Mishra_2, Schwefel_2.20, Mishra_7, Mishra_1, Levy_8, Inverted Cosine Wave, Schwefel_2.25, Hyper-ellipsoid, Holzman_2, Griewank, Exponential, Extended Easom, Dixon & Price, Deb_1, Deb_3, Csendes, Chung Reynolds, Brown, Alpine_1, and Ackley_1), the third group considered the second group with the 100 maximum dimensions (176–232), and fourth group three composite and three hybrid mathematical functions (233–239). The findings of the CryStAl were contrasted with the other MH-OAs (PSO, ABC, HS, FA, ACO, BA, GA, MVO, MFO, SA, SSA, and SCA) [43]. JS optimizer algorithm was proposed by Jui-Sheng Chou, and Dinh-Nhat Truong (2021), that's population-based MH-OA. The behaviour of jellyfish in the ocean inspires this OA. This OA was verified with fifty renowned BTFs (Stepint, FletcherPowell_10, Fletcher Powel_l5, Fletcher Powel_l2, Shekel_5, Langermann_10, Langermann_5, Langermann_2, Penalized, Penalized_2, Ackley, Griewank, Hartman_6, Shekel_7, Powersum, Perm, Shekel_10, Kowalik, GoldStein-Price, Shubert, Bohachevsky_2, Hartman_3, Bohachevsky_3, Six Hump Camel Back, Schaffer, Michalewicz_2, Michalewicz_5, Michalewicz_10, Schwefel, Rastrigin Booth, Bohachevsky_1, Branin, Foxholes, Dixon-Price, Rosenbrock, Schwefel_1.2, Schwefel_2.22, Powell, Zakharov, Trid_6, Trid_10, Colville, Matyas, Easom, Beale, Quartic, SumSquares, Sphere, and Step), twenty-five test functions CEC-2015: unimodal CF1-CF5, expanded test functions CF13-CF14, and hybrid composite CF15-CF25 This OA was also evaluated with three engineering challenges (25-Bar tower, 52-Bar tower, and 582-Bar tower design challenges). The JS algorithm's findings were contrasted with the other MH-OAs (TLBO, GA, SAS, FA, GSA, DE, WOA, PSO, ABC, and TSA) [285]. The CMBO was proposed by Mohammad D. et al. (2021), that's population-based MH-OA. This OA mimicked the natural behaviour between cats and mice. This OA was evaluated with twenty-three illustrious BTFs. The findings of the CMBO were contrasted with the other MH-OA (WOA, GSA, GA, PSO, TLBO, TSA, MPA, and TOA) [286]. TOA was proposed by Mohammad D. and Pavel Trojovský (2021), that's population-based MH-OA for function minimization/maximization. This OA is inspirited by the teamwork behaviours of the members of a team in order to achieve their desired goal. This OA was evaluated with twenty-three renowned BTFs. The outcomes of the TOA have been contrasted with the other MH-OA (WOA, TLBO, GSA, MPA, TSA, GWO, GA, and PSO) [287]. MLBO was proposed by M. Dehghani1et al. (2021), that's population-based MH-OA. This OA is inspirited by the process of advancing members of the population and following the leaders. This OA was evaluated with twenty-three renowned BTFs: unimodal (1–7), multimodal (8–13), as well as multimodal fixed-dimension (14–23). The findings of the MLBO were contrasted with the other MH-OAs (HOGO, SGO, EPO, GOA, GWO, TLBO, PSO, and GA) [288]. The TSO was proposed by Sajjad Amiri Doumari et al. (2020), that's population-based MH-OA. This OA is inspirited by employing a selected group of good members of the population. This OA was evaluated with twenty-three illustrious BTFs. The findings of the TSO were contrasted with the other MH-OAs (TLBO, GS, GWO, PSO, GSA, and MPA) [289].

The DOX was proposed by Amit Kumar Bairwa et al. (2021), that's a population-based MH-OA for engineering Problems. The behaviour of the dingo inspirited this OA. This OA was evaluated with twenty-three illustrious BTFs, in addition to this OA also evaluated with engineering design challenges (PVD). The findings of the DOX were contrasted with GWO and PSO [94]. ROA was proposed by Heming Jia et al. (2021), that's a population-based, new bionics-based MH-OA. The parasitic behaviour of remora inspires this OA. This OA was evaluated with twenty-nine illustrious BTFs and five real-world engineering design challenges (I-beam, REBD, 3-BTD, PVD, and WBD). The ROA outcomes were contrasted with the other MH-OA (SHO, GWO, MVO, MFO, WOA, SSA, SOA, SFO, and EPO) [290]. The FDA was proposed by Hojat Karami et al. (2021), a population-based physics-inspirited MH-OA. This OA was encouraged by the direction of flow to the drainage basin's outlet point with the lowest height. This OA was evaluated with thirteen renowned classical BTFs: unimodal (1–7) and multimodal (8–13), and ten modern benchmarks (Ackley, Happy Cat, Expanded Schaffer's_F6, Modified_Schwefel's, Weierstrass, Griewangk's, Rastrigin's, Lennard–Jones Minimum Energy Cluster, Inverse Hilbert Matrix Problem, as well as Storn's Chebyshev Polynomial Fitting). It also evaluated five real-world engineering design challenges (CBD, WBD, T/CSD, 3-BTD, and SRD). The FDA findings were contrasted with the other MH-OA (PSO, ABC, WOA, GA, and GWO) [291]. SNS has been proposed by Siamak T. et al. (2021), that's population-based MH-OA for global optimization. This OA was encouraged by the social network users' attempts to increase their popularity by simulating their users' emotions when expressing their ideas. This OA was evaluated with two-hundred-ten illustrious BTFs, including one hundred twenty fixed dimensions, sixty-N dimensions, and thirty CEC 2014 test functions. The findings of the SNS algorithm were contrasted with the other MH-OA (TLBO, CS, GWO, SOS, CSA, WOA, and CGO) [292]. The AFT was proposed by Malik Braik et al. (2021), that's population-based MH-OA. This OA is inspirited by the famous story of Ali Baba and the forty thieves. This OA was evaluated with twenty-three renowned BTFs, IEEE CEC 2017, IEEE CEC-C06-2019, and real-world engineering challenges (WBD, REBD, SRD, T/CSDP, and PVD). The findings of the AFT algorithm were contrasted with the other MH-OA (ACO, WOA, DA, SSA, GSA, SCA, MVO, GWO, SHO, CSA, PSO, DE, GA, SOA, and MFO) [293]. PPF optimization_ algorithm was proposed by Anima Naik and Suresh Chandra Satapathy (2021), that's population-based MH-OA. This OA was stimulated by the technique by which a person can learn from a successful member of society. This OA was evaluated with twenty-three renowned BTFs and also evaluated with five engineering problems (CBD, WBD, T/CSDP, 3-BTD, and SD). The findings of the PPF have been contrasted with the other MH-OA (PSO, GA, ABC, DE, BBO, BA, HS, CS, FPA, TLBO, GWO, WOA, BOA, GOA, SGO, SSA, CSA, LAPO, TSA, JS, MPA, AOA, SMA, HBO, GTA, FBI, ChOA, STOA, SOA, PPA, HHO, SCA, and MVO) [294]. EOSA was proposed by Olaide N. Oyelade and Absalom E. Ezugwu (2021), that's a population-based bio-inspirited MH-OA. The propagation model of the Ebola virus disease inspires this OA. This OA was evaluated with forty-seven renowned BTFs (Weierstrass, Salomon, Zakharov, Wavy_1, Shifted And Rotated_Rastrigin's, Shifted And Rotated_ Rosenbrock's, Shifted And Rotated_Zakharov, Shifted And Rotated_Sum Of Different Power, Sum Of Different Power, Sum-Power, Sum/Sumsquares, Step, Sphere, Schwefel_2.21, Rosenbrock, Rotated Hyperellipsoid, Rastrigin, Quartic, Powel, Schwefel_2.22, Schwefel_1.2, Perm, Pathological, Noise, Levy And Montalo, Levy, Lévy_3, Shifted And Rotated_Bent Cigar Schwefel_2.26, Inverted Cosine Mixture, Hybrid_2, Hybrid_1, High Conditioned_Elliptic, Hgbat, Holzman_2, Generalized Penalized_2, Generalized Penalized_1, Griewank, Fletcher–Powel, Discus, Dixon And Price, Ackley, Bent Cigar, Brown, Alpine, Composition_1, and Composition_2), and thirty constrained IEEE CEC 2017. The outcomes of the EOSA have been contrasted with the other MH-OAs (BOA, ABC, WOA, PSO, DE, GA, and HGSO) [295]. The SAO algorithm was proposed by Ahmed T. Salawudeen et al. (2021), that's population-based MH-OA. This OA is inspirited by the interaction between a biological being that has the ability to smell, leading to the evaporation of a small molecule. This OA was evaluated with thirty-seven illustrious BTFs (Styblinski–Tang, Schaffer, Quadratic, Michalewicz_2, McComick, Matyas, Easom, Deckkers–Aarts, Chichinadze, Camel—Six Hump, Bukin_ F6, Brent, Branin RCOS_1, Branin RCOS_2 Booth, Bohachevsky_1, Bird, Beale, Adjiman, Shubert, Michalewicz, Step, Miele Cantrell, Csendes, Colville, Box-Betts, Sphere, Salomon, Rosenbrock, Rastrigin, Quartic, Mishra, Griewank, Ellipsoid, Brown, and Ackley), and sizing of the hybrid renewable energy engineering challenges. The findings of the SAO were contrasted with other MH_OA (PSO, OFA, GA, CSA, and ABC) [296]. SSA was proposed by Farouq Zitouni et al. (2021), that's population-based MH-OA. This OA is inspirited by the orbiting behaviour of some objects found in the solar system. This OA was evaluated with thirty renowned BTFs and also evaluated with engineering problems (3-BTD, PVD, WBD, T/CSD, and CBD). The findings of the SSA were contrasted with other MH-OAs (SC, MBA, ABC, PSO, CSA, and GA) [297]. The AHO was proposed by Farouq Zitouni et al. (2021), that's population-based MH-OA. This OA mimics the archerfish's jumping as well as shooting techniques for catching flying insects. This OA was evaluated with ten renowned BTFs as well as also evaluated with engineering challenges (SRD, 3-TBD, PVD, WBD, T/CSD, and MDCBD) [95]. The CSOA was proposed by Heng Wen et al. (2021), a population-based bio-inspirited MH-OA. This OA is inspirited by the process by which early people sought out habitable areas. This OA was evaluated with twenty-six renowned BTF(Rosenbrock, Quadric, Michalewicz, Matyas, Kowalik, Griewank, GoldsteinPrice, DixonPrice, Branin, Beale, Ackley, Weierstrass, Rastrigin, Zacharov, YaoLiu04, Trid, ThreeHumpCamel, SumSquares, Sphere, Sphere, 1 Composition_1 (CF1), Composition _2 (CF2), Composition _3 (CF23, Composition_4 (CF4), Composition_5 (CF5), and Composition_6 (CF6)), and classical engineering problems (T/CSD, PVD, WBD, and SRD). The findings of the CSOA were contrasted with other MH-OAs (PSO, CSA, WOA, and GWO) [298]. BCA was proposed by Drishti Yadav (2021), that's population-based bio-inspirited MH-OA. The process of blood coagulation in the human body inspires this OA. This OA was evaluated with twenty-three renowned illustrious BTFs and real-life engineering challenges (PVD, CBD, T/CSD, WBD, 3-BTD, and SRD). The findings of the BCA has been were contrasted with other MH-OAs (PSO, DE, GA, GWO, CS, FPA, MFO, BAT, FA, AOA, GSA, and BBO) [299]. WHO algorithm was proposed by Iraj Naruei and Farshid Keynia (2021) that's bio-inspirited population-based MH-OA. This OA is inspirited by the arachnida salticidade. This OA was evaluated with CEC201, CEC2019, and real-world applications (Two-reactor, Process synthesis and design, Heat exchanger network, T/CSD, 3-BTD, REBD, Process Synthesis, SCPD, Gas transmission compressor, and Himmelblau's function). The outcomes of the WHO algorithm were contrasted with other MH-OA (PSO, GA, FA, GSA, HHO, MVO, WOA, SSA, GWO, and PRO) [300]. JSOA was proposed by Hernán Peraza-Vázquez et al. (2021), that's a population-based bio-inspirited MH-OA. This OA is inspirited by the Arachnida Salticidade. This OA was evaluated with twenty illustrious BTF(Xin-She Yang N. 4, Schwefel_2.20, Xin-She Yang N. 2, Salomon, Rosenbrock, Rastrigin, Quartic, Xin-She Yang, Quartic, Ackley N. 4, Ackley, Schwefel_2.21, Zakharov, Xin-She Yang N. 3, Sum Squares, Sphere,, Griewank, Schwefel_2.22, Schwefel_2.23, and Brown) and real world applications (Process Flow Sheeting, Process Synthesis, WBD, Optimal Design of an Industrial Refrigeration System, and optimal tuning parameters of a Proportional-Integral-Derivative (PID) controller). The findings of the JSOA were contrasted with other MH-OAs (AOA, MAO, GBO, GEO, COOT, CGO, HGS, and HHO) [96]. The FSO algorithm proposed by Mathew Mithra Noel et al. (2021) that's population-based bio-inspirited MH-OA. This OA is inspirited by the reproductive swarming behaviour of Firebugs. This OA was evaluated with CEC 2013 test functions. The outcomes of the FSO algorithm were contrasted with other MH-OA (ABC, GSO, PSO, DE, and

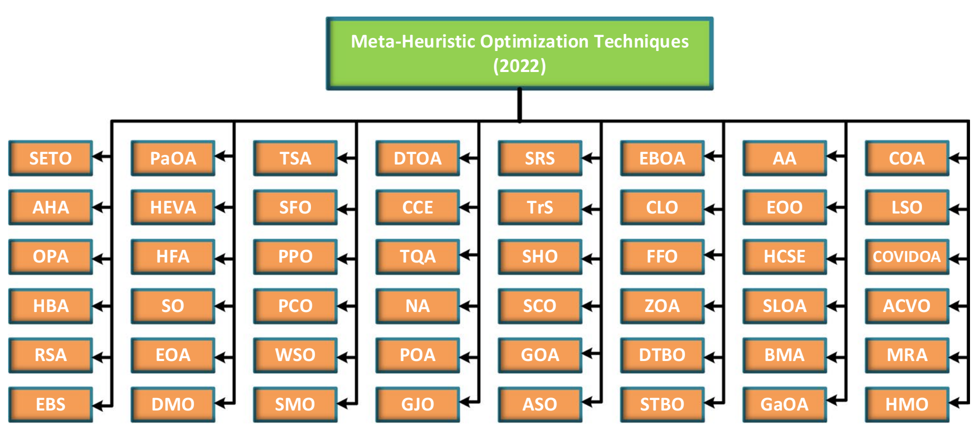
AAA) [301]. NGO algorithm was proposed by Mohammad D. et al. (2021), that's population-based MH-OA. The behaviour of northern goshawk during prey hunting inspirited this OA. This OA was evaluated with sixty-eight renowned test functions and engineering design challenges (WBD, PVD, SRD, and T/CSD). The findings of the NGO algorithm were contrasted with other MH-OAs (MPA, GSA, GA, TLBO, GA, GWO, TSA, and WOA) [97]. The AGTO algorithm was proposed by B Abdollahzadeh et al. (2021), that's population-based MH-OA. The collective intelligence of natural organisms in nature inspirited this OA [358]. This OA was evaluated with fifty-two renowned test functions and seven engineering design challenges [302].

4.5.8 Part VIII (2022)

Part VIII of phase V consists of 49 MH-OA, as shown in Fig. 18. SETO algorithm has been proposed by Hojjat Emami (2022), that's population-based MH-OA. The behaviour of traders as well as stock price changes in the stock market inspire this OA. This OA was evaluated with forty BTFs: fixed dimension (Adjiman, Zettle, Three-Hump Camel, Schafer N. 4, Matyas, Egg Crate, Easom, Bukin_6, Brent, and Bartels Conn), single-objective unimodal functions (Schwefel's_2.22, Xin-She Yang_1, Sum Squares, Sphere, Schwefel's_2.21, Powell Sum, Schwefel's_2.20, Powell Singular, Dixon Rosenbrock, and Price, Schwefel's_2.23, and Brown), multimodal functions (Xin-She Yang N. 4, Trignometric_2, Salomon, Rastrigin, Periodic, Xin-She Yang_2, Griewank, Alpine N. 1, Xin-She Yang N. 2and Ackley), and shifted, rotated, hybrid and composite functions (F33-F40). This OA was also evaluated with engineering challenges (3-BTD, REBD, SRD, and PVD). The findings of the SETO were contrasted with other MH_OAs (PSO, GA, GSA, SCA, and HBO) [303]. AHA proposed by Weiguo Zhao et al. (2022) is a population-based bio-inspired MH-OA. The foraging and flights of hummingbirds inspirited this OA. This OA was evaluated with 3 set experiments: experiment 1st was evaluated with fifty renowned BTFs (Bohachevsky_1, Branin, Foxholes, Dixon–Price, Rosenbrock, Schwefel_1.2, Schwefel_2.22, Powell, Zakharov, Trid_10, Trid_6, Colville, Matyas, Easom, Beale, Quartic, SumSquares, Sphere, Step, Stepint, Bohachevsky_2, Bohachevsky, 3 Six Hump Camel Back, Schaffer, Michalewicz_2, Michalewicz_5, Michalewicz_10, Schwefel, Rastrigin, Booth, Hartman_6, Hartman_3, PowerSum, Perm, Shekel_10, Shekel_5, Shekel_7, Kowalik, GoldStein–Price, Shubert, Griewank, Ackley, Penalized, Penalized_2, Langerman_2, Langerman_5, Langerman_10, FletcherPowell_2, FletcherPowell_5, and FletcherPowell), experiment 2nd CEC 2014 was used to evaluate the performance of this OA and the 3rd experiment consist of ten engineering design problems (CBD, 3-BTD, REBD, T/CSD, Belleville SD, PVD, Hydrostatic thrust bearing design, WBD, MDCBD, and SRD). The AHA result has been contrasted with other MH-OAs (PSO, DE, GSA, TLBO, CS, ABC, WOA, SSA, and BOA) [304]. OPA has been proposed by Yuxin Jiang et al. (2022), that's population-based bio-inspired MH-OA. The predatory behaviour of orcas inspirited this OA. This OA was evaluated with sixty-seven illustrious BTFs, CEC 2015, CEC 2017, and also experimented with engineering challenges (WBD, SRD, T/CSD, and 3-BTD). The OPA outcomes have been contrasted with the other MH-OAs (ABC, DE, SOA, GWO, SSA, HHO, PSO, MFO, WOA, and GSA) [98].

The HBA has been proposed by Fatma A. Hashim et al. (2022), that's population-based MH-OA. The intelligent foraging behaviour of the honey badger inspires this OA. This OA was evaluated with twenty-four illustrious BTFs: unimodal from 1 to 8 (Chung Reynolds, Sum Squares, Schwefel_2.23, Schwefel_2.20, Powell Sum, Powell Singular_2, Schwefel_2.22, and De Jong's (sphere)), multimodal from 9 to 16 (Ackley, Brown, Zakharov, Schwefel_2.25, Rastrigin, Griewank, Csendes, and Cigar), fixed dimension multimodal from 17 to 24 (Chen Bird, Colville, Zirilli, Trecanni, Sawtoothxy, Price, Matyas, and Damavandi), twenty-nine functions from CEC 17 test suite, and also evaluated with engineering challenges (WBD, PVD, T/CSD, and SRD). The

Fig. 18 MH-Optimization Algorithm (2022)



outcomes of the HBA were contrasted with the other MH-OAs (HHO, PSO, SA, EHO, WOA, GOA, and MFO) [99]. The RSA was proposed by Laith Abualigah et al. (2022), a population-based MH-OA. The hunting behaviour of Crocodiles inspirited this OA. This OA was evaluated with twenty-three renowned BTFs, thirty functions from CEC 2017, ten functions from CEC 2019, and real-world engineering design challenges (REBD, PVD, 3-BTD, CBD, T/CSD, WBD, MDCBD, and SRD). The findings of the RSA have been contrasted with the other MH-OAs (SSA, GOA, SCA, WOA, GWO, DA, PSO, ALO, MPA, and EO) [100]. The EBS algorithm was proposed by Mohsen Shahrouzi and Ali Kaveh (2022), that's population-based MH-OA. The avian life-saving manoeuvres inspirited this OA. EBS optimization techniques are efficient derivative-free MH-OA. This OA was evaluated with twelve renowned BTF(Powell Sum, Ackley, Griewank, Foxholes, Rastrigin, Cosine Mixture, Alpine, Branin, Schwefel_1.2, Easom, Aluffi-Pentini, and Step), and seven real-world engineering design challenges (Optimal ground motion scaling, Coil SD, CBD, WBD, 3-BTD, PVD, and 15-BTD). The findings of the EBS algorithm were contrasted with the other MH-OA (DE, PSO, GOA, CS, ICA, TLBO, CSA, and LAPO) [101]. The PaOA proposed by Jingbo Wang et al. (2022) is a population-based MH-OA. This OA was simulated by the peafowls swarm's courtship, foraging, and chasing behaviours. This OA was evaluated with twenty-three illustrious BTFs. The outcomes of the PaOA have been contrasted with the other MH-OA (DA, GA, PSO, ALO, GWO, MFO, and GOA) [102]. The HFA has been proposed by Mohammad Verij kazemi and Elham Fazeli Veysari (2022), that's population-based MH-OA. This OA has been encouraged by human society to become felicity. This OA has been evaluated with CEC 2014, CEC 2019, and CEC 2020. In addition to this, this OA was evaluated with real-world engineering design challenges. The findings of the HFA were contrasted with the other MH-OA (RFO, PSO, CCS, EHO, and ASMO) [306]. CCE algorithm has been proposed by Peng Chen et al. (2022), that's population-based MH-OA. The evolution of city councils has inspirited this OA. This OA has been evaluated with twenty general test functions (Ackley, Griewank, Rastrigin, Michalewicz_10, Schwefel_1.2, Michalewicz_5, Shubert, Boachevsky_3, Boachevsky_2, Matyas, Schwefel_2.22, Six Hump Camel Back, Schafer, Booth, Bohachevsky_1, SumSquares, Sphere, Step, Zakharov, and Easom), and twenty-nine benchmark functions from CEC 2017. CCE was also evaluated with three engineering design problems (MDCBD, T/CSD, and WBD). The outcomes of the CCE were contrasted with the other MH-OA (EO, BWO, BMO, PO, AO, CHOA, and WHO) [317]. The TQA was proposed by Peng Chen et al. (2022), that's population-based MH-OA. The division of labor in termite populations under a queen's rule has inspirited this OA. This OA has been evaluated with twenty-three renowned BTFs. The TQA also evaluated with real-world engineering challenges (3-BTD, CBD, WBD, I-beam structure design, CBD, and SRD). The outcomes of the TQA were contrasted with the other MH-OAs (SSA, GWO, STOA, SCA, MVO, WOA, and TSA) [318]. NA has been proposed by Na Lin et al. (2022), that is population-based MH-OA. This OA has been inspirited by the Nomadic tribe. This OA has been evaluated with twenty-eight renowned BTFs. The NA outcomes were contrasted with the other MH-OAs (PSO, WOA, ABC, FPA, and GSA) [319]. The POA has been proposed by Debao Chen et al. (2022), which is a population-based MH-OA. The sexual and asexual propagation mechanism has inspirited this OA. This OA has been verified with twenty-five test functions from CEC 2005, thirty functions from CEC 2017, and multilevel thresholding image segmentation. The findings of the POA were contrasted with the other MH-OAs (CBO, FWA, BSA, SCA, and TLBO) [320]. The GJO has been proposed by Nitish Chopra and Muhammad Mohsin Ansari (2022) that's population-based MH-OA. This OA mimics the hunting behaviour of the golden jackals. This OA has been evaluated with twenty-three mathematical BTFs and engineering design challenges (WBD, PVD, GTD, T/CSD, Weight minimization of a SRD, 3-BTD, and Economic load dispatch). The results of the GJO algorithm were contrasted with the other MH-OA (MFO, GWO, GSA, ES, PSO, GA, HS, and DE) [103]. The SRS was proposed by Shijie Zhao et al. (2022), that's population-based MH-OA. An electromagnetic field's particle interaction has inspirited this OA. This OA was verified with fifty mathematical BTFs, twenty-three from CEC 2005 and ten from CEC 2019 test suite. The findings of the SRS were contrasted with the other MH-OA (TLBO, GA, GOA, PSO, SCA, MPA, GWO, and RSA) [321]. TrS algorithm has been proposed by Shijie Zhao et al. (2022), which is population-based MH-OA. This OA has been evaluated with the exoplanet exploration method. This OA was evaluated with sixty-six constrained and unconstrained problems (fifteen low-dimensional, twenty-eight high-dimensional, ten CEC function, and thirteen constrained mathematical benchmark problems), and engineering design challenges (PVD, MDCBD, 3-BTD, T/CSD, SRD, as well as REBD). The findings of the TrS algorithm were contrasted with the other MH-OA (WO, SS, ICA, GW, HS, CS, BA, ABC, GA, PSO, DE, and HHO) [322]. The SHO has been proposed by Shijie Zhao et al. (2022), that's population-based MH-OA. This OA has been evaluated with the behaviors of sea horses in nature. This OA was evaluated with twenty-three BTFs (Quartic, Step, Rosenbrock, Schwefel_2.21, Shifted Schwefel's_1.2, Schwefel_2.22, Sphere, Penalized_2, Penalized_1, Shifted Rotated_Griewank's without Bounds, Ackley, Rastrigin, Schwefel, Shekel_10, Shekel_7, Shekel_5, Hartman_6, Hartman_3, GoldStein Price, 6-Hump Camel Back, Branin, Kowalik, and

Foxholes), CEC 2014 test suite and real-world engineering challenges (SRD, T/CSD, PVD, WBD, and CBD). The findings of the SHO were contrasted with the other MH-OA (SFO, TSA, ChOA, DA, SCA, and GA) [104]. SCO has been proposed by Tareq M. Shami et al. (2022), that's single solution-based MH-OA. This OA has been encouraged by the single-candidate solution. This OA was verified with twenty-three BTFs, CEC 2019 test suite (Ackley, Happy Cat, Expanded Schafer's_F6, Modifed_Schwefel's, Weierstrass, Griewangk's, Rastrigin's, Lennard-Jones Minimum Energy Cluster, Inverse Hilbert Matrix, as well as Storn's Chebyshev Polynomial Fitting) and engineering design challenges (WBD, SRD, PVD, and T/CSD). The findings of the SCO algorithm were contrasted with the other MH-OA (GSA, AOA, MA, SSA, PSO, GWO, and EO) [4]. GOA has been proposed by Jeffrey O. Agushaka1 (2022), that's a population-based MH-OA. This OA has been inspirited by the gazelles' survival. This OA has been evaluated with ten composited, fifteen classical functions, as well as four mechanical engineering design challenges (WBD, PVD, T/CSD, and SRD). The outcomes of the GOA algorithm were contrasted with the other MH-OA (SSA, SCA, GWO, GWO, DE, AOA, and PSO) [108]. COVIDOA has been proposed by Asmaa M. Khalid et al. (2022), that's population-based MH-OA. This OA has been inspirited by the mechanism of coronavirus when hijacking human cells. This OA has been evaluated with thirty classical BTF (Dixon-price, Happy Cat, Crosslegtable, Eggholder, stybtang, Schwefel, Keane, Trid, Schaffern_4_fcn, Branin, Wolfe, Zettl, Alpine N. 2, Cross-in-Tray, McCormick, Gramacy and Lee, Testtubeholder, Shubert, price 2, and Dejong5), five CEC test function (CEC 01, CEC 03, CEC 06, CEC 07, and CEC 10) and five real-world from CEC 2011. The outcomes of the COVIDOA algorithm were contrasted with the other MH-OA (GWO, PSO, DE, GA, FPA, WOA, CHIO, and SOA) [323]. The ASO has been proposed by Yongliang Yuan et al. (2022), that's population-based MH-OA. This OA has been inspirited by the behaviours of skiers competing for the championship. This OA has been verified with twenty-three BTFs. This MH-OA is also evaluated with real-world engineering challenges (3-BTD, MDCBD, SRD, and REBD). The outcomes of the ASO were contrasted with the other MH-OAs (WCA, ABC, HHO, PVC, TLBO, WCA) [324]. EBOA has been proposed by Pavel Trojovský and Mohammad D. (2022), that's population-based MH-OA. The voting process to select the leader has inspirited this OA. This OA has been evaluated with thirty-three BTFs: CEC 2019. The outcomes of the EBOA have been contrasted with the other MH-OA (LPB, FDO, MPA, TSA, PSO, GSA, GA, TLBO, GWO, and WOA) [325]. CLO algorithm has been proposed by EVA TROJOVSKÁ and Mohammad D. (2022), that's population-based MH-OA. The behaviour of clouded leopards in the wild has simulated this OA. This OA has been evaluated with sixty-eight BTFs: CEC 2017, as well as CEC 2015. This OA is also verified with real-world engineering design challenges (WBD, T/CSD, SRD, and PVD). The findings of the CLO were contrasted with the other MH-OA (MPA, TSA, PSO, GSA, GA, TLBO, GWO, and WOA) [105]. The FFO has been proposed by Eva Trojovská et al. (2022), that's population-based MH-OA. The behaviours of the animal Fennec Fox in nature have stimulated this OA. This OA has been evaluated with sixty-eight BTFs: CEC 2017, as well as CEC 2015. This OA is also verified with real-world engineering design challenges (WBD, T/CSD, SRD, and PVD). The findings of the FFO were contrasted with the other MH-OAs (MPA, TSA, PSO, GSA, GA, TLBO, GWO, and WOA) [106]. ZOA has been proposed by Eva Trojovská et al. (2022), that's population-based MH-OA. The behaviour of zebras in nature has inspirited this OA. This OA has been evaluated with sixty-eight BTFs: CEC 2017, as well as CEC 2015 This OA is also verified with real-world engineering design challenges (WBD, T/CSD, SRD, and PVD). The outcomes of the ZOA have been contrasted with the other MH-OA (MPA, TSA, PSO, GSA, GA, TLBO, GWO, and WOA) [107]. DTBO has been proposed by Mohammad D. et al. (2022), that's population-based MH-OA. This OA has been encouraged by the human activity of driving training. This OA has been verified with fifty-three BTFs and CEC 2017. This OA is also evaluated with real-world engineering design challenges (WBD, and PVD). The findings of the DTBO were contrasted with the other MH-OA (RSA, MPA, PSO, TSA, WOA, TLBO, MVO, GSA, GA, and AVOA) [326]. The STBO has been proposed by Mohammad D. et al. (2022), that's population-based MH-OA. This OA has been inspirited by the trainee tailors are being taught the stitching method. This OA has been evaluated with fifty-three BTFs and CEC 2017. This OA is also verified with real-world engineering design challenges (T/CSD, WBD, SRD, and PVD). The findings of the STBO were contrasted with the other MH-OA (RSA, MPA, PSO, TSA, WOA, TLBO, MVO, GSA, GA, and AVOA) [327]. The AA has been proposed by Fatemeh Ahmadi Zeidabadi et al. (2022), that's population-based MH-OA. This OA has been encouraged by the archer's shooting behaviour toward the target panel. This OA has been evaluated with twenty-three BTFs. The AA findings has been contrasted with the other MH-OAs (GWO, PSO, TLBO, GSA, WOA, GA, and TSA) [328]. The EOO has been proposed by Ahmad Salim et al. (2022), that's population-based MH-OA. The food behaviour of Eurasian oystercatcher has inspirited this OA. This OA has been evaluated with fifty-eight BTFs: unimodal from 1-20 (Sum squares, Sum squares, Brent, Drop wave, Power sum, Schaffer N_1, Schaffer N_3, Schaffer N_2, Schwefel_2.20, Schwefel_2.23, Matyas, Exponential, Dixon-Price, Zakharov, Booth, Bohachevskyn N.1, Ackley_2, Schwefel_2.21, Schwefel_2.22, and Sphere), and multimodal from 21 to 41 (Branin, Brown, Xin-She Yang N. 4, Salomon, Qing, Periodic, Michalewicz, Xin-She Yang N. 2, Schwefel, Holder, Egg Holder, Keane, Cross in Tiny, Brid, Bohachevskyn N.2, Camel Three, Goldstein Price, Six-Hump Camel, Quartic, Step_1, Wolfe, McCormick, Levi N. 13, Himmelblau, Egg Crate, Deckkers-Aarts, Beale, Bartels Conn, Alpine N. 2, Alpine N. 1, Adjiman, Gramacy & Lee, Trid, Easom, Ackley N. 3, Hartmann_6, Hartmann_3, and Ackley). The result of the EOO has been contrasted with the other MH-OA (GWO, BBO, PSO, GSA, and ABC) [109]. The HCSE has been proposed by Ajay Sharma et al. (2022), that's population-based MH-OA. The different species' natural behavior has inspirited this OA. This OA has been verified with forty-one BTFs (Ellipsoidal, Levy Montalvo_2, Levy Montalvo_1, Rotated hyperellipsoid, Neumaier_3 (NF3), Inverted cosine wave, Step function, Sum of different powers, Axis parallel hyperellipsoid, Salomon problem, Schewel, Brown_3, Cigar, Exponential, Cosine mixture, Michalewicz, Alpine, Ackley, Rastrigin, Rosenbrock, Griewank, De Jong f4, Sphere, Moved axis parallel hyper-ellipsoid, Sinusoidal, Shubert, Meyer and Roth Problem, McCormick, Hosaki Problem, Dekkers and Aarts, Six-hump camel back, Goldstein-Price, Shifted_Ackley, Shifted_Griewank, Shifted_Sphere, Shifted_Rosenbrock, 2D Tripod, Kowalik, Branins′ s, Colville, and Beale), and engineering design problems (Coil compression string, Pressure vessel, and Welded beam). The outcomes of the BMA were contrasted with the other MH-OA (PSO, DE, ABC, GSA, BBO, and TLBO) [110].

The SLOA was proposed by Petr Coufal et al. (2022), that's population-based MH-OA. The behaviours of snow leopards have inspirited this OA. This OA has been evaluated with twenty-three BTFs. The outcomes of the BMA were contrasted with the other MH-OAs (PSO, TLBO, GA, GSA, GOA, GWO, TSA, and MPA) [329]. The BMA was proposed by M. Tanhaeean et al. (2022), that's population-based MH-OA. The boxer's behaviour has inspirited this OA. This OA has been verified with twenty BTFs (Schwefel_1.2, Ackley, Rastrigin, Schwefel_2.21, SumSquares, Sphere, Zakharov, Schwefel_2.22, Colville, Shubert, Boachevsky_3, Boachevsky_2, Six hump camel back, Schaffer, Michalewicz_2, Booth, Bohachevsky_1, Matyas, Easom, and Beale), 0–1 Knapsack problem, and engineering design challenges (3-BTD, CBD, and T/CSD). The findings of the BMA were contrasted with the other MH-OAs (PSO, SA, GA, HS, FA, COA, GWO, VPL, CSA, and RDA) [330]. The GaOA was proposed by Jeng-ShyangPan et al. (2022), that's population-based MH-OA. The behaviours of gannets during foraging have inspirited this OA. This OA has been evaluated with eight benchmark functions in the CEC2013 and engineering design challenges (SRD, 3-BTD, CBD, Tubular column design, and WBD). The findings of the GOA were contrasted with the other MH-OAs (PSO, WOA, SCA, AO, BOA, HHO, STOA, and AOA) [111]. COA has been proposed by Mohamed Abdel-Basset (2022), that's a population-based science-inspirited MH-OA. The power allocation policy has inspirited this OA for users in non-orthogonal multiple access (NOMA)-based wireless communication networks. This OA has been evaluated with thirteen standard BTFs. The COA's outcomes were contrasted with the other MH-OAs (PSO, SSA, MFO, GSA, FDA, and SSA) [331]. The LSO algorithm has been proposed by Mohamed Abdel-Basset (2022), that's population-based MH-OA. This OA has been inspirited by the light dispersions with various angles while traveling through rain droplets. This OA has been evaluated with one-hundred-one test functions: CEC 2005, CEC 2014, CEC 2017, CEC 2020, as well as CEC 2022. The LSO also evaluated with engineering challenges (T/CSD, WBD, and PVD). The findings of the LSO were contrasted with the other MH-OAs (WOA, GWO, EO, GTO, SMA, RSA, DE, GBO, and SSA) [332]. ACVO was proposed by Hojjat Emami (2022), that's population-based MH-OA. This OA has been encouraged by the measures recommended to mitigate the spread of COVID-19. This OA has been verified with CEC 2018 and CEC 2019 test suites. The ACVO also evaluated with seven engineering problems (Frequency-modulated sound waves, Spread spectrum radar polyphase code design, Transmission network expansion planning, SRD, Static economic load dispatch, WBD, and REBD). The outcomes of the ACVO were contrasted with the other MH-OA (ABC, PSO-GSA, WOA, HHO, and TLBO) [333]. The MRA has been proposed by Abeer S. Desuky et al. (2022), that's population-based MH-OA. This OA mimics the bottlenose dolphins in Florida's Atlantic coast exhibit mud ring feeding behaviour. This OA has been evaluated with twenty-nine BTFs and four engineering design challenges (3-BTD, T/CSD, PVD, and WBD). The outcomes of the MRA algorithm were contrasted with the other MH-OA (ALO, GWO, PSO, EO, HBA, HHO, and WOA) [112]. The HMO algorithm has been proposed by Amin Mahdavi-Meymand and Mohammad Zounemat-Kermani (2022), that's population-based MH-OA. This OA has been inspirited by the arrangement of electrons surrounding atoms according to the Bohr atomic model, as well as the structure of homonuclear molecules. This OA was evaluated with ten-classical BTFs and CEC 2017. The outcomes of the HMO were contrasted with the other MH-OA (PSO, DE, and GA) [334]. The MGO algorithm has been proposed by Benyamin Abdollahzadeh et al. (2022), that's population-based MH-OA. This OA has been inspirited by the wild mountain gazelle's life. This OA was evaluated with twenty-four-classical BTFs and CEC 2017. The outcomes of the MGO were contrasted with the other MH-OA (WOA, TSA, FFA, MVO, SCA, PSO, MFO, GSA, and GWO) [335].

4.5.9 Part IX (2023)

Part IX of phase V consists of 24 MH-OA, as shown in Fig. 19. The SGOa was proposed by Mahdi Aziz et al. (2023), that's population-based MH-OA. The primary rules of a traditional Korean game have inspirited this OA. This OA has been evaluated with twenty-five benchmark functions (Ackley 1, Schumer Steiglitz, Salomon, Rosenbrock, Quintic, Qing, Rastrigin, Powell Sum, Powell Singular, Pint´er, Pathological, Mishra 1, Levy 8, Inverted cosine wave, Hyper-ellipsoid, Holzman 2, Griewank, Chung Reynolds, Exponential, Extended Easom, Dixon & Price, Deb 1, Csendes, Brown, and Alpine 1) and engineering design challenges (SRD, Hydro-static thrust bearing, and REBD). The findings of the GOA were contrasted with the other MH-OAs (CSA, DE, MGA, CGO, TLBO, ABC, GWO, ALO, ACO, FA, PSO and GA) [148]. The AZOA has been proposed by Sarada M, and Prabhujit M (2023), that's population-based MH-OA. This OA mimics the American zebra's behaviour. This OA has been evaluated with CEC-2005, CEC-2017, and CEC-2019 along with four engineering design challenges (SRD, GTD, 3-BTD, T/CSD, PVD, and WBD). Also, solving the optimal placement of wind turbines in wind farms, and economic load dispatch problems. The outcomes of the AZOA algorithm were contrasted with the other MH-OA (FFA, MGO, AVOA, GTO, GA, and PSO) [113]. The EVO algorithm has been proposed by Mahdi Azizi (2023), that's population-based MH-OA. This OA has been inspired by the physics principles related to the stability and diferent modes of particle decay. This OA has been evaluated with twenty test functions: CEC 2020 as well as CEC 2020 real-world problem. The findings of the EVO were contrasted with the other MH-OAs (ACO, HS, FA, CSA, MVO, and ISA) [134]. The KOA has been proposed by Mohamed Abdel-Basset et al. (2023), that's population-based MH-OA. The Kepler's laws of planetary motion have inspirited this OA. This OA has been verified with CEC-2014, CEC-2020, CEC-2022, and engineering design problems (Coil compression string, Pressure vessel, and WBD, T/CSD, PVD, 10-BTD, CBD, GTD, and Parameter estimation of solar PV). The outcomes of the BMA were contrasted with the other MH-OA (FLA, COA, GTO, RUN, GWO, WOA, SMA, DO, and POA) [135]. The SAO has been proposed by Lingyun D and Sanyang Liu (2023), that's population-based MH-OA. The sublimation and melting behavior of snow has inspirited this OA. This OA has been evaluated with twenty-nine CEC 2017, twenty-two CEC 2020 BTFs, and fifteen real word design problems. And also, parameter extraction for photovoltaic systems is used to validate the SAO algorithm. The results of the SAO were contrasted with the other MH-OA (MVO, AO, AVOA, EO, HHO, and PSO) [136]. The FLA has been proposed by Fatma A. H et al. (2022), that's population-based MH-OA. This OA has been evaluated with the Fick's first rule. This OA was evaluated with thirty CEC-2017 BTFs test suite and real-world engineering challenges (WBD, T/CSD, PVD, SRD, and 3-BTD). The findings of the FLA were contrasted with the other MH-OA (HGS, HHO, AEO, TEO, HGSO, WOA, SSA, SCA, GSA, and SFO) [137]. The LAB was proposed by Ruturaj Reddy. et al. (2016), that's population-based MH-OA for real-parameter optimization. This OA was mimicked by the AI-based competitive behavior. Twenty-seven BTFs have been used to evaluate this OA (Zakharov, Foxholes, Sumsquares, Step2, Sphere2, Ackley, Six-hump camelback, Schwefel 1.2, Bohachecsky1, Schwefel 2.22, Schaffer, Rastrigin, Bohachecsky2, Quartic, Bohachecsky3, Matyas, Langermann5, Booth, Langermann10, Kowalik, Hartman6, Hartman3, Griewank, Fletcher, and Dixon-Price), and real word design problems (Abrasive Water Jet Machining (AWJM), Micro-machining processes, Process parameter optimization for turning of titanium alloy, and Electric Discharge Machining (EDM)). The outcomes

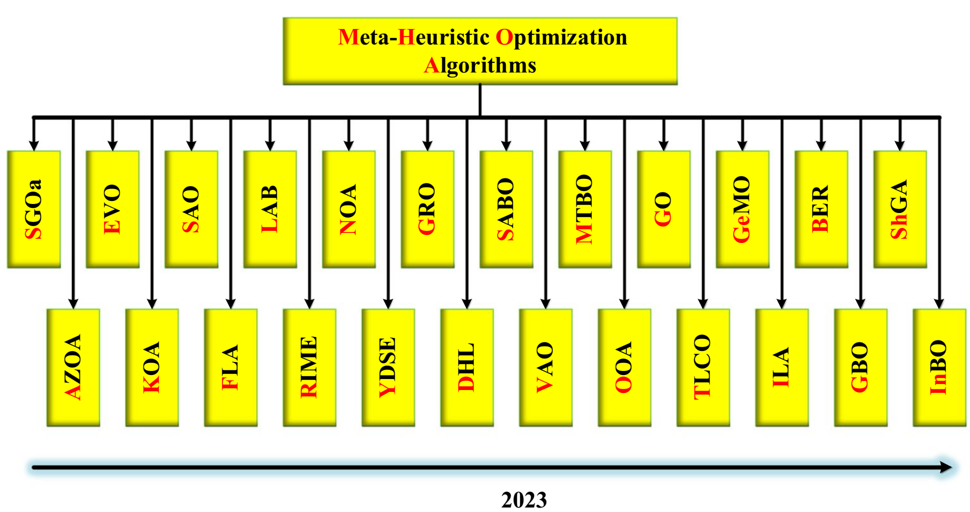


Fig. 19 MH-Optimization Algorithm (2023)

of the LAB were contrasted with other MH-OA (ABC, JDE, SADE, BSA, LA, and CLPSO) [142]. The RIME algorithm has been proposed by Hang Su et al. (2023), that's population-based MH-OA. This OA has been inspirited by the rime-ice physical phenomenon. This OA has been evaluated with forty-two test functions: CEC 2017, as well as CEC 2022. The RIME also evaluated with engineering challenges (MDCBD, SRD, IBD, WBD, and PVD). The findings of the RIME were contrasted with the other MH-OAs (WOA, PSO, HHO, SCA, JAYA, MFO, RFO, FA, BA, and GWO) [138]. NOA has been proposed by Mohamed Abdel-Basset et al. (2023), that's population-based MH-OA. The search, cache, and recovery behaviors of nutcrackers inspires this OA. Twenty-three illustrious standard benchmark functions and three challenges (CEC-2014, CEC-2017, and CEC-2020) were employed to evaluate this OA. And also, the effectiveness of this algorithm can be tested by real world engineering problems (WBD, T\CSD, PVD, and 10-BTD). The outcomes of the NOA were contrasted with other MH-OAs (WOA, EO, RUN, GBO, and SSA) [114]. The YDSE was proposed by Mohamed Abdel-Basset et al. (2023), that's population-based MH-OA for solving real-life engineering problems. This OA was based on young's double-slit experiment. CEC 2014, CEC 2017, as well as CEC 2022. BTFs have been used to evaluate this OA, as well as real-world engineering design challenges (WBD, PLD, TCD, I-BVD, GTD, SRD, PVD, CBD, T/CSD, and 3-BTD). The findings of the YDSE algorithm were contrasted with other MH-OA (RSO, HGS, WSO, CHIO, SCA, SMA, WOA, AVOA, PSO, MTDE, and DE) [139]. GRO proposed by Kamran Zolf (2023) is a population-based MH-OA. This OA is inspirited by the how gold-seekers prospected for gold during the Gold Rush Era. Twenty-nine BTFs have been used to evaluate this OA in both low and high-dimension problems, and three engineering challenges (T/CSD, PVD, and WBD). The findings of the GRO were contrasted with other MH-OA (SMA, WCA, KMA, WOA, SSA, SCA, PSO, IGWO, GSA, DE, FA, and GA) [143]. The DHL has been proposed by Iman A. et al. (2020), that's population-based MH-OA. This OA was stimulated by wild animal hunting. The DHL was evaluated by twenty-three mathematical test functions (unimodal, multimodal, hybrid, and composite) and six engineering challenges (T\CSD, PVD, WBD, and smart grid problems). The outcomes of the DHL were contrasted with other MH-OAs (BAT, MVO, PSO, SCA, and GWO) [115]. The SABO has been proposed by Pavel T. and M. Dehghani (2023), that's a population-based MH-OA for solving engineering optimization problems. The searcher agent subtraction average is used to update the location of population members in the search space. mimicked this OA. Fifty-two BTFs evaluated this OA, CEC-2017, and mechanical design problems (WBD, SRD, PVD, and T/CSD). The outcomes of the SABO were contrasted with other MH-OA (GSA, PSO, GA, TLBO, GWO, MVO, WOA, MPA, TSA, RSA, WSO, and WSO) [336]. VAO was proposed by Seyed Muhammad H. M. (2023), that's population-based MH-OA. The Victoria Amazonica plant inspires this OA in humans. Twenty-four BTFs have been used to evaluate this OA (Ackley, Schwefel, Powell, Rastrigin, Pyramid, Booth, Zakharov, De Jong, Easom, Beale, Rosenbrock, Bohachevsk Y, Bukin 6, Trid, Egg Holder, Michalewicz, Branin, Cross-Intray, Griewank, Goldstein Price, Dixon, Levy, And Bird). The findings of the VAO algorithm were contrasted with other MH-OA (BBO, FA, TLBO, GGO, PSO, ABC, GA, GWO, and ACO) [337]. The MTBO has been proposed by Iman F. et al. (2023), that's population-based MH-OA. This OA has been evaluated with the social performance and cooperation of humans. This OA was evaluated with three BTFs, and real-world engineering challenges (3-TBD, T/CSD, and PVD). The findings of the MTBO were contrasted with the other MH-OA (DE, GA, ABC, PSO, and SA) [144]. The OOA has been proposed by Mohammad D. and Pavel T. (2023), that's population-based MH-OA. This OA has been inspirited by the osprey behavior. This OA has been evaluated with CEC 2017. This OA is also verified with real-world engineering design challenges (T/CSD, WBD, SRD, and PVD). The findings of the OOA were contrasted with the other MH-OA (GA, TLBO, GSA, PSO, GWO, MVO, WOA, MPA, TSA, RSA, and WSO) [116]. The GO, proposed by Qingke Zhang et al. (2023), that's population-based MH-OA for solving optimization challenges with single and multiple objectives.

GO was influenced by Individuals' learning and reflection mechanisms in their social development processes. This OA was evaluated with CEC 2017 BTFs and an image benchmark test suite. The outcomes of the GO have been contrasted with other MH-OAs (GSK, SA, ASO, SFS, DE, AEFA, MPA, EO, COA, DS, SDO, FA, SO, CS, MVO, AEO, INFO, HBO, TLBO, FPA, CHIO, PSO, GA, HS, SSA, GSA, CMA-ES, SFLA, WSO, ICA, RUN, DMOA, ABC, GWO, LSA, ACO, BSO, HHO, CA, WOA, MFO, AFSA, SCA, AOA, BOA, and BFO) [145]. The TLCO algorithm was proposed by Hoang-Le Minh (2023), that's population-based MH-OA. This OA has been stimulated by the termite colony's life cycle and the modulation of movement methods utilized by many animal species in nature. This OA was evaluated with twenty-three unconstrained mathematical test functions, CEC 2005, and five constrained engineering design problems (T\CSD, PVD, WBD, SRD, and 72-BTD). The outcomes of the TLCO were contrasted with other MH-OA (GSA, CS, GWO, WOA, SCA, MFO, HHO, and AOA) [117]. The GeMO algorithm has been proposed by Amir Hossein G. and Amir H. A. (2023), that's physics-inspirited population-based MH-OA. The unique properties of the geometric mean operator in mathematics inspirited this OA. For more precise modelling of this OA.

This OA was evaluated with fifty-two renowned BTFs, and engineering design problems (WBD, SRD, T\CSD, PVD, 3-BTD, CBD, Gas transmission compressor design, and Himmelblau's nonlinear constrained problems). The findings of GeMO were contrasted with other MH-OAs (HHO, AOA, AO, GBO, EO, and FDA) [140]. The ILA has been proposed by Masoomeh Mirrashid, and Hosein Naderpour (2023), that's population-based MH-OA for global optimization. The IbI logic theory inspirited this OA. This OA was evaluated with forty-three illustrious BTFs (Six-hub camel, Schaffer function n.2, Schaffer function n.4, Hartmann 3, Power sum, Hartmann 4, Perm function, Perm function 0, Michalewicz, Matyas, Mccormick, Langermann, Holder table, Hartmann 6, Gramacy and Lee, Goldstein-price, Forrester, Eggholder, Easom, Drop-wave, De jong function n.5, Cross-in-tray, Colville, Three-hump camel, Bukin function n.6, Branin, Bohachevsky function 1, Beale, Zakharov, Trid, Sum squares, Sum of different powers, Styblinski-Tang, Sphere, Schwefel, Rotated hyper-ellipsoid, Rosenbrock, Rastrigin, Levy function n.13, Levy, Griewank, Dixon-price, and Ackley), CEC-2019 and five engineering designs (PVD, MDCB, REBD, SRD, T\CSD, 3-BTD, and WBD). The findings of the ILA were contrasted with other MH-OAs (PSO, DE, GA, HS, ABC, ICA, BA, CS, WO, TLBO, EHO, GW, SS, MBO, HGSO, HHO, AOA, AHA and TL) [146]. The BER was proposed by El-Sayed M. El-kenawy. et al. (2023), that's population-based MH-OA. This OA was encouraged by the swarm members in achieving their global goals. Seven BTFs and engineering design problem (T/CSD) have been used to evaluate this OA.The outcomes of the BER were contrasted with PSO, WOA, GA, and GWO [338]. The GrBO was proposed by Shuyin Xia et al. (2023), that's population-based MH-OA. This OA is inspirited by granularball computing. Twenty BTFs have been used to evaluate this OA (Bohachevsky Function3, Bohachevsky Function2, Bohachevsky Function1, Rotated Hyper-Ellipsoid Function, Generalized Griewank's, Sum Squares, Rastrigin, Sum of Different Powers, Easom, Generalized Rastrigin's, Styblinski-Tang, Goldstein-Price, Three-Hump Camel, Matyas, Levy Function N. 13, Cross-in-Tray, Quartic, Generalized Rosenbrock's, Schwefel's Problem 2.22, and Sphere Model). The outcomes of the GrBO algorithm were contrasted with another MH-OA (PSO, DE, GA, AFSA, SA, and FWA) [339]. ShGA was proposed by Amir Thanh Sang-T et al. (2023), that's nature-inspirited population-based MH-OA. This OA mimicked the Shrimp and Goby Association behaviour. This OA was evaluated with twenty-three renowned BTFs and engineering problems (25-BTD, and 72-BTD). The findings of the ShGA were contrasted with other MH-OAs (GA, GSA, PSO, SSA, BAT, and DA) [118]. The InBO was proposed by Rahul Kottath, and Priyanka Singh (2023), that's population-based MH-OA. This OA is inspirited by the influenced by a group of individuals rather than a single person. Twenty-one BTFs have been used to evaluate this OA, twenty-four noiseless black-box optimization benchmarking (BBOB) functions. And also, InBO is combined with RNN and ANN architectures to solve real-world electricity load as well as price forecasting problems The outcomes of the InBO algorithm were contrasted with another MH-OA (PSO, GWO, and COA) [147].

5 Matlab and Python Code of MH Optimization Algorithm

GitHub is a web and cloud-based service that helps developers store and manage their code, as well as make code available for other users. GitHub encourages teams to work together to build and edit their site content. GitHub encourages teams to work together to build and edit their site content. Anyone can sign up and host a public code repository for free, which makes GitHub especially popular with open-source projects. Codes to be hosted can be in any language like Matlab, Python, etc. MATLAB is a high-performance language for technical computing. It integrates computation, visualization, and programming environments. Furthermore, MATLAB is a modern programming language environment: it has sophisticated data structures, contains built-in editing and debugging tools, and supports object-oriented programming. These factors make MATLAB an excellent tool for academic researchers, engineers, students, and professionals. In the case of Matlab, the mathematical modelling of an objective function is less cumbersome. Moreover, Matlab provides a provision for creating a real-world environment considering all the constraints. The Matlab codes of MH-OAs are referenced from MathWorks of MATLAB central, journal papers, web pages, and GitHub. Python is a multipurpose programming language, and it has applicability pretty much anywhere that uses data, mathematical computation, or lines of code. Like most programming languages, Python works in tandem with an interpreter that executes the finalized lines of code. There are lots of free resources to learn the Python coding language, which, with its basis in English syntax, is considered one of the least fussy and most straightforward coding languages to learn and read. The Python codes of MH-OAs are referenced from GitHub. Table 2 summarizes the MH optimization technique, Matlab code reference, and Python code reference. In Table 2, NA represents not available.

6 Discussion and Recommendations

This paper has presented various algorithms and their MATLAB as well as Python code. For future work, more enhancements can be made to the novel proposed

Table 2 Matlab and Python code of MH-Optimization Algorithms

S. no.	Optimization techniques	Matlab code reference	Python code reference
1	GA	[359]	[360]
2	SA	[361]	[362]
3	TS	[363]	[364]
4	PSO	[365]	[366]
5	DE	[367]	[368]
6	ACO	[369]	[370]
7	VNS	[371]	[372]
8	ABC	[373, 374]	[375]
9	BB-BC	[376]	NA
10	IWO	[377]	[378]
11	ICA	[379, 380]	[381]
12	IWD	NA	[382]
13	FA	[383]	[384]
14	BBO	[385]	[386]
15	LCA	[387]	[388]
16	GSA	[389]	[390]
17	CS	[391, 392]	[393]
18	BA	[394]	[395]
19	CSS	[396]	NA
20	TLBO	[397, 398]	[399]
21	SO	NA	[400]
22	KH	[401]	[402]
23	DSA	[403]	NA
24	FPA	[404]	[405]
25	WCA	[406]	NA
26	BH	[407]	[408]
27	RO	[409]	
28	SMS	[410]	NA
29	GWO	[411]	[412]
30	BSA	[413]	[414]
31	AWDA	[415]	NA
32	CSO	[416]	[417]
33	SFS	[418]	[419]
34	SOS	[420]	[421]
35	SSO	[422]	[423]
36	PIO	NA	[424]
37	ISA	[425]	[426]
38	CBO	[427, 428]	[429]
39	SLCA	[430]	NA
40	MOA	[431]	NA
41	VSA	[432]	NA
42	ALO	[433]	[434]
43	MFO	[435]	[436]
44	DA	[437]	[438]
45	AAA	NA	[439]
46	EHO	[440]	NA
47	GSO	[441]	[442]
48	EFO	[443]	NA
49	LSA	[444]	NA
50	ABO	[445]	[446]
51	MVO	[447]	[448]
52	WSA	[449]	NA
53	GRSA	[450]	NA

Table 2 (continued)

S. no.	Optimization techniques	Matlab code reference	Python code reference
54	TSA	[451]	NA
55	HTS	[452]	NA
56	WCO	[453]	NA
57	WOA	[437]	[454]
58	WEO	[455]	NA
59	SCA	[456]	[457]
60	CSA	[458]	[459]
61	NAA	[460]	NA
62	OFA	[461]	NA
63	YYPO	[462]	NA
64	TWO	[463]	NA
65	SIO	[464]	NA
66	LAPO	[465]	NA
67	MVPA	[466]	NA
68	SSA	[467]	[468]
69	GOA	[469]	NA
70	SHO	[470, 471]	NA
71	HBBO	[472]	NA
72	TGA	[473]	NA
73	ASO	[474]	NA
74	SSA	[475]	NA
75	EPO	[476]	NA
76	YSGA	[477]	NA
77	FF	[478]	NA
78	FSA	[479]	NA
79	BOA	[480]	[481]
80	SSO	[482]	NA
81	STOA	[483, 484]	NA
82	AEFA	[485, 486]	NA
83	HHO	[487]	[488]
84	SOA	[489, 490]	[491]
85	PFA	[492]	NA
86	HGSO	[493]	NA
87	BMO	[494]	NA
88	MRFO	[495]	NA
89	PRO	[496]	NA
90	SMO	[497]	NA
91	RDA	NA	[498]
92	TFWO	[499]	NA
93	TuSA	[500, 501]	NA
94	SMA	[502]	[503]
95	WSA	NA	[504]
96	ChOA	[505]	NA
97	PO	[506]	NA
98	MPA	[507]	NA
99	GTOA	[508]	[509]
100	DDAO	[510]	NA
101	SPBO	[511]	NA
102	GBO	[512]	[513]
103	HBO	[514]	NA
104	LFD	[515]	NA
105	FBI	[516]	NA
106	CHIO	[517]	NA

Table 2 (continued)

S. no.	Optimization techniques	Matlab code reference	Python code reference
107	CapSA	[518]	NA
108	LPB	[519]	NA
109	RSO	[520]	NA
110	CGO	[521]	NA
111	AOS	[522]	NA
112	AOA	[523]	[524]
113	GEO	[525]	NA
114	BWOA	[526, 527]	[528]
115	BRO	[529]	NA
116	ChSA	[518]	NA
117	AO	[530]	NA
118	LA	[531]	NA
119	MAO	[532]	NA
120	MGA	[533]	NA
121	AVOA	[534]	NA
122	ArOA	[535]	[536]
123	HGS	[537]	NA
124	COOT	[538]	NA
125	CryStAl	[539]	NA
126	JS	[540]	NA
127	DOX	[541]	NA
128	AFT	[542]	NA
129	WHO	[543]	NA
130	NGO	[544]	NA
131	FSO	[545]	NA
132	JSOA	[546]	NA
133	HBA	[523]	NA
134	SETO	[547]	NA
135	AHA	[548, 549]	[549]
136	RSA	[550, 551]	NA
137	SO	[552]	NA
137	POA	[553]	NA
138	TSA	[309]	NA
139	DMO	[310]	NA
140	WSO	[554]	NA
141	GJOA	[555]	NA
142	TrS	[556]	NA
143	SHO	[557]	NA
144	CCE	[558]	NA
145	COA	[559]	NA
146	SCO	[560]	NA
147	DTBO	[561]	NA
148	COVIDOA	[562]	NA
149	GOA	[563]	NA
150	LSO	[564]	NA
151	ACVO	[565]	NA
152	MRA	[566]	NA
153	HMO	[567]	NA
154	KOA	[568, 569]	NA
155	SAO	[570]	NA
156	FLA	[571]	NA
157	RIME	[572]	NA
158	NOA	[573, 574]	NA

Table 2 (continued)

S. no.	Optimization techniques	Matlab code reference	Python code reference
159	YDSE	[575]	[576]
160	GRO	[577]	NA
161	DHL	[578, 579]	NA
162	SABO	[580]	NA
163	VAO	[581, 582]	NA
164	MTBO	[583]	NA
165	OOA	[584]	NA
166	GO	[585]	NA
167	TLCO	[586]	NA
168	GeMO	[587]	NA
169	ILA	[588]	NA

algorithms. One of them is to improve these algorithms by employing new enhanced mutation and adaptive strategies to solve prospective research problems. Apart from parametric modifications, the hybridization of two or more nature-inspired algorithms into one can be done for improving the performance without compromising the complexity. Hybridizing approaches will help in using the strengths of multiple algorithms to improve the overall performance. This could require widening existing taxonomies to account for a mixture of algorithms in hybrid search techniques. Till date, no such technique has been proposed, and once such hybrid algorithms are proposed, they will provide a significant improvement over the traditional algorithms. So, it is imperative that the research community should modify the algorithm with respect to already proposed challenging algorithms to reflect the importance of their proposal in the field. Apart from this, more work can be done in specific challenging conditions. Such proposals include not only single-objective optimization problems but problems relating to other diverse fields, including dynamic and stochastic optimization, where problem dimension varies with respect to time. Multi-and many-objective optimization is also a challenging task, and the goal here is to optimize two or more conflicting objectives simultaneously. Multi-modal and large-scale optimization where there are the large number of global optima and variable dimension sizes of the order of thousand, respectively. New techniques for Pareto front exploration, ranking solutions, and diversity preservation must be formulated. he parameter tuning and parametric adaptations are also followed to adapt algorithms with respect to the problem during the search. It is required that the above-said points should be kept in mind for further investigation before proposing a new algorithm. Also, it would be interesting if the newly proposed algorithms are compared with respect to state-of-the-art variants and not the classical optimization algorithms.

For most of the newly proposed algorithms, when compared with other newly proposals, they find limited applications and hence lose their significance. So here, researchers should be encouraged to increase the number of algorithms used in the comparative analysis along with the state-of-the-art algorithms and not the classical algorithms. And unless and until they are proved to be competitive with respect to prospective algorithms, they will not be used in practice and hence will not attract the research community. The algorithm should also be tested on highly challenging datasets such as CEC 2015, CEC 2014, CEC 2017, real word problems, and not just the classical benchmarks. The comparison should include high dimensional, multi-modal, hybrid and composite functions from the above-said datasets. Apart from this, it would also be interesting if the source code of the proposed algorithms is made available to the research community. This will provide a clean implementation of the proposed algorithm and further improve the visibility of the proposed research.

Real world problems often involve dynamic environment and optimal solution change over time. New algorithms must be more adaptive and capable of tracking changes, making them suitable for forecasting applications, finance management, logistic support, and autonomous systems. Optimization in high dimensional search spaces is also very challenging and algorithms must incorporate techniques which can help in reducing the dimensionality of the problem, with enhanced exploration and exploitation. These techniques can be handier if we can effectively perform parallel computing. Apart from that, new technologies can be integrated into the optimization techniques such as explainable and interpretable optimization techniques for transparent and interpretable solutions in healthcare and finance. Edge and fog computing can be used in collaboration with these algorithms for optimizing decentralized systems with limited resources as in IOT devices. More work can be done for real-time and online optimization tasks such as autonomous vehicles, drones, and robotics. New and enhanced algorithms will enable these systems to navigate complex environments, make real-time decisions and adapt to future complex unforeseen scenarios.

Overall, these are exciting times for research on nature-inspired algorithms, and dynamic taxonomies should be followed to design new prospective algorithms and their application to respective fields. The future of optimization algorithms is likely to be shaped by a combination of algorithm-based enhancements, interdisciplinary collaborations, and increased integration of optimization algorithms into industrial and other real-world applications. More benefits will add on from increased collaboration between researchers of different domains such as computer science, medicine, mathematics, engineering, management, and others, to produce skilled professionals. We hope that the above-discussed critical analysis will help the prospective researchers to take a sensible step in designing new algorithms and contribute to achieving scientific and technical soundness in this field.

7 Conclusion and Future Work

Bibliometric analyses of MH-OAs are presented in this review paper. In literature, various MH-OAs are available to solve a real-world complex optimization problem. A brief description of MH optimization techniques is presented along with inspiration sources, BTFs, their Matlab code references, and Python code references. At least one or more MH optimization techniques are published in our scientific community. Since 1975-till the present, a lot of articles have been published based on novel optimization_algorithms in different international journals (Elsevier, IEEE Transactions, Wiley, MDPI, Allen, Hindawi, Sage, Springer, and Taylor and Francis), and the proceeding of international conferences. Thus, this review article is highly believed to be appropriate and practical for academic researchers, engineers, students, and professionals. In this review paper, we presented 304 MH-OA, which are carried out from the literature. The mathematical optimization field has recently attracted the scientific community's attention, which has proposed and developed many MH optimization techniques. There was an outstanding contribution by the researcher in introducing the MH-OA into the engineering world. With a simple and easy understanding of the evolution of these algorithms, most algorithms are considered a general solution to many problems.

Analyzing the literature, it is challenging to find concrete suggestions for which MH-OAs will be the most appropriate for a particular problem. As a result, it's logical to presume that the MH optimization techniques research area will remain an attractive area to search for new solutions for at least several years. From this review article, academic researchers, engineers, students, and professionals can get help for literature review in the field of MH optimization methods under the same roof. As a result, extended work can be carried out. In the future, improving the effectiveness as well as the efficiency of the population-based and the single solution-based existing MH-OA. Several MH-OA studies have been conducted with the goal of solving the challenge of single-objective optimization. As a result, academic researchers, engineers, students, and professionals should concentrate their efforts on addressing the multi-objective problem. In addition to these, to develop novel practical MH-OA that deal with real-world problems.

Apart from these, there are a large number of algorithms inspired from various phenomena's have been proposed in the literature and new hybrid as well as enhanced versions of these algorithms have been proposed. These new algorithms can be widely applied to various research problems including time series forecasting of infections from a biologists perspective; energy management in renewable resources such as solar PV systems, wind farms, fuel cells, among others. New studies for formulating agent based models for high risk diseases such as (SEIR for COVID-19), protein protein interactions for DNA sequencing, medical imaging diagnosis for cardiac and neuro-patients. Other than these, these algorithms can serve as the basis for making decision support models to help governments in finding optimal solutions under conflicting criteria's. Overall, we can say that the present work can act as the starting point for people who are new to the field of MH optimization research.

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Data Availability Data sharing is not applicable to this article as no datasets were generated or analyzed during the current study.

Declarations

Competing interests The authors declare that they have no conflict of interest.

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