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Glossary of Metaheuristic Algorithms

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***Abstract*: Metaheuristic algorithms have been an interesting area for researchers, scientists and academicians due to their specific and significant characteristics and capabilities. Their ability to solve and give near optimal solutions to the problems of versatile domain without in-depth details and definition of the problems, provides an edge over traditional techniques. Most of the metaheuristic algorithms are inspired by some real world phenomenon, generally a natural method of optimization. Over the last few decades a number of metaheuristic algorithms have been introduced and applied on various problems of different domains. This paper is aimed to provide the researchers of the field with a comprehensive list of such algorithms developed so far. The algorithms are listed in alphabetical order having authors' credentials and a brief discussion of the method. The aim of this work is to provide an introduction of the field to the new and interested researchers.**

***Keywords*:** Nature Inspired Algorithms, Metaheuristic Algorithms.

I. Introduction

Optimization refers to the process of finding out the best available solution to a problem. When modeled mathematically, optimization generally figures out to be a method of finding out optimized value of a function (objective/fitness function). Equation (1) is an example of such optimization. This process of optimization is generally performed under some system imposed binding conditions known as constraints. Optimization may have single objective or multiple objectives. There may be many maxima or minima in a search space. All of them may not be necessarily the best solutions. Finding out any of these local optima may disguise the search method of successfully optimizing the problem (Figure 1). Global optimization refers to finding out the global optimum avoiding local optima.

Minimize $f(x) = \sum_{i=1}^{D}[x_i^2 - 10\cos(2\pi x_i) + 10]$ (1)
where $-5.12 < x_i < 5.12$

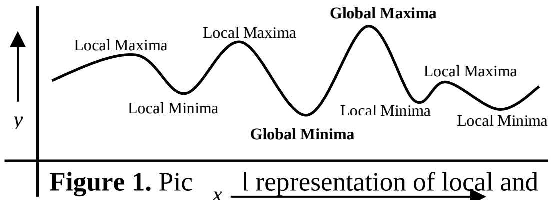

Figure 1. Pic l representation of local and global optima

There are many categorizations provided for various optimization approaches. One such categorization is shown in figure 2. Deterministic methods are unable to solve non-linear problems, heuristic search methods provide near optimum and acceptable solutions to such problems. Metaheuristic search methods are a category of algorithms that do not require detailed information of the search space; rather they need the objective function and domain of the variables. Algorithms falling in further categories of metaheuristic search methods often overlap in more than one categories.

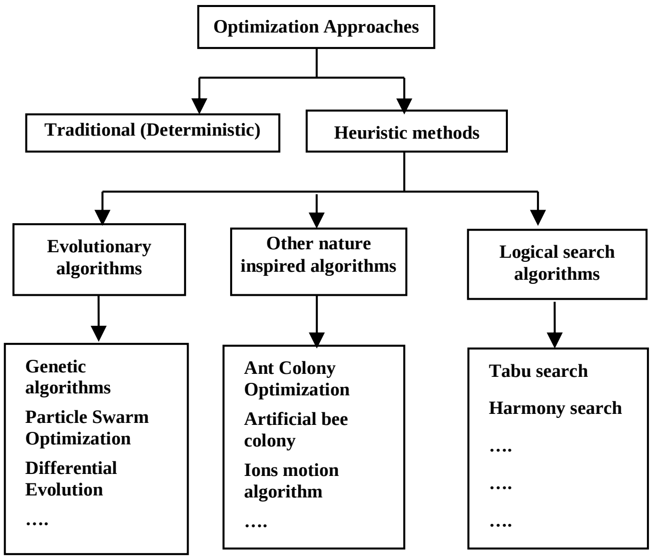

Figure 2. A categorization of optimization approaches

An Evolutionary Algorithm (EA) initializes with few random member solutions and continues searching for the best solution governed by rules of the specific algorithm. The best solution after each generation is either equal or better than the previous generation. Most of the researchers working in the field of EA chose a few algorithms to work upon, but only a few attempts have been made to figure out that how many such algorithms have been developed [1].

> "Till now, madness has been thought a small island in an ocean of sanity. I am beginning to suspect that it is not an island at all but a continent." -Machado de Assis, *The Psychiatrist*.

When the work of creating a list of all of them started, the above sentence of Assis felt to be true. EA's have been in existence for more than a half century. It is a computational method that has enabled researchers and mathematicians to solve problems that cannot be solved by conventional computational strategies. Almost all the evolutionary computational methods are inspired by some real world phenomenon. Figure 3 illustrates the process of development of an EA. Nature and its species have evolved for millions of years to optimize their problem solving skills.

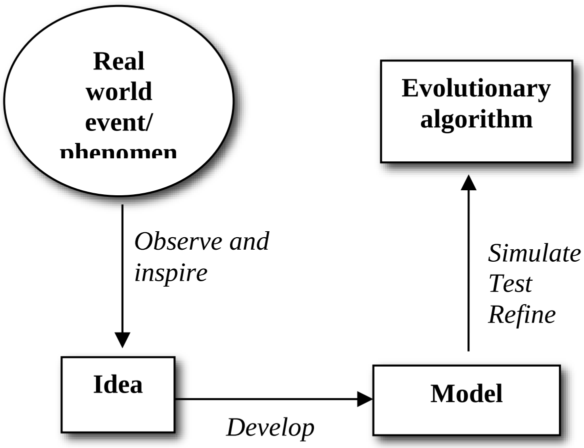

Figure 3. Process of development of an EA

Most of the evolutionary algorithms are thus based on these problem solving strategies adopted by natural species. Even the strangest of the species have evolved over time and have the ability to act as a basis of an EA. Few such species are insects, mammals, birds, fishes and many more. Many of the weird species have also been studied and used to base an EA like bacteria, sperm, Japanese tree frog, raven, blind naked-mole rats, dragon-fly, glowworm, krill etc. Many EAs draw inspiration from plants also. Algorithms based on runner-root, plant growth, paddy, strawberry etc. exist. Humans being the most intelligent species have also contributed to inspire many algorithms. Algorithms were also found inspired by man-made processes like brain-storming, scientists' cooperation, consultation, tournaments, grenade blast , teaching-learning, society, exchange market etc. Many natural processes like galaxies, big bang, river formation, chemical reactions, cloud formation, crystals, electromagnetism, gravitation etc. have also been able to inspire the researchers. Few very weird and hypothetical concepts like zombies, reincarnation, flying elephants etc. have also been used. EAs can be divided into nine groups according to the method they are inspired by [2]. These groups are: biology-based, physics-based, social-based, music-based, chemical – based, sport – based, mathematics – based, swarm – based, and hybrid methods which are combinations of these. In this paper, we are presenting a glossary of evolutionary algorithms with their brief descriptions.

II. Glossary of Metaheuristic Algorithms

Development of EAs started way back in 1960s. The rate of introduction of new and innovative EAs has increased continuously since then. Steep increase in the cumulative number of EAs over the last decade indicates increasing number of researchers contributing to the field. Figure 4 gives an idea of cumulative number of algorithms over the years.

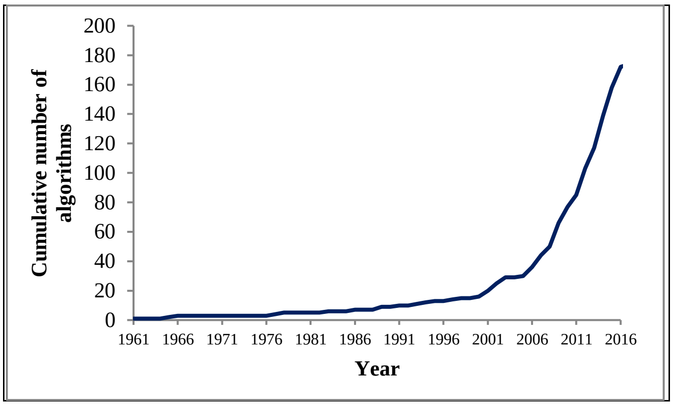

Figure 4. Increasing cumulative number of EAs over the years

Table 1 contains the glossary of metaheuristics found so far. The discussion has been kept limited to a brief introduction of the method and not many technical details. Attempts have been made to include each existing method but still there may be a few algorithms left out.

Table 1. Glossary of Metaheuristic Algorithms

Algorithm	Authors (Year)	Brief Description
	A	
African Buffalo Optimization [3]	J.B. Odili and M.N. Mohmad Kahar (2016)	Inspired from the intelligence, organizational skills and navigational skills displayed by African buffalos in search of food
African Wild Dog Algorithm [4]	C. Subramanian , A.S.S. Sekar and K. Subramanian (2013)	Communal hunting behavior of African wild dogs. Does not require any parameter other than pack size and termination criteria

Anarchic Society Optimization [5]	H. Shayeghi and J. Dadashpour (2012)	Models the problem in the form of a group of anarchist individuals fickle, adventurous and dislike stability to overcome the trapping in local optima.
Animal Migration Optimization Algorithm [6]	Xiangtao Li, Jie Zhang and Minghao Yin(2014)	Inspired by migration of animals in groups and how they leave a group and join another for survival.
Ant Colony Optimization [7]	A. Colorni, M. Dorigo, V. Maniezzo (1991)	Inspired by the method used by ants to search path between their colony and food source. Ants use pheromone trails to find the best food source. Pheromone evaporates with time, so shorter paths have less time to evaporate and are more attractive.
Ant Lion [8]	S. Mirjalili (2015)	Mimics the hunting behavior of antlions. Models the algorithm based on five basic steps i.e. random searching, building traps, entrapping preys, catching prey and rebuilding trap.
Artificial Algae Algorithm [9]	Sait Ali, Uymaz, GulayTezel and Esra Yel (2015)	Involves evolutionary process, adaptation and helical movement of Algae.
Artificial Bee Colony Algorithm (ABC) [10]	Dervis Karaboga and Bahriye Basturk (2007)	A colony of artificial bees is created having three types of bees namely employed bees, onlooker bees and scouts. These bees communicate with each other to optimize food search around their hive.
Artificial Chemical Reaction Optimization Algorithm [11]	Bilal Alatas (2011)	Models the optimization problem in terms of objects, states, processes and events of a chemical reaction. Uses the natural tendency of chemical reactions to move towards highest entropy and lowest enthalpy.
Artificial Cooperative Search [12]	Pinar Civicioglu (2013)	Mutualism based biological interaction between two living species for mutual benefits.
Artificial Ecosystem Algorithm [13]	Manal T. Adham and Peter J. Bentley (2014)	Property of ecosystem being distributed in many sub-components but to synergize with each other to evolve as a whole.
Artificial Fish School Algorithm [14]	X.L. Li, Z.J. Shao and J.X. Qian (2002)	Method used by fish swarm to search for food and avoid dangers to the colony. Three basic behaviors of fishes are modeled namely prey, swarm and follow.
Artificial Plant Optimization Algorithm [15]	Jun Li, Zhihua Cui and Zhongzhi Shi (2012)	Based on the growing process of plants. There are three operators i.e. photosynthesis operator, phototropism operator and apical dominance to match the actual process of plant growth.
Artificial Searching Swarm Algorithm [16]	T. Chen (2009)	Based on the principles of Bionic Intelligent Optimization algorithm. If an individual member of the population finds a better solution it communicates with the other members and they move towards this solution by one step. If the individual does not receive any peer communication than it moves according to the historical pattern. Still, if it does not find a better solution than it moves randomly.
Atmosphere Clouds Model [17]	Gao Wei Yan and Zhan Ju Hao (2013)	Imitates the generation, moving and spreading behavior of clouds for exploration, movement within and exploitation of the search space
	B	
Backtracking Search Optimization [18]	Pinar Civicioglu (2013)	Has a single control parameter. Trial population is generated using two new crossover and mutation operators. Has a memory to store a random previous generation to assist in search
Bacteria Chemotaxis Algorithm [19]	S.D. Muller, J. Marchetto , S. Airaghi and P. Kournoutsakos, 2002	Survival strategies used by bacteria such as acquiring information from the environment, using this

		information for adapting to the environment and survive.
Bacterial Colony Optimization [20]	Ben Niu and Hong Wang (2012)	Based on development behaviors of Escherichia coli like chemotaxis, communication, elimination, reproduction, and migration.
Bacterial Evolutionary Algorithm [21]	Swagatam Das , Archana Chowdhury and Ajith Abraham (2009)	It is an evolutionary clustering method to partition data sets into optimal number of groups. BEA is inspired by microbial evolution. Uses two special operators i.e. bacterial mutation and gene transfer operation.
Bacterial Foraging Algorithm [22]	K.M. Passino (2002)	Property of natural selection to eliminate individuals with poor foraging strategies such as locating, handling and absorbing food and at the same time favoring the individuals with good foraging strategies.
Bacterial Swarming [23]	Ying Chu, Hua Mi and Huilian Liao (2008)	Combines the foraging process of E-coli from Bacterial Foraging Algorithm and the swarming process of Particle Swarm Optimization. Few new operators like attraction factor and adaptive step length are also incorporated.
Bat Algorithm [24]	Xin-She Yang (2010)	Inspired by echolocation behavior of bats which they use to search directions and location of insects. It also combines the advantages of other nature inspired algorithms
Big bang-big Crunch [25]	Osman K. Erol and Ibrahim Eksin (2006)	Mimics the theory of evolution of the universe the big-bang big-crunch theory. In the big-bang phase particles are randomly distributed and in the big-crunch phase the random particles are arranged in an order.
Biogeography Based Optimization [26]	Dan Simon (2008)	Inspired by geographical distribution of biological organisms. Uses basic operators like migration and mutation
Bird Mating Optimizer [27]	Alireza Askarzadeh (2014)	Imitates the mating strategies used by birds. Methods adopted by bird species to select superior genes is replicated to find optimum solution of continuous optimization functions
Bird Swarm [28]	Xian-Bing Meng, X.Z. Gao, Lihua Lu, Yu Liu & Hengzhen Zhang (2016)	Based on foraging, vigilance and flight behaviors of birds shown in bird swarms.
Black Holes Algorithm [29]	Abdolreza Hatamlou (2013)	Inspired by the black hole phenomenon. At each iteration, the best candidate solution is selected to be the black hole which then attracts all the other solutions (stars) towards it. If a star gets too close to the black hole it merges with the black hole and a new random star is generated.
Blind, Naked Mole-rats Algorithm [30]	Mohammad Taherdangkoo, Mohammad Hossein Shirzadi , Mehran Yazdi and Mohammad Hadi Bagheri (2013)	It is a data clustering algorithm that imitates the social behavior of blind, naked mole rates displayed to search food and protection of their colony.
Brain Storm Optimization [31]	Y. Shi (2015)	Inspired by the brain storming process for problem solution. Introduces two variants BSO-I and BSO-II. Operators like inter-cluster distance and inter-cluster diversity are used to monitor cluster centroids and entropy during iterations.
Bull Optimization Algorithm [32]	Oguz FINDIK, 2015	Modifies the selection process of Genetic Algorithm. Allows only the best individuals to participate in the crossover operation.
Bumble Bees Mating Optimization [33]	F. Comellas and J. Martinez Navarro (2009)	Mimics the colony of insects bumble bees. Correlates fitness of each bumble bee with its life span to eliminate worst bees and retain better solutions.

C		
Camel Algorithm [34]	M. K. Ibrahim, R. S. Ali, (2016)	Inspired by camel's travelling behavior in the desert. Uses several factors and operators like temperature effect, water supply, endurance, visibility, land conditions etc.
Cat Swarm Optimization [35]	Shu-Chuan Chu, Pei-Wei Tsai, and Jeng-Shyang Pan (2006)	Based on the behavior of cats. Has two sub models namely tracing mode and seeking mode. Member solutions are termed as cats. Each cat has an associated velocity for each dimension, a fitness value and a flag representing its mode.
Central Force Optimization [36]	Richard A. Formato (2007)	Models the movement of bodies under gravitational force. Uses the principle that moving bodies moving in space are trapped in close orbits around massive objects which is similar to finding out optimum value of a function.
Charged System Search [37]	A. Kaveh, and S. Talatahari (2010)	A multi-agent model where each agent is termed as a charged particle. Uses the theories of electro-magnetic and gravitational forces. Each charged particle attracts each other based upon its fitness and mutual distance.
Chicken Swarm [38]	Xianbing Meng, Yu Liu, Xiaozhi Gao, Hengzhen Zhang (2014)	Simulates the hierarchical behavior of chicken swarm. Includes roosters, hens and chicks. The swarm is divided into several groups each having a rooster and many hens and chicks. Chickens compete in a specific hierarchical order.
Clonal Selection Algorithm [39]	L.N. de Castro, F.J. von Zuben (2000)	Simulates the method used by the immune system to decide about the basic features of the immune response for an antigenic stimulus. Uses the idea that only the cells that recognize the antigen participate in the response
Cockroach Swarm Optimization [40]	I. C. Obagbuwa and A. O. Adewumi (2014)	Inspired by the cockroaches. Models three basic tendencies of cockroaches namely chase-swarming, dispersion and ruthlessness. Algorithm investigates the specific behaviors of cockroaches like interaction with each other for searching food, making friends, dispersion when in danger and ruthless eating of peers when in need.
Colliding Bodies Optimization [41]	A. Kaveh and V. R. Mahdavi (2014)	Member solutions are termed as bodies in one dimensional space. These bodies then collide with specific velocities. After the collision, the bodies have new velocities. These collisions make the bodies to search for better positions.
Community of Scientist Optimization [42]	Alfredo Milani and Valentino Santucci (2012)	Inspired by the social behavior within community of scientists to share results and arrange funds needed for their research activities. The framework involves competition for research funds, developing communication channels and evolving research strategies.
Consultant-guided Search [43]	S. Iordache (2009)	Based on the direct information exchange model between individuals and real world scenario of people acting based on advice by a consultant.

Coral Reefs Optimization Algorithm [44]	S. Salcedo-Sanz, J. Del Ser, I. Landa-Torres, S. Gil-López, and J. A. Portilla-Figueras (2014)	Models an artificial coral reef. Member solutions are termed as corals that live and reproduce in colonies. Coral choke out other corals for space. This fight combined with other specific characteristics of corals form a meta-heuristic computational process.
Covariance Matrix Adaptation- Evolution Strategy [45]	Nikolaus Hansen, Sibylle D. Müller and Petros Koumoutsakos (2006)	Focuses on reducing the number of generations required for convergence. To compensate the reduced number of generations it uses larger population size. Results in a highly parallel algorithm for distributed systems with large number of processors.
Crystal Energy Optimization Algorithm [46]	X. Feng, M. Ma, and H. Yu (2016)	Inspired by the features like parallelism, openness, local interactivity and self organization of the lake freezing natural activity.
Cuckoo Search Algorithm [47]	Xin-She Yang and Suash Deb (2009)	Inspired by brood parasitic behavior of some cuckoo species and levy flights of some birds and flies.
Cultural Algorithms [48]	Robert G. Reynolds (1994)	A branch of evolutionary algorithms in which there is a knowledge component in addition to the population component. There are different categories of belief space namely Normative knowledge, Domain specific knowledge, Situational knowledge, temporal knowledge and spatial knowledge.
Cuttlefish Algorithm [49]	Adel Sabry Eesa, Adnan Mohsin Abdulazeez Brifcani and Zeynep Orman (2013)	Inspired by the strange property of cuttlefish to change its skin color. The operator “reflection” simulates the reflection mechanism used by the cuttlefish skin while visibility operator simulates visibility pattern used by cuttlefish.
	D	
Dialectic Search [50]	S Kadioglu, Meinolf Sellmann (2009)	Hegel and Fichte’s dialectic search has been implemented as a search metaheuristic for constraint optimization. The mental concept of dialectic has been implemented for balance in exploitation and exploration.
Differential Evolution [51]	Storn, R.; Price, K. (1997)	This is one of the highly used nature inspired algorithms. Models the reproduction system where chromosomes exchange information to generate better off-springs. Models operators like mutation and crossover.
Differential Search Algorithm [52]	P. Civicioglu (2012)	Provides a model to transform geocentric coordinates into geodetic coordinates. The algorithm has been compared with ABC, JDE, CMA-ES etc. to prove its superiority in terms of robustness and convergence speed.
Dolphin Echolocation [53]	A. Kaveh, N. Farhoudi (2013)	According to some beliefs dolphins are just next to humans in intelligence. Models the sonar like echolocation capabilities of dolphins. The algorithm also uses less number of parameters.
Dolphin Partner Optimization [54]	Y Shiqin, J Jianjun, Y Guangxing (2009)	Models the intelligent behavior of dolphins. Simulates their Cluster forming, role recognition, communication, follow and leadership characteristics. Uses an operator named nucleus.
Dragonfly Algorithm [55]	S. Mirjalili (2016)	Exploration and exploitation are inspired by social behavior of dragonflies while they search food, navigate and avoid enemies in a swarm. Separate binary and multi-objective versions of the algorithm are also designed.
	E	

Eagle Strategy [56]	X.S. Yang, S. Deb (2010)	It is a two stage hybrid search method combining random search of levy flights with the fire fly algorithm.
Eco-inspired Evolutionary Algorithm [57]	R.S. Parpinelli, H.S. Lopes (2011)	Models several populations and members of each population modify themselves according to the search strategy and parameter settings. Uses the environment, relationships and successions of ecology as inspiration.
Egyptian Vulture Optimization [58]	Chiranjib Sur, Sanjeev Sharma, and Anupam Shukla (2013)	Inspired by natural behaviors and key skills of Egyptian vultures when they search for food. Primarily designed for combinatorial optimization problems.
Electro-magnetism Optimization [59]	Erik Cuevas, Diego Oliva , Daniel Zaldivar, Marco Pérez-Cisneros, Humberto (2012)	Based on electro-magnetic principle of collective attraction and repulsion to find the optimum solution. Fitness of each member is modeled as charge over the particle. The algorithm has been implemented for circle detection problem of digital image processing.
Elephant Herding Optimization [60]	Gai-Ge Wang, Suash Deb, Leandro dos S. Coelho (2015)	Inspired by herding behavior of elephants. Two elephant herding activities leadership by a matriarch and adult male elephants leaving the group are simulated as two operators namely clan updating operator and separating operator respectively.
Elephant Search Algorithm [61]	Suash Deb, Simon Fong, and Zhonghuan Tian (2015)	Members of population are termed as elephants of a herd. Male members are search agents to explore the space while female members are local search agents to exploit the search space locally.
Evolution Strategy [62]	Rechenberg & Schwefel (1965)	One of the oldest categories of strategies under evolutionary computational concept. Based on the basic idea to initialize with a set of values and step by step changing them slightly with randomness. If the changed set is better than to keep it otherwise to discard it and keep the previous one.
Evolutionary Programming [63]	David B. Fogel, Lawrence J. Fogel (1966)	One of the foundation approaches of most of the modern evolutionary computing methods. Defined most of the operations like mutation and crossover. Implemented it on finite state machine
Exchange Market Algorithm [64]	N. Ghorbani, E. Babaei (2014)	Based on trading mechanism of shares in the stock market. Algorithm runs in two modes. The first mode has oscillations while the second mode does not have oscillations. At the end of each mode the fitness of all the members is calculated. These two rounds enable exploration and exploitation of the search space respectively. Algorithm uses two searching operators and two absorbent operators.
F		
FIFA World Cup [65]	N. Razmjooy, M. Khalilpour, M. Ramezani (2016)	Simulates the competition method followed in sports competitions like the soccer world cup of FIFA. It has a number of parameters that have been formulated in line of the FIFA world cup.
Firefly Algorithm [66]	Xin-She Yang (2009)	Mimics the flashing light property of fireflies. Models the members of population as a set of fireflies where each firefly gets attracted by another in the magnitude of its light intensity and mutual distance. Fitness of a member is denoted as light intensity.

Fireworks Algorithm [67]	Y. Tan, Y. Zhu (2010)	Simulates the explosion of fire crackers. Two separate methods for explosion are adopted for maintaining global and intensive search processes.
Fish-school Search [68]	Carmelo J. A. Bastos Filho , Fernando B. de Lima Neto, Anthony J. C. C. Lins, Antonio I. S. Nascimento, Marilia P. Lima (2008)	Fish schools are large groups of fishes that stay together to increases their chances of survival by mutual cooperation. Derives three operators based upon the behavior of fishes in the fish school namely feeding, swimming and breeding.
Flower Pollination Algorithm [69]	Xin-She Yang (2012)	Based on the pollination process used for reproduction by plants having flowers. Algorithm uses a model for pollination where pollinators are used to spread the pollens over the landscape.
Flying Elephants Algorithm [70]	Adilson Elias Xavier, Vinicius Layter Xavier (2016)	The algorithm is a generalization of hyperbolic smoothing approach. Though the algorithm does not mimic any biological property of elephants and provides just a method to flight of functions referred as heavy elephants.
Forest Optimization Algorithm [71]	Manizheh Ghaemi, Mohammad-Reza Feizi-Derakhshi (2014)	Algorithm mimics the seeding process of trees in a forest. It models the observation that seeds under the tree may not grow up while the seeds dispersed away from the tree itself may grow up as trees.
Fruit Fly Optimization Algorithm [72]	W. T. Pan (2012)	Inspired by the behavior of fruit flies. Mainly the algorithm mimics the foraging skills of fruit flies.
	G	
Galaxy-based Search Algorithm [73]	Hamed Shah-Hosseini (2011)	Mimics the spiral arms of spiral galaxies to explore the search space. Chaos is used to get rid of local optimums. A local search component is also embedded to balance the result obtained by spiral arm.
Gases Brownian Motion Optimization [74]	M. Abdechiri, M.R. Meybodi, H. Bahrami (2013)	Inspired by Gases Brownian motion and turbulent rotational motion. The search method is based upon the dynamics of gas molecules under pressure.
Gene Expression Programming [75]	C. Ferreira (2002)	A complete genotype phenotype system in the sense that it has linear structures of fixed length chromosomes. All of the operators like mutation, transposition and recombination results in valid off-springs.
General Relativity Search Algorithm [76]	Hamzeh Beiranvand, Esmaeel Rokrok (2015)	Based on the concept of General Relativity Theory. Members of population are modeled as particles in space free from all other forces other than gravity. The particles are then projected to reach the most stable position. Particles move in geodesic path. Step size and directions are calculated using velocity and geodesics.
Genetic Algorithm [77]	David E. Goldberg (1989)	Foundation for many evolutionary algorithms. It is the basis for even the older algorithms like DE. Simulated the natural process of evolution like Selection, Mutation and Crossover
Glowworm Swarm Optimization [78]	K. N. Krishnanand and Debasish Ghose (2009)	This method is specifically designed for parallel searching in multiple optimums of a multimodal function. The search agents model the glowworms that possess luminescence called luciferin. Fitness of each glowworm is encoded as luciferin. Each glowworm uses a probability function to move towards another glowworm that has luciferin value higher than its own.
Golden Ball [79]	E. Osaba, F. Diaz, E. Onieva (2014)	Simulated as a soccer game where population is divided into multiple teams who search independently

		and compete with each other. This competition decides about the transfer of solutions among teams.
Good Lattice Swarm Algorithm [80]	Shoubao Su, Jiwen Wang, Wangkang Fan, Xibing Yin (2007)	Good lattice is a random search method based on number theory using hidden parallel evolutionary algorithms and random sampling. Good Lattice Swarm algorithm is a combination of Good Lattice and Particle Swarm Optimization to include the features of both.
Grasshopper Optimisation Algorithm [81]	Shahrzad Saremi, Seyedali Mirjalili, Andrew Lewis (2017)	Models the optimization problems as swarm of grasshoppers. Swarming behavior in grasshoppers is found in both nymph and adulthood. The algorithm models the larval stage as well as the adult stage. Young grasshoppers move slowly with small step size while adult swarms move abruptly with large step size.
Gravitational Search Algorithm [82]	B. Webster and P.J. Bernhard (2003)	The algorithm starts searching at an arbitrary point and keeps repairing the solution repeatedly by modifying some of its search agents. For repairing process is inspired by the motion of a mass under influence of gravitational force applied by other bodies.
Great Deluge Algorithm (and Record-to-record Travel) [83]	G. Dueck (1993)	It is an algorithm with only one parameter. Initially one set of values is chosen then each step slightly changes the values and fitness is compared with the previous one. If the new fitness value is better than the new set of values is treated as the old values.
Great Salmon Run [84]	A. Mozaffari, A. Fathi, S. Behzadipour (2012)	The Great Salmon Run is a natural annual event in which millions of salmon fishes return from pacific ocean to the streams of North America where they were born. Grizzly bears of North America also depend upon this event for their survival. The algorithm simulates this event as a population based optimization method.
Greedy Politics Optimization [85]	J.M.L. Melvix (2014)	Inspired by the methods adopted by the politicians to win elections and form government. Surprisingly, the algorithms works better when the parameters related to unfair means used by the politicians are set.
Grenade Explosion Method [86]	Ali Ahrari and Ali A. Atai (2010)	Modeled like the way of explosion of a grenade. Uses the concept that the shrapnel damage the locality of the explosion. Loss caused by each shrapnel is calculated and next grenade is targeted at the place maximum damage occurred in the previous explosion.
Grey Wolf Optimizer [87]	Seyedali Mirjalili, Seyed Mohammad Mirjalili, and Andrew Lewis (2014)	Inspired by the hierarchical leadership approach and hunting methods of grey wolves. It has implemented three main methods of hunting strategies of grey wolves namely searching, encircling and attacking.
Group Counseling Optimization [88]	M.A. Eita and M. M. Fahmy (2010)	Emulates the problem solving behavior of humans by counseling. The iterations of the algorithm are termed as counseling sessions where members improve their positions by either self or group counseling.
Group Search Optimizer [89]	S. He, Q.H. Wu, J.R. Saunders (2009)	Mimics the group searching behavior shown by many animals. Based on producer-scrounger model where animals search either for new food source (producer) or an already engaged food source (scrounger).
	H	
Harmony Search [90]	Zong Woo Geem, Joong Hoon Kim, and G. V. Loganathan (2001)	Harmony is a relationship between various sound waves of different frequencies. Best harmony is the one which provides best aesthetic experience to the

		listener. The algorithm draws similarity between finding harmony in a musical performance and finding the optimum solution to an optimization problem.
Heart [91]	Abdolreza Hatamlou (2014)	The algorithm models the optimization problem as heart and circulatory system. The member of the population with best fitness is termed as heart and other members are called blood molecules. The blood molecules are moved towards or away the heart to search for a better fitness point.
Hierarchical Swarm Model [92]	Hanning Chen, Yunlong Zhu, Kunyuan Hu and Xiaoxian He (2010)	The model suggests a hierarchical approach for swarm based optimization algorithms. It suggests that an agent in the higher level of hierarchy may be composed of a swarm of lower level agents and different swarms from different levels evolve on different scales.
Honey-bees Mating Optimization Algorithm [93]	H.A. Abbass (2001)	Honey bees exhibit special characteristics in terms of communication, cooperation and division of work. The algorithm simulates marriage in honey bees. It simulates a bee colony with a single bee without a family and evolves in a colony of one or more queens with family.
Hoopoe Heuristic Optimization [94]	Mohammed El-Dosuky, Ahmed El-Bassiouny, Taher Hamza, and Magdy Rashad (2012)	Search agents are termed as hoopoes (a bird). Only one hoopoe is allowed to explore the landscape using Levy flights. The hoopoes penetrate the landscape by digging a bill to look for food such as insects. If the search results are good then the neighborhood of the current dig is to be explored.
Human-inspired Algorithm [95]	L.M. Zhang, C. Dahlmann, Y. Zhang (2009)	The algorithm mimics the search methods adopted by mountaineers to find the highest mountain peak using modern facilities like binoculars and phones. The unique feature of the method is that it divides the search space into equal subspaces and deploys equal number of search agents in each subspace.
Hunting Search [96]	R. Oftadeh , M. J. Mahjoob (2009)	Mimics the hunting behaviors of animals like lions, wolves and dolphins. Algorithm imitate the hunting method in which the hunting animals search for prey in a group, encircle it and gradually tighten the encircling ending up to catch the prey.
	I	
Imperialist Competitive Algorithm [97]	Esmaeil Atashpaz-Gargari and Caro Lucas (2007)	The members of population are termed as countries. Initial population of countries is divided into two parts imperialists and colonies forming several empires. During the iterations, weak empires fall and strong ones take control of their colonies. Convergence is the state in which there is only one empire and all the colonies have the fitness similar to it.
Intelligent Water Drops Algorithm [98]	Hamed Shah-Hosseini (2009)	The algorithm is based upon the property of rivers to find out optimum path between source and destination. It models the action and reaction between water drops and river bed. Intelligent water drops are the search agents that cooperate to find out optimum solution.
Interior Design and Decoration [99]	A.H. Gandomi (2014)	An optimization method inspired by interior design and decoration. Constitute two search methods namely composition optimization and mirror search. Three different strategies are introduced for tuning the only parameter for the algorithm.

Invasive Tumor Growth Optimization Algorithm [100]	D Tang, S Dong, Y Jiang, H Li, Y Huang, (2015)	Based on the growth mechanism of an invasive tumor. In an invasive tumor each cell fights for nutrient for its survival and growth. For the working of the algorithm, the cells are divided into three categories namely proliferative cells quiescent cells and dying cells. Then the cells move in the space to improve their fitness. This movement depends upon chemotaxis, random walk and communication among cells
Invasive Weed Optimization [101]	A.R. Mehrabian, C. Lucas (2006)	The algorithm is inspired by weed colonies. Weed colonies are vigorous in growth and poses a threat to the desirable plants. Weeds are also adaptable to environmental changes. The properties of robustness, randomness and adaptation are modeled as a numerical optimization method.
Ions Motion Algorithm [102]	B. Javidy, A. Hatamlou, S. Mirjalili (2015)	The algorithm is inspired by natural phenomenon of motion of ions. Simulates the attraction and repulsion of anions and cations. Population is divided into two sets of positive and negative ions. Ions are relocated in the search space based on the principle that ions with opposite charge attract each other and with same charge repel each other.
	J	
Jaguar Algorithm with Learning Behavior [103]	Chin-Chi Chen, Yung-Che Tsai, I-I Liu, Chia-Chun Lai, Yi-Ting Yeh, Shu-Yu Kuo, Yao-Hsin Chou (2015)	Inspired by the hunting behavior of jaguars. Once a jaguar identifies its prey it moves swiftly and directly to the target. Jaguars also use to hunt as teams. Algorithm mimics the hunting characteristics of jaguar to balance the exploitation and exploration of the search.
Japanese Tree Frogs Calling [104]	H. Hernández, C. Blum (2012)	Based on calling behavior of Japanese tree frogs. Male frogs call to attract the females. Different groups of male frogs located in the same area avoid calling at the same time to try and make the female frogs able to locate them. The algorithm uses this desynchronization approach for graph coloring
	K	
Kaizen Programming [105]	V. V. Melo (2014)	Kaizen is a Japanese approach of problem solving. Unlike other evolutionary approaches where each agent is a complete solution, in this approach, each expert suggests an idea to solve the problem and the final solution is composed of all the ideas put together. Each idea's fitness is measured by its contribution to the final solution.
Keshtel Algorithm [106]	M. Hajiaghaei-Keshteli, M. Aminnayeri (2014)	Keshtel algorithm has been used for mathematical modeling of the assembly line and transportation scheduling problem. Performance improvement has been done using the Taguchi approach. In addition, Genetic Algorithm has also been implemented.
Krill Herd [107]	Amir Hossein Gandomi and Amir Hossein Alavi (2012)	Based on the herding behavior of krill. Members of population are modeled as krill individuals of a herd. Objective function for each individual's movement depends upon its distance from the food and from the highest density of the herd. The movement is also affected by presence of other members, foraging and randomness.
	L	

League Championship Algorithm [108]	Ali Husseinzadeh Kashan (2009)	Based on the competition of teams in a sports league. Search agents are termed as teams who compete for several weeks (iterations). This competition is in pairs and the winner is one with better fitness value. At the end of each iteration, all the teams apply necessary changes and prepare for the next week.
Lightning Search Algorithm [109]	H. Shareef, A.A. Ibrahim, A.H. Mutlag (2015)	Inspired by the natural phenomenon of lightening. A concept of projectiles is used to update population. Three types of projectiles are used namely step leader projectile, space projectile and lead projectile. The exploration of the search space is performed using exponential random behavior of space projectiles.
Lion Optimization Algorithm [110]	Maziar Yazdani and Fariborz Jolai (2016)	Motivated by social and cooperative behavior of lions. Lions reside in two categories residents and nomads. A pride consists of around five female lions and their cubs of both genders called residents. Adult male lions leave the pride and move freely. Residents are modeled as agent for local intensive search while nomads represent agents to explore search space.
Locust Swarms [111]	Stephen Chen (2009)	Inspired by locust swarms, the algorithm starts with smart initial points. Then it uses PSO and a greedy local search method to explore the search space. The scouts (search agents) start with a minimum distance from previous optimum.
	M	
Magnetotactic Bacteria Optimization Algorithm [112]	Hongwei Mo and Lifang Xu (2013)	Magnetotactic bacteria (MTB) have developed a capability to orient and swim along the geomagnetic field. The concept of the algorithm is that only the MTBs with magnetosomes which can divert the magnetic field to minimize their magnetic energy can survive. MTBs need to maximize their swimming efficiency to find optimum oxygen levels and survive.
Migrating Birds Optimization [113]	Ekrem Duman, Mitat Uysal, Ali Fuat Alkaya (2011)	Based on the "V" formation used by birds to minimize energy when they migrate. Birds need to maintain the air pressure above their wings lower than the air pressure below their wings. The V formation helps them reduce the energy required to maintain this air pressure constraint.
Mine Blast Algorithm [114]	Ali Sadollah, Ardeshir Bahreininejad, Hadi Eskandar, Mohd Hamdi (2012)	Based on the real world event of a mine blast. A number of shrapnel are spread in an explosion. Each piece of shrapnel may trigger a new blast. The shrapnel piece that created the maximum damage is selected to explode the new mine.
Monarch Butterfly Optimization [115]	G. Wang, S. Deb, Z. Cui (2015)	Modeled on the migration of monarch butterflies from North America and South Canada Mexico in the summers. Initially all the butterflies (search agents) are situated in one of the two land i.e. North America and Mexico. Then, migration operator generates new off-springs which are updated using migration ratio.
Monkey Search [116]	Antonio Mucherino and Onur Seref (2007)	Mimics the way monkeys climb trees in search of food. Tree branches represent perturbations between two probable food sources. Monkeys as search agents mark and later update these branches when they climb the tree up and down.
Moth-flame Optimization Algorithm [117]	Seyedali Mirjalili (2015)	Inspired by the travel methods of moths. Moths use to fly at night keeping a fixed angle with the moon to travel in straight line for long distances. Local optima

		are modeled as artificial lights that trap the moths in useless spiral distractions.
Multi-verse Optimizer [118]	S. Mirjalili, S. M. Mirjalili, A. Hatamlou (2015)	Based upon three major theories of Cosmology namely Black hole, White hole and Warm hole. All three have been mathematically modeled to perform exploration, exploitation and local search respectively.
	O	
Optics Inspired Optimization [119]	A.H. Kashan (2015)	A concave mirror converges the incident light rays where as a convex mirror scatters the light. The optical phenomenon has been modeled as an optimizer. The algorithm treats the surface of the search space as a reflecting mirror in which each peak works as convex mirror and each valley works as a concave mirror.
	P	
Paddy Field Algorithm [120]	U. Premaratne, J. Samarabandu, T. Sidhu (2009)	The algorithm starts with scattering the seeds (search agents) randomly. After that the number of seeds generated by each plant depends upon the fitness value. The plant with better fitness will produce more seeds. Further, seeds with better fitness only will be allowed to grow. All plants dissipate seeds to overcome local optimum.
Parliamentary Optimization Algorithm [121]	A. Borji (2007)	Simulates the intra and inter group competitions similar to those used in a parliament. All members are divided into some groups randomly. Members of a party belong to either regular or candidate category. A candidate is chosen as the leader of the group who competes with the leaders of other groups in the next round.
Particle Swarm Optimization [122]	R. Eberhart, J. Kennedy (1995)	One of the most popular metaheuristic. Each search agent (particle) keeps information about the best position it has gained so far. The global best value is also kept track of. In each step a particle is moved towards the best particle with a changed velocity and added randomness.
Pattern Search [123]	R. Hooke, T. A. Jeeves (1961)	It is a class of optimization methods derived from the approach introduced by Hooke and Jeeves in 1961. This category of methods need only to return the value of $f(x)$ for some point x. It was also called direct search or black box search. It performs local and global search by its two steps namely Exploratory Search and Pattern Move.
Penguins Search Optimization Algorithm [124]	Y. Gheraibia, A. Moussaoui (2013)	Based upon the cooperative behavior of penguins shown while they hunt. Each penguin starts search process from its own locality and inform about its position and fishes found to the other members of the group. The global best is selected by identifying the group that hunted most fishes.
Photosynthetic Learning Algorithm [125]	Haruhiko Murase, Akira Wadano (1998)	Uses the Benson-Calvin cycle which governs the conversion of carbon molecules from one substance to another during the process of photosynthesis in pants. The algorithm has been implemented to solve Travelling Salesman Problem.
Plant Growth Optimisation [126]	Wei Cai, Weiwei Yang and Xiaoqian Chen (2008)	Inspired by plant growth process, the algorithm proposes an artificial plant growth model. Specific

		operators include leaf growth, branching, phototropism and spatial occupancy.
Plant Propagation Algorithm [127]	Abdellah Salhi, Eric S Fraga (2011)	It is based on the observation that plants scatter their runners in the areas full of nutrients and light. If such good spot is away from its location it sends long runners and if the plant itself is at a good spot it will send short runners in high concentration.
POPMUSIC: Partial Optimization Metaheuristic Under Special Intensification Conditions [128]	Éric D. Taillard, Stefan Voss (2001)	The methodology is to divide a problem into subparts and iteratively optimize each of them locally. Thus the global solution found will also be optimized. The algorithm can be seen as a local optimizer working in a large neighborhood.
	Q	
Queen-bee Evolution [129]	S.H. Jung (2003)	Based on the concept that only the queen bee is the parent of most of the bees in a bee colony. In the algorithm, the fittest bee crossbreeds with other bees selected by the algorithm. Though this increases the exploitation but at the same time increase the chances of trapping into local optima. To avoid this, few members of population undergo strong mutation.
	R	
Raven Roosting Optimization Algorithm [130]	Anthony Brabazon, Wei Cui, Michael O'Neill (2014)	Inspired by the social roosting behavior of raven (a bird). A number of species specially birds display the behavior of social roosting. These social roosts work as centers for information exchange among the members about food sources and nearby threats.
Ray Optimization [131]	A. Kaveh and M. Khayatazad (2012)	Models the refraction property of light rays. Search agents are termed as rays. When the ray travels from lighter medium to denser or vice versa its direction changes. This change in the direction enables to explore in the early stage of the algorithm and later to converge.
Reincarnation [132]	A. Sharma (2010)	Inspired by the religious belief of rebirth of a human soul with a different biological entity. All the humans (search agents) are divided into two categories namely gurus and commoners. Gurus are the ones having higher fitness value. All the humans may be upgraded or degraded depending upon their deeds. All the commoners get influenced by their gurus.
River Formation Dynamics [133]	P. Rabanal, I. Rodríguez, F. Rubio (2007)	Designed to solve travelling salesman problem in general. Improves the shortcomings of Ant Colony Optimization. Nodes are assigned altitude values. Drops either increase or decrease the altitudes of the edges as they move. Probability of a drop to take an edge depends upon the slope of the edge.
Roach Infestation Optimization [134]	Timothy C. Havens, Christopher J. Spain, Nathan G. Salmon and James M. Keller (2008)	Mimics the collective and individual behavior of cockroaches. Cockroaches try to search the darkest place; fitness of a cockroach is proportional to the darkness of its location. They communicate with each other with a predefined probability. At a certain point in time, cockroaches leave the comfortable darkness and search for food.
Root Growth Optimizer [135]	Xiaoxian Hea , Shigeng Zhang , Jie Wang (2015)	Inspired by the growth mechanisms of plant roots, mainly self-similar propagation and optimization of continuous space search. Also models the concept that

		different roots adopt different strategies according to their roles.
Rooted Tree Optimization Algorithm [136]	Yacine Labbi, Djilani Ben Attous, Hossam A. Gabbar, Belkacem Mahdad, Aboelsood Zidan (2016)	Mimics the growth process of plant roots. The optimized solution is modeled as wet soil and the roots grow in the direction of wet soil. One root grows in the direction of current best soil, another in the direction of previous best soil and one more root grows in a random direction to search a new wet place.
Runner-root Algorithm [137]	F. Merrikh-Bayat (2015)	Models the purpose of runners and roots of plants. Runners help them search in a wide area with large steps while roots assist in search in nearby small area. Similarly, the algorithm has two functions matching the runners and roots for exploration and exploitation respectively.
	S	
Saplings Growing Up Algorithm [138]	Ali Karci, Bilal Alatas (2006)	Inspired by sowing and growing up of saplings. The algorithm contains two phases: sowing phase and growing-up phase. Uniform sowing aims to evenly distribute the search agents in the space. Growing up phase contains three operators: mating, branching and vaccinating.
Scatter Search [139]	F. Glover(1977)	Different from other evolutionary algorithms because it is based on the concept of systematic methods to create new solutions that yields several benefits over randomization. Uses systematic methods for diversification and intensification of the search process.
Scientific Algorithms for the Car Renter Salesman Problem [140]	D. Felipe, E. Goldbarg, and M. Goldbarg (2014)	Mimics the methodology of scientific research. Uses the idea of theme to search the space. Steps of research that imitates the blocks of the algorithm are thinking, knowledge sharing and disclosing ideas.
Seven-spot Ladybird Optimization [141]	Peng Wang, Zhouquan Zhu, and Shuai Huang (2013)	Based on the foraging behavior of the seven-spot ladybird (an insect). Whole search space is divided into equal subspaces in each dimension called patches. Each seven-spot ladybird improves its fitness by moving towards either the best in the patch or the global best.
Shark Smell Optimization [142]	Oveis Abedinia, Nima Amjady, and Ali Ghasemi (2014)	Sharks are one of the cleverest hunters. The algorithm is inspired by the smelling capabilities of the shark. The mathematical steps of the algorithm imitate the intelligent behavior of shark used by it to find the source of smell in the oceanic environment.
Sheep Flocks Heredity Model [143]	Hyunchul Kim and Byungchul Ahn (2001)	Mimics sheep flocks. Based on the concept that sheep generally live and reproduce within their flock allowing the biological inheritance from within a flock only. But occasionally, sheep from different flocks meet to reproduce and propagate better qualities.
Shuffled Frog Leaping Algorithm [144]	Eusuff and K.E. Lansey (2003)	Mimics the cooperative behavior of frogs displayed while they search for food in a swamp. Frogs are distributed into few groups. Each frog moves towards either the best frog of the group or the global best frog. At the end of each iteration, all the groups are merged and distributed again.
Simplex Heuristic [145]	J.P. Pedroso (2007)	An extension of Nelder and Mead simplex algorithm which is applicable for non-linear problems also. A

		number of methods are suggested to jump out from the local optima. Uses large simplex at initialization and large moves initially.
Simulated Annealing [146]	S. Kirkpatrick, D. Gelatt Jr., and M. P. Vecchi, (1983)	Inspired by the heating and cooling of metals. “Temperature” is the most important parameter of the algorithm. It is usually decreased by some predefined factor at the end of each iteration.
Small-world Optimization Algorithm [147]	H Du, X Wu, J Zhuang (2006)	Based on some scientific experiments performed by psychologists on the communication and networking methods of human beings. Uses “local short-range searching operator” and “random long-range searching operator” for local and global searching respectively.
Soccer Game Optimization [148]	H.D. Purnomo, H.-M. Wee (2012)	The algorithm combines information sharing and evolution operators from swarm intelligence and evolutionary algorithms respectively. Move off and move forward activities of a soccer player are used to describe the steps of the algorithm.
Social Cognitive Optimization [149]	Xiao-Feng Xie, Wen-Jun Zhang, Zhi-Lian Yang (2002)	Based on the knowledge and intelligence development in humans. Utilizes the belief that humans learn by observing others and by looking the outcome of others’ efforts. Takes personal, behavioral and environmental factors into account.
Social Emotional Optimization [150]	Y. Xu, Z. Cui, J. Zeng (2010)	Emulates the efforts by human beings to acquire higher social status. Members of population are termed as human beings living in a society. Each member tries to increase its emotional index. Based on this emotional index and the feedback from the other members of society, social status keeps updating. At the end, the individual with highest social status is the optimum solution.
Social Spider Algorithm [151]	Erik Cuevas, Miguel Cienfuegos, Daniel Zaldívar , Marco Pérez-Cisneros (2013)	Emulates the cooperative behavior of individual spiders in a colony. The search agents are termed as spiders. There are two categories of spiders; male and female. Both of them have separate rules to update their position and communicate depending upon the
Society and Civilization [152]	Ray, Tapabrata, and Kim Meow Liew (2003)	Based on the concept that social communication plays an important role in development of species along with the biological evolution. Simulates intra-society and inter society communications.
Sperm Motility Algorithm [153]	Raouf, Hezam (2017)	Based on the human reproduction system. The search agents (sperms) are randomly distributed in the search space. Random movement of the sperm in search of the ovum has been modeled using Stokes equations. A chemical secreted from the ovum attracts the sperms towards the optimum solution.
Sperm Whale Algorithm [154]	A. Ebrahimi, E. Khamehchi (2016)	Sperm whale is the largest toothed predator. It has many unique features evolved to survive and develop the oceanic conditions. The most outstanding feature of the algorithm is that it uses best as well as worst point to reach to global optima.
Spider Monkey Optimization [155]	Jagdish Chand Bansal, Harish Sharma, Shimpi Singh Jadon, Maurice Clerc (2014)	Inspired by the foraging behavior of spider monkeys. Spider monkeys follow fission-fusion based social structure. They alter the size of groups from smaller to larger or vice-versa depending upon the quantity of food available.
Spiral Dynamics Inspired Optimization [156]	K. Tamura, K. Yasuda (2011)	Inspired by the spiral phenomenon frequently found in nature. Many natural constructs like galaxies,

		cyclones, whirlpools observe such motion. The algorithm uses multidimensional spiral to search the space. There are control parameters to balance diversification and intensification.
Stochastic Diffusion Search [157]	Bishop, J.M. (1989)	Based on “The Restaurant Game” in which a group of delegates in a new town search for the best restaurant to dine. In the algorithm, a member shares its fitness with another member via direct one-to-one communication and the better one is selected. In the end, a cluster wise best solution is available.
Stochastic Fractal Search [158]	H. Salimi. (2015)	Imitates the natural phenomenon of growth called fractal. Each particle is assumed to possess an electric charge. Then this particle diffuses and few new particles are created. The charge is divided among these child particles. Unfit particles keep being discarded in each generation.
Strawberry Algorithm [159]	F. Merrikh-Bayat (2014)	Inspired by the functioning of runners and roots of strawberry plant. Runners mimic the exploration while roots mimic local search. The algorithm is different from others in the sense of duplicate elimination, both small and large step sizes for all agents and lack of communication between agents.
Swallow Swarm Optimization Algorithm [160]	Mehdi Neshat, Ghodrat Sepidnam (2013)	Imitates the movement and other cooperative behaviors of swallow swarms. The particles are divided into three categories namely explorer, aimless and leader. Influence of neighbor, local leader and global leader is modeled while moving in the search space.
Symbiotic Organisms Search [161]	M.Y. Cheng, D. Prayogo, (2014)	Mimics the symbiotic cooperation methods adopted by two distinct species to survive in the nature. This cooperation may be obligate or facultative. The algorithm iteratively performs Mutualism, communism and parasitism phases representing the types of symbiotic relationships.
	T	
Tabu Search [162]	Fred Glover (1986)	An extension of local search used in mathematical optimization. The algorithm enhances the local search by modifying its basic rule. The first modification is: at each step a worse solution is also acceptable if no better solution is found. Second: discouragement to search at a previously visited location.
Teaching-learning based Optimization [163]	R. V. Rao, V. J. Savsani, D. P. Vakharia (2011)	Based on the teacher-learner relationship. Members of population are termed as a class of learners. Search process consists of two phases. In the first phase learning is done by teacher’s influence while, in the second phase learners learn by mutual interaction.
Termite Colony Optimization [164]	Ramin Hedayatzadeh, Foad Akhavan Salmassi, Reza Akbari, Koorush Ziarati (2010)	Inspired by the methods used by termites to adjust their search paths. Although termites move randomly in the search space but their search trajectories are influenced by directions of more pheromones.
	V	
Viral Systems [165]	Cortés P., García J.M., Muñuzuri J. and Onieva L0 (2008)	Designed for combinatorial optimization. Mimics the specific features of viruses like replication and infection of the host environment. Application has been shown on series of Steiner problem.

Virus Colony Search [166]	Mu Dong Li, Hui Zhao, Xing Wei Weng, Tong Han (2016)	Virus colony or viral plaque is a structure formed in a cell structure such as bacterial colony. They can be detected visually using colony counters. Like other virus based algorithms, this algorithm also simulates the diffusion and propagation strategies adopted by viruses to infect the host.
Virus Optimization Algorithm [167]	Chia Liang, Josue Rodolfo Cuevas Juarez (2016)	Imitates the virus infection of a living cell. To model exploration and exploitation, the algorithm defines two categories of viruses as strong and common viruses. Interaction is allowed between only those viruses that can co-exist.
Vortex Search Algorithm [168]	B. Dogan, T. Olmez (2015)	A single solution based metaheuristic. Inspired by the vertical flow pattern of fluids. To balance the exploitation and exploration of the search, the algorithm uses the scheme of adaptive step size.
	W	
Wasp Swarm Optimization [169]	P Pinto, TA Runkler, JM Sousa (2005)	Imitates the social behavior of wasps that they exhibit while foraging and caring of their broods. Using cooperation, wasps efficiently manage all the tasks without any predefined planning. They do have a hierarchy of members within a colony. The algorithm has been designed specifically with reference to logistics system optimization.
Water Cycle Algorithm [170]	Hadi Eskandar, Ali Sadollah, Ardeshir Bahreininejad, Mohd Hamdi, (2012)	Imitates the natural process of water cycle. Rains bring water to surface and rivers take it back to the oceans. Specifically, it models how rivers and streams link and proceed towards sea.
Water Evaporation Optimization [171]	A. Kaveh and T. Bakhshpoori (2016)	The algorithm is based on the evaporative properties of water molecules from solid surfaces with different wettabilities. Water molecules are considered as members of population and the solid surface as search space. Wettability of the surface along with other molecular properties is coded as different search parameters.
Water Wave Optimisation [172]	Y.J. Zheng (2015)	Based on the shallow water wave theory. Various operators like propagation, refraction and breaking have been implemented inspired by the phenomena of water flow.
Water-flow Algorithm [173]	Trung Hieu Tran, Kien Ming Ng (2011)	The algorithm is inspired by hydrological cycle and natural phenomenon of erosion. The erosion capacity has been made scalable by using variable precipitation and falling force. This helps in guiding the search towards promising region.
Whale Optimization Algorithm [174]	Seyedali Mirjalili and Andrew Lewisa (2016)	Inspired by the social behavior of humpback whales. The algorithm consists of three steps, each inspired by the habitual behaviors of whales. These steps are Encircling prey, Bubble-net attacking method (Exploitation step) and Search for prey (Exploration step).
Wind Driven Optimization [175]	Zikri Bayraktar, Muge Komurcu, and Douglas H. Werner (2010)	Imitates the natural phenomenon of wind in which it blows from higher to lower pressure. Models various factors that affect the motion of wind like air pressure, friction, gravitational force and coriolis force (caused by the rotation of the earth).
Wolf Search Algorithm [176]	Rui Tang, S. Fong, Xin-She Yang, and S. Deb (2012)	Inspired by the way wolves search for food and survive the dangers around their habitat. Each agent searches independently and keeps its previous

		positions in its memory. It merges with any other agent only when it finds it better than all of its previously visited points.
Worm Optimization [177]	J.P. Arnaout (2014)	Mimics the unique biological features of Caenorhabditis elegan, a nematode having only 302 neurons. Mimics its various properties like searching food, avoiding toxins, foraging, balance between searching and dwelling food etc. Has been successfully applied on Travelling Salesman problem.
	Z	
Zombie Survival Optimization [178]	Hoang Thanh Nguyen, Bir Bhanu (2012)	Based on the hypothetical foraging behavior of zombies. Models the optimization problem in an environment where zombies search for an air born antidote which can cure and turn zombies back into humans. Defines three modes for search agents namely exploration mode, human mode and hunter mode.

III. Conclusion

This paper is an attempt to provide the list of concepts that are basis for many metaheuristic algorithms. Considering the length of the list, it was not possible to provide detail working of these algorithms. Thus we have focused on outlining the core source of inspiration only. The glossary may amaze young researchers and motivate them to explore their surroundings, find out their source of inspiration and use it to develop new and more efficient metaheuristics.

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