

A Comprehensive Review on Meta-Heuristic Algorithms and their Classification with Novel Approach

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PAPER INFO	ABSTRACT
Chronicle: Received: 10 July 2020 Reviewed: 19 August 2020 Revised: 04 February 2021 Accepted: 10 February 2021	Conventional and classical optimization methods are not efficient enough to deal with complicated, NP-hard, high-dimensional, non-linear, and hybrid problems. In recent years, the application of meta-heuristic algorithms for such problems increased dramatically and it is widely used in various fields. These algorithms, in contrast to exact optimization methods, find the solutions which are very close to the global optimum solution as possible, in such a way that this solution satisfies the threshold constraint with an acceptable level. Most of the meta-heuristic algorithms are inspired by natural phenomena. In this research, a comprehensive review on meta-heuristic algorithms is presented to introduce a large number of them (i.e. about 110 algorithms). Moreover, this research provides a brief explanation along with the source of their inspiration for each algorithm. Also, these algorithms are categorized based on the type of algorithms (e.g. swarm-based, evolutionary, physics-based, and human-based), nature-inspired vs non-nature-inspired based, population-based vs single-solution based. Finally, we present a novel classification of meta-heuristic algorithms based on the country of origin.
Keywords: Meta-Heuristic Algorithms. Meta-Heuristic Optimization. Classification of Meta-Heuristic Algorithms. Evolutionary Algorithms. Swarm Algorithms.	


1. Introduction

From the creation of human beings, they are constantly searching for perfection in many aspects of life. So, one of the most important concerns in the world is the search for optimal situations [1]. In the real world, many problems such as transportation, warehousing and product sales locations, communication networks design, scheduling, planning and etc. are all complicated and hybrid problems. These problems are practically large in such a way that they cannot be optimally solved within a reasonable and acceptable time. However, these problems need to be solved, so the alternative way is to accept the local or sub-optimal solutions with a suitable accuracy and optimization time. As a result, the heuristic algorithms are developed. They can be very effective and in some cases offer the global optimal

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solution. But one of their drawbacks is falling into local optimal traps without being able to get out of the situation. Therefore, meta-heuristic algorithms have been proposed to deal with this drawback [2]. Nowadays, new optimization methods have attracted many attentions and are under the spotlight in comparison with classical methods. Moreover, the application of new methods in complicated problems is increasing extensively [3].

Fig. 1. illustrates the optimization methods briefly [4] and [5].

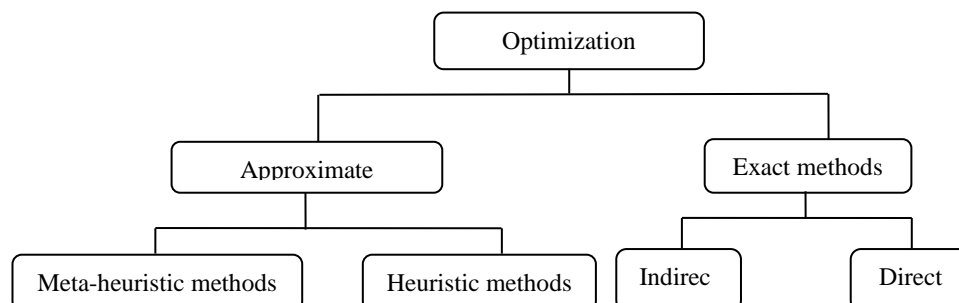


Fig. 1. Optimization methods.

Although, exact methods are very efficient in many problems [6]-[8], but they are not suitable for large-scale and non-linear problems. The more the size of the problem increases, the more the search space exponentially increases and it becomes impossible to search the solution space thoroughly [4]. Also, sometimes it is not possible to obtain the optimal solution with exact methods within a reasonable time due to the large scale and complexity, the scope of application of optimization in different fields, such as mathematics, computer science, engineering, economics and management. Such challenges have made the researcher to accept the local or sub-optimal solutions within a reasonable optimization time (i.e. approximate methods) [1]. In recent years, the application of meta-heuristic algorithms to solve NP-hard problems has been increased dramatically and is widely used in various fields. Unlike exact optimization methods, these approaches find the solutions that are very close to global optimal solution, in such a way that satisfies the threshold constraint with an acceptable level [9]. Also, these algorithms can solve such problems in an acceptable time [10]. Laporte and Osman [11] have defined meta-heuristic algorithm as "an iterative process that intelligently combines some heuristic concepts for searching and investigating in the whole solution space". Also, according to Voss et al. [12], a meta-heuristic algorithm is "A high-level iterative process that modifies and categorizes low-level heuristic solutions to generate high quality solutions. It may also manipulate a single or set of complete or incomplete solutions, iteratively". Combining meta-heuristic algorithms and their application is increasing these days. For examples: combinatorial optimization of permutation-based quadratic assignment problem using optics inspired optimization [13], factual power loss reduction by augmented monkey optimization algorithm [14] and a multi-level image thresholding approach based on the crow search algorithm and Otsu method [15].

Meta-heuristic algorithms which are a way to solve optimization problems start by generating random response (s) then move forward toward optimizing based on their operators and through changing the created random answers [16]. In general, all meta-heuristic algorithms use the similar mechanism to find the optimal solution. In most of these algorithms, the search starts by generating one or more random solutions in an acceptable range of variables. The primary generated solution in population-based algorithms is called population, colony, group, etc. and also each of solutions is called chromosome, particle, ant, and etc. Then, using operators and various methods of combining primary

solutions, new solutions are generated. Moreover, the new solution will be chosen from the previous ones, and this process will continue until the stop criterion is met [17]. This process is illustrated in Fig. 2.

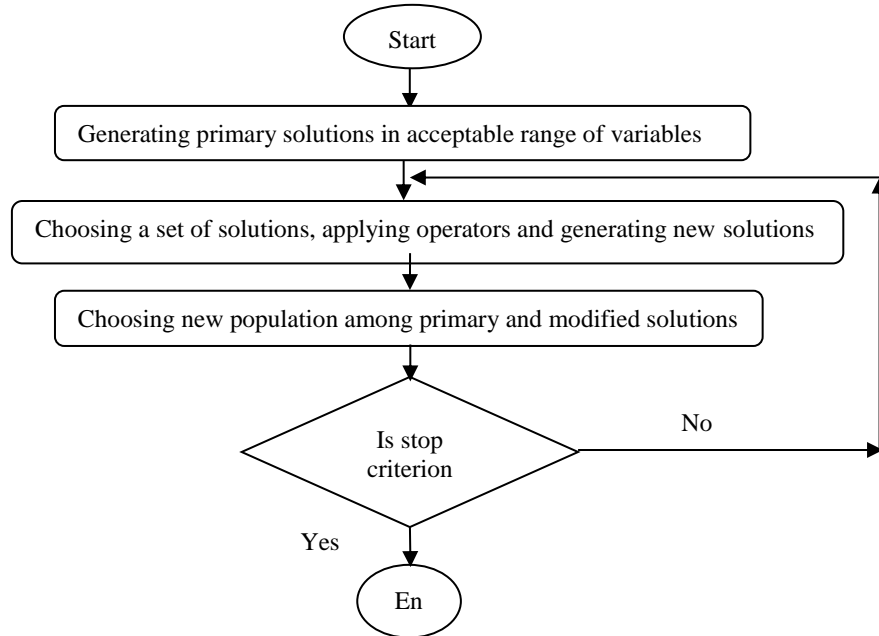


Fig. 2. The overall process of meta-heuristic algorithms to find the optimal solution.

In this research, a comprehensive review on meta-heuristic algorithms is presented to introduce a large number of them (i.e. about 110 algorithms). Also, this research provides a brief explanation along with the source of their inspiration for each algorithm. Moreover, these algorithms are categorized based on the type of algorithms (e.g. swarm based, evolutionary, physics based, and human based), nature-inspired vs. non-nature-inspired based, and finally we present a novel classification of meta-heuristic algorithms based on the country of origin. Accordingly, the rest of this paper is organized as follows: in Section 2, a comprehensive list of meta-heuristic algorithms with a brief explanation is provided. Section 3 discusses about the growth of meta-heuristic algorithm over time while Section 4 classifies the algorithms. Finally, the paper is concluded in Section 5.

2. A Comprehensive Introduction to 110 Meta-Heuristic Algorithms

A wide range of 110 meta-heuristic algorithms which have been developed in recent years, in order of presenting time and along with their developers and explanations, are provided in Table 1.

Table 1. A wide range of 110 meta-heuristic algorithms.

Row	Algorithm	Developer(s)	Brief explanation	Year	Ref.
1	Evolutionary Programming (EP)	Fogel & Fogel	<i>This algorithm is one of the basic approaches for most modern and evolutionary methods that defines many operators such as mutations and crossover.</i>	1965	[18]
2	Genetic Algorithm (GA)	Holland	<i>This algorithm is a searching method for finding the approximate solution of optimization problems using biological concepts such as inheritance and mutation. This algorithm is one of the most popular population-based, heuristic algorithms. The main operator of this algorithm is combination, but the mutation operator is also used to prevent unacceptable convergence and falling into the local optimal traps. This algorithm is based on the Darwin's theory and the principle of survival of the fittest. Also, the basic idea is to inherit traits by genes.</i>	1975	[19]
3	Scatter Search Algorithm (SSA)	Glover	<i>This algorithm is different from other evolutionary algorithms. It is based on the concept of systematic approaches to generate new solutions. This systematic approach has some advantages in comparison with purely randomized choosing solutions. Systematic approaches are used for diversification and intensification in searching process.</i>	1977	[20]
4	Simulated Annealing (SA)	Kirkpatrick et al.	<i>This algorithm is a probability-based method for finding the global optimal solution in problems with large solution space. Also, it is single-solution (different from most of meta-heuristic algorithms). SA is proposed based on the process of melting and freezing metals on the molecular scale. This process requires heating and then cooling a material gradually, in order to obtain a strong and solid crystal structure.</i>	1983	[21]
5	Tabu Search (TS)	Glover	<i>This algorithm works almost like local search algorithms, except that it uses a concept called Tabu List to avoid falling into the local optimal traps. The algorithm starts with an initial solution and searches for the neighborhood around it and chooses the best one and moves to that point under some conditions. Moving from current solution to candidate neighbor solution is allowed when it is not on the tabu list. Otherwise, the next neighbor solution, which is ranked next in the evaluation of neighbor solutions, will be chosen. The length of the tabu list indicates the maximum number of tabu iterations in the search process.</i>	1986	[22]

Row	Algorithm	Developer(s)	Brief explanation	Year	Ref.
6	Cultural Algorithms (CA)	Reynolds	<i>This algorithm is a category of evolutionary algorithms which in comparison with other algorithm and along with population component, has knowledge component too. There are various classifications of belief space called temporal knowledge, domain specific knowledge, situational knowledge, and spatial knowledge.</i>	1994	[23]
7	Particle Swarm Optimization (PSO)	Kennedy & Eberhart	<i>The algorithm is inspired by group flight of birds. Each particle calculates the value of the objective function in a position of solution space. Then, for each particle, by combining the information of current location and the best location it previously had, as well as the information of one or more of the best particles in the group, it chooses the direction to move. After moving all particles, one step finishes. These steps are repeated several times to obtain the desired result i.e. when the stop criterion is met. This algorithm has two operators: speed updating and position updating operators.</i>	1995	[24]
8	Ant Colony Optimization (ACO)	Dorigo et al.	<i>ACO is inspired by nature which explores the behavior of real ants. This algorithm is one of the population-based meta-heuristic algorithms. Researchers have shown that ants are social animals that live in colonies, and their behavior is more about the survival of colony than about the survival of a component. One of the most interesting and important behavior of ants is their approaches in finding food, and in particular how to find the shortest route between food resources and nests. Communication between ants with each other or between ants and the environment is based on the use of a chemical called pheromones. The ants leave a pheromone trace of themselves while walking. Although this material evaporates rapidly, but in the short term it remains as the ant's track on the surface of the earth. When ants want to choose between two paths, they usually choose a path that has more pheromones.</i>	1996	[25]
9	Differential Evolution (DE)	Storn & Price	<i>This algorithm is based on the theory of natural evolution and, similar to genetic algorithm, is based on mutation and combination operators. Although this algorithm uses mutation and combination operators but their utilization is different from GA. Moreover, in the step of comparison between new and old population and also choosing the best solution, this algorithm operates different from GA.</i>	1997	[26]

Row	Algorithm	Developer(s)	Brief explanation	Year	Ref.
10	Variable Neighborhood Search (VNS)	Mladenović & Hansen	<i>This algorithm is proposed based on the rules of simple local search. In this algorithm, the solution space is divided into several neighborhoods, and then one of these neighbors is randomly selected and local search is performed. If the solution is better than the best one recorded, a new neighborhood will be generated around the solution.</i>	1997	[27]
11	Sheep Flocks Heredity Model (SFHM)	Kim & Ahn	<i>This algorithm is an evolutionary computation algorithm based on sheep flocks heredity. It simulates heredity of sheep flocks in a prairie.</i>	2001	[28]
12	Harmony Search (HS)	Geem et al.	<i>Harmony is a relationship between different sound waves with different frequencies. The best harmony provides the best aesthetic experience for the audiences. This algorithm traces the similarity between finding a harmony in a music performance and finding the optimal solution for an optimization problem.</i>	2001	[29]
13	Bacterial Foraging Optimization (BFO)	Passino	<i>The algorithm is inspired by the bacterial motility process for finding food resources. Individual bacterial search behavior, probability of reproduction regarding the fact that reproduction is only for those bacteria that are well fed and finally, bacterial decomposition are the key elements of this algorithm.</i>	2002	[30]
14	Social Cognitive Optimization (SCO)	Xie et al.	<i>This algorithm is based on the development of knowledge and intelligence in humans and uses the concept that people learn by seeing others and the consequences of their behavior. It also considers personal, behavioral, and environmental factors.</i>	2002	[31]
15	Shuffled Frog Leaping Algorithm (SFLA)	Eusuff & Lansey	<i>This algorithm combines deterministic and probabilistic approaches. The deterministic aspects allow the algorithm to efficiently use the solution information to lead the evolutionary approach while probabilistic aspects guarantee the flexibility of algorithm. The base of SFL is to simulate the behavior of frogs to find food in wetlands. The algorithm tries to make a balance between extensive investigation in a solution space and searching around possible solutions. In this algorithm, population consists of a set of frogs (i.e. solutions) and each frog has a chromosome-like structure similar to genetic algorithm.</i>	2003	[32]
16	Electromagnetism-like algorithm (EMA)	Birbil & Fang	<i>This algorithm is proposed based on electrostatic system rules. In this algorithm, each particle has a virtual electric charge in such a way that the amount of this charge is related to the optimality of the point at which the particle is located.</i>	2003	[33]

Row	Algorithm	Developer(s)	Brief explanation	Year	Ref.
17	Space Gravitational Algorithm (SGA)	Hsiao et al.	The algorithm is inspired by the simulation of several asteroids in space and they are constantly moving to find the heaviest ones. The SGA utilizes Einstein's theory of relativity and Newton's law of gravitation to search the global optimal solution. Asteroids change their position independently, so the computational complexity decreases and the probability of falling into local optimal traps is very low.	2005	[34]
18	Particle Collision Algorithm (PCA)	Sacco & Oliveira	This algorithm is inspired by the nuclear collision reactions, especially scattering and absorption. The PCA structure is similar to SA but does not rely on user-defined parameters and does not require a cooling plan.	2005	[35]
19	Big Bang-Big Crunch (BB-BC)	Erol & Eksin	This algorithm is proposed based on the Big Bang theory and freezing the universe. In BB-BC, a weighted center of gravity is firstly constructed using each of the solutions and their fitness. Then, new solutions are generated in the neighborhood of this center, using the Gaussian distribution.	2006	[36]
20	Group Search Optimizer (GSO)	He et al.	This algorithm is inspired by the behavior of group of animals in the search for food resources. In this algorithm, the group is divided into three types namely producers, scrounger and rangers, and each type has its specific behavior.	2006	[37]
21	Invasive Weed Optimization (IWO)	Mehrabian & Lucas	This algorithm is inspired by weed colonies. Weed colonies are strong enough to pose a threat to useful plants. Weeds are also adaptable to environmental changes. Being strong, random, and adaptable is modeled as a numerical optimization method.	2006	[38]
22	Small-world Optimization Algorithm (SWOA)	Du et al.	This algorithm is proposed based on some scientific experiments on human communication and networking approaches. This method uses local short-range and random long-range search agents for local and global search, respectively.	2006	[39]
23	Cat Swarm Optimization (CSO)	Shu et al.	This algorithm is based on the behavior of cats and has two sub-models, namely: tracking and searching. In this algorithm, cats are considered as the number of solutions. Each cat has a relative velocity for on each dimension, a proportional value, and a parameter indicating the status.	2006	[40]
24	Saplings Growing UP Algorithm (SGA)	Karci & Alatas.	This algorithm is inspired by the planting and growth of saplings, which has two stages: the planting stage and the growth stage. Uniform planting is done with the aim of uniformly distributing the searching agents in the solution space. The growth stage consists of three operators: mating, branching, and vaccination.	2006	[41]

Row	Algorithm	Developer(s)	Brief explanation	Year	Ref.
25	Imperialist Competitive Algorithm (ICA)	Atashpaz-Gargari & Lucas	<i>In this algorithm, members are considered as countries. Countries are divided into colonial and colonizer groups and empires are built. During the iterations, the weak empires collapse and the strong empire takes control of its colonies. Convergence occurs when there is only one empire left and all the other colonies are equal.</i>	2007	[42]
26	Artificial Bee Colony Algorithm (ABC)	Karaboga & Basturk	<i>In this algorithm, bee group behavior is used to find the food resources. The performance of worker bees, watchdogs and scouts are modeled. The equivalent to these three types of bees, three operators are considered namely deterministic obtaining information from neighborhood, probabilistic obtaining information from neighborhood and the searching for new areas if no improvement is achieved.</i>	2007	[43]
27	Central Force Optimization (CFO)	Formato	<i>Unlike many stochastic algorithms, CFO is a deterministic method and do not need to generate random solutions. In this algorithm, searching process moves under the influence of gravity in the decision space and changes the position of agents according to equations and constraints. Therefore, during the searching process, the solution moves slowly towards the searches with highest proportion or mass.</i>	2007	[44]
28	Integrated Radiation Algorithm (IRA)	Chuang & Jiang	<i>This algorithm is based on the concept of gravitational radiation in Einstein's theory of general relativity. This important theory is used to search for the optimal solution in the solution space. In IRA, the search space is regarded as a simplified astrophysics that contains search agents, and these agents are randomly distributed in the search space. It is assumed that the solution which finds the best objective function has a supernova with an incomplete symmetrically expanding shape.</i>	2007	[45]
29	Multi Point Simulated Annealing Algorithm (MPSA)	Lamberti & Pappalitere	<i>This algorithm utilizes a multi-level simulated annealing scheme where different candidate designs are compared simultaneously.</i>	2007	[46]
30	River Formation Dynamics Algorithm (RFDA)	Rabanal et al.	<i>This algorithm is inspired by how the river and its bed are formed using erosion and sedimentation process. Some important factors such as moving from high to low, erosion and sedimentation are considered in this model.</i>	2007	[47]
31	Big Crunch Algorithm (BCA)	Kripka & Kripka	<i>This algorithm is based on closed world theory. The kinetic energy generated by the first cosmic explosion (i.e. the Big Bang) overcomes the gravitational energy of components. As the beginning of universe, this explosion will be done with infinite heat and energy. This process will continue as long as only one component (i.e. mass) remains in the world and this leads to an acceptable result.</i>	2008	[48]

Row	Algorithm	Developer(s)	Brief explanation	Year	Ref.
32	Biogeography Based Optimization (BBO)	Simon	This algorithm is inspired by the geographical distribution of biological organisms and uses the basic operators such as migration and mutation.	2008	[49]
33	Firefly Algorithm (FFA)	Yang	The algorithm is inspired by the illumination of firefly insects to mate, hunt, and scare the enemies. In FFA, insects with the ability to generate more light attract the weaker insects and it relates inversely to the distance between them.	2009	[50]
34	Paddy Field Algorithm (PFA)	Premaratne et al.	This algorithm starts with randomly spreading the seeds (i.e. search agents). After a while and turning seeds into plants, those with higher growth (i.e. better fitness) are more likely to be re-used. All plants spread their seeds to overcome local optimal traps.	2009	[51]
35	Gravitational Search Algorithm (GSA)	Rashedi et al.	This algorithm is based on the laws of gravity and motion. According to the law of gravity, each particle in the universe attracts another particle with a force that is proportional to the mass and inversely proportional to the square of the distance between the particles. In this algorithm, each agent is considered as an object and the performance of these objects is measured by their mass. Therefore, it is expected that at the end of optimization process the position of object with the heaviest mass shows the optimal global solution.	2009	[52]
36	Cuckoo Search (CS)	Yang & Deb	This algorithm is proposed based on the cuckoo behavior in laying nests of other birds. The final aim is to maximize the production of chickens while these eggs not to be identified by the host bird.	2009	[53]
37	Hunting Search (HuS)	Oftadeh & Mahjoob	This algorithm is inspired by the group hunting of animals such as lions, wolves and dolphins. The algorithm indicates that although the hunting methods of these animals are different, but they share the same approach for hunting and chasing the prey. In other words, hunters encircle the prey and gradually tighten the siege to catch it. In addition, each member of the group adjusts its position according to the position of its own and other members. If the prey escapes the siege, the hunters reorganize the group to re-siege the prey.	2009	[54]
38	Intelligent Water Drops (IWD)	Shah-Hosseini	The algorithm is inspired by the flow of water along the path. As the water flows between two points, the water speed, the amount of soil with the water, and the soil bed change. In this algorithm, these changes are modeled, accordingly. In other words, intelligent water drops are used as search agents that work together to find the optimal solution.	2009	[55]
39	Artificial Physics Optimization Algorithm (APOA)	Xie et al.	This algorithm is inspired by physical forces. In APA, each agent is regarded as a physical particle that has a certain mass, velocity and position. Virtual forces move these particles to areas with better fitness. The amount of fitness depends on the user defined agent mass. With these physical rules, agents search the solution space.	2009	[56]

Row	Algorithm	Developer(s)	Brief explanation	Year	Ref.
40	Bacterial Evolutionary Algorithm (BEA)	Das et al.	This algorithm is an evolutionary clustering method to classify datasets for optimal number of groups. The algorithm is inspired by microbial evolution and utilizes two specific operators: bacterial mutation and gene transfer operations.	2009	[57]
41	Human-inspired Algorithm (HIA)	Zhang et al.	The algorithm mimics search methods according to climbers who use modern facilities such as binoculars and cell phones to find the highest mountain peak. The interesting feature of this method is that it divides the search space evenly into sub-spaces and allocates an equal number of search agents to them.	2009	[58]
42	League Championship Algorithm (LCA)	Kashan	This algorithm is based on the competition between teams in a sports league. Search agents are considered as teams that compete for several weeks (i.e. iterations). The competition is between two competitors and the fittest is considered as winner. At the end of each iteration, all teams are ready to make changes for the next week.	2009	[59]
43	Locust Swarms (LS)	Chen	This algorithm is inspired by the swarm of locusts. The algorithm starts with intelligent starting points. Then, the PSO method and greedy local search algorithm are used to explore the search space. Search agents start with a little distance from the previous solution.	2009	[60]
44	Consultant-Guided Search (CGS)	Iordache	This algorithm is based on the direct exchange of information between individuals within a population. CGS is a collective intelligence technique inspired by the real-world decision making approaches.	2010	[61]
45	Bat Algorithm (BA)	Yang	This algorithm is inspired by the bat sound system for detecting the prey, barrier and nest locations in the darkness. In BA, each bat changes its speed and position according to the best existing positions.	2010	[62]
46	Charged System Search (CSS)	Kaveh & Talatahari	In this algorithm, each agent is considered as a charged particle (CP) and is a candidate for solution. The law of motion is also used to guide the CP movements. Each CP according to the distance and value of the objective function (i.e. its charge value), is affected by other CPs and the force applied to each CP determines the new position, velocity and acceleration.	2010	[63]
47	Chemical Reaction Optimization (CRO)	Lam & Li	The algorithm is inspired by the behavior of molecules in chemical reactions and the exchange of energy between them. By modeling the chemical combination and decomposition reactions, the molecules behave in such a way that they can minimize their potential energy (i.e. cost function).	2009	[64]
48	Eagle Strategy Algorithm (ESA)	Yang & Deb	This algorithm is a two-step hybrid search method that combines random search with firefly algorithm.	2010	[65]
49	Group Counseling Optimization (GCO)	Eita & Fahmy	This algorithm mimics human problem solving behavior through consultation. Iterations in this algorithm are considered as counseling sessions. In these sessions members constantly improve their position with the help of themselves or the counseling team.	2010	[66]

Row	Algorithm	Developer(s)	Brief explanation	Year	Ref.
50	Social Emotional Optimization (SEO)	Xu et al.	This algorithm uses the concept of human efforts to gain higher social status. Members of a population are treated as individual persons in a society. Each person tries to increase his /her emotional score. Based on this emotional index and feedback from other members of the society, social status becomes updated. Finally, members with the highest social status are the optimal solution.	2010	[67]
51	Galaxy Based Search Algorithm (GbSA)	Shah-Hosseini	This algorithm is inspired by the spiral arm of galaxies to approach optimal solution. This means that GbSA searches the solution space for better solutions using these spiral-like arms. To escape the local optimal traps, spiral movements are improved by chaos.	2011	[68], [69]
52	Spiral Dynamics Inspired Optimization (SDIO)	Tamura & Yasuda	This algorithm is inspired by spiral phenomenon in the nature. This spiral movement is observed in many structures, such as galaxies, tornadoes and vortices. The algorithm uses a multidimensional spiral to search the solution space. It also has several control parameters to balance the variation and intensification.	2011	[70]
53	Teaching-learning based Optimization (TLBO)	Rao et al.	This algorithm is based on the mutual teaching-learning relationship, while the members of population are treated as students of a class. The searching process consists of two phases: in the first phase the learning process proceeds by teacher's influence, while in the second phase it is done by mutual interactions.	2011	[71]
54	Anarchic Society Optimization (ASO)	Shayeghi & Dadashpour	The algorithm simulates the problem as a group with abnormal, unstable and disruptive members to overcome local optimal traps.	2012	[72]
55	Current Search (CS)	Sakulin & Puangdownreong	This algorithm is based on the electrical flow behavior in electric circuits. Usually, current chooses the less resistive path among other paths.	2012	[73]
56	Water Cycle Algorithm (WCA)	Eskandar et al.	This algorithm is inspired by the nature of water cycle process. The solutions in this algorithm are: creek, river (i.e. some of the best solutions) and sea as the best solution. The algorithm is implemented by moving creeks toward the river and rivers toward the sea. If the creeks have enough qualification they can join the river or even the sea.	2012	[74]
57	Wolf Search Algorithm (WSA)	Tang et al.	The algorithm is inspired by the life of wolves and how they search for food and survive from threats. In this algorithm, each agent searches independently while keeps the previous position in its memory. If the new position is the best among all previous ones, then algorithm integrates the current agent with another agent.	2012	[75]
58	Mine Blast Algorithm (MBA)	Sadollah et al.	This algorithm is proposed based on a real world mine-blast event. In an explosion a number of explosive bullets are fired. Each piece of explosive may generate another new explosion. The explosive component that causes the most damages is chosen to expand the new mine.	2012	[76]

Row	Algorithm	Developer(s)	Brief explanation	Year	Ref.
59	Atmosphere Clouds Model (ACM)	Yan & Hao	<i>This algorithm mimics the behaviors of a cloud in the natural world. It simulates the generation, move and spread behavior of a cloud for intensification and diversification / exploration in the search space.</i>	2013	[77]
60	Black Holes Algorithm (BHA)	Hatamlou	<i>The algorithm is inspired by the black hole phenomenon. In this algorithm, the best solution in each iteration is considered as a black hole that other stars are attracted to it. When a star becomes very close to the black hole, they merge and a new star (i.e. solution) creates randomly.</i>	2013	[78]
61	Egyptian Vulture Optimization (EVO)	Sur et al.	<i>The algorithm is inspired by the natural behaviors of Egyptian vultures and how they search for food resources. This algorithm was originally designed for hybrid optimization problems.</i>	2013	[79]
62	Penguins Search Optimization Algorithm (PSOA)	Gheraibia & Moussaoui	<i>The basic idea of this algorithm is the group behavior of penguins when they go for hunting. Each penguin starts the local search process while he is aware of its own location and the food that other members were found. The group with the most food (i.e. fishes) is selected as the best solution.</i>	2013	[80]
63	Swallow Swarm optimization (SSO)	Neshat et al.	<i>This algorithm is proposed from the behavior of swarm of swallows and their movements. The particles in this algorithm are divided into three categories: explorer or discoverer, aimless and leader.</i>	2013	[81]
64	Grey Wolf Optimizer (GWO)	Mirjalili et al.	<i>This algorithm is inspired by gray wolves and mimics the predation process and hierarchy of gray wolves. In GWO, four types of gray wolves, namely Alpha, Beta, Delta and Omega, are introduced to simulate leadership hierarchies. In addition, three major hunting steps called searching for prey, sieging the prey and attacking to prey are considered in this method.</i>	2014	[82]
65	Golden Ball (GB)	Osaba et al.	<i>This algorithm is based on a multiple population approach and relies on the concepts of football game.</i>	2014	[83]
66	Animal Migration Optimization Algorithm (AMOA)	Li et al.	<i>This algorithm is inspired by the group migration of animals and how they leave one group to survive in other ones.</i>	2014	[84]
67	Soccer League Competition Algorithm (SLC)	Moosavian & Roodsari	<i>The theory behind this approach is inspired by soccer leagues and is based on the competition between teams and players. Competition between teams for better ranking in the league and internal competition between players for personal development will result in convergence towards global optimality. The simulation results of applying the SLC to nonlinear systems verifies that this algorithm in comparison to other meta-heuristic algorithms converges to solution faster and more accurately.</i>	2014	[85], [86]
68	Chicken Swarm (CS)	Meng et al.	<i>This algorithm simulates the hierarchical behavior of a group of chickens and consists of: roosters, hens and chickens. Chickens are divided into several groups. Each group has a rooster and a large number of hens and chickens and they compete in a particular hierarchical order.</i>	2014	[87]

Row	Algorithm	Developer(s)	Brief explanation	Year	Ref.
69	Forest Optimization Algorithm (FOA)	Ghaemi & Feizi-Derakhshi	This algorithm is based on the process of sowing seeds in a forest. In this algorithm, the model assumes that the seeds right under the trees cannot grow, but the seeds scattered elsewhere may grow and become another trees.	2014	[88]
70	Heart Algorithm (HA)	Hatamlou	This algorithm models the optimization problem as the heart and circulatory system. In this method, a member of population that has the best fits is considered as the heart and other members are considered as blood molecules. Blood molecules move toward or against the heart to gain better fitness.	2014	[89]
71	Kaizen Programming (KP)	De Melo	Kaizen is a Japanese approach to solve problems. Unlike evolutionary approaches which each agent is a complete solution, in this method each expert proposes an idea to solve the problem and the final solution combines all ideas together. The fitness of each idea is measured by its contribution to find the final solution.	2014	[90]
72	Exchange Market Algorithm (EMA)	Ghorbani & Babaei	This method as an evolutionary algorithm is inspired by the procedure of trading the shares on stock market.	2014	[91]
73	African Buffalo Optimization (ABO)	Odili et al.	This algorithm draws its inspiration from the behavior of African buffalos in the vast African forests and savannahs. African buffalos are a wild species of domestic cattle and are always mobile tracking the rainy seasons in different parts of Africa in search of lush green pastures to satisfy their large appetites.	2015	[92]
74	Elephant Herding Optimization (EHO)	Wang at el.	This algorithm is a kind of swarm-based meta-heuristic search method, and is inspired by the herding behavior of elephant group.	2015	[93]
75	Ions Motion Algorithm (IMA)	Javidy at el.	This algorithm uses the ionic movements and the tensile force and pressure of anions and cations. In this algorithm, the candidate solutions are divided into two groups: 1-anions (negative ions) and 2-cations (positive ions). Ions introduce the candidate solutions for a particular problem and tensile /pressure forces allow the ions to move in the search space.	2015	[94]
76	General Relativity Search Algorithm (GRSA)	Beiranvand & Rokrok	This algorithm is based on the concept of general theory of relativity. In this algorithm, members of population are modeled as particles in space in such a way that they are not affected by any forces except gravity. These particles are designed to reach to their most stable situation and move in the shortest possible paths. Length of steps and directions are calculated according to speed and shortest paths.	2015	[95]
77	Jaguar Algorithm with Learning Behavior (JALB)	Chen et al.	This algorithm is inspired by the jaguar's hunting behavior. A jaguar aims to catch a prey and moves rapidly toward the target. Jaguars are also used to go for hunting as a team. This algorithm mimics the jaguar's hunting behavior to balance exploration and exploitation.	2015	[96]
78	Optics Inspired Optimization (OIO)	Kashan	A concave mirror converges light beams while a convex mirror diverges light beams. In this algorithm, the optics phenomenon is modeled as an optimizer. This algorithm considers the search space as a reflective mirror in such a way that each peak and valley acts as a convex mirror and concave mirror, respectively.	2015	[97]

Row	Algorithm	Developer(s)	Brief explanation	Year	Ref.
79	Runner-Root Algorithm (RRA)	Merrikh-Bayat	This algorithm models the goals of roots and runners in plants. Runners search for a large area with large steps while roots search for a small area. The algorithm also has two functions corresponding to runners and roots for exploration and exploitation, respectively.	2015	[98]
80	Vortex Search Algorithm (VSA)	Doğan & Ölmez.	This method is one of meta-heuristic algorithm which is based on the vertical flow pattern of fluids. This algorithm uses an adaptive step length mechanism to exploit and explore the searches.	2015	[99]
81	Stochastic Fractal Search (SFS)	Salimi	The algorithm is inspired by the natural phenomenon of growth that uses a mathematical concept called fractal.	2015	[100]
82	Prey-Predator Algorithm (PPA)	Tilahun & Ong	The algorithm is inspired by the predator-prey relationship in animals.	2015	[101]
83	Water Wave Optimization (WWO)	Zheng	This algorithm is inspired by the theory of water waves. It is verified that some phenomena which have the characteristics of water waves such as propagation, reflection, and breaking, can be used to develop an effective mechanisms for searching in a high-dimensional solution space.	2015	[102]
84	Bull Optimization Algorithm (BOA)	Findik	This algorithm modifies the selection process in the genetic algorithm in such a way that only better members can participate in crossover.	2015	[103]
85	Elephant Search Algorithm (ESA)	Deb et al.	In this algorithm, members of a population are considered as elephants in a herd. Male members and female ones are considered as exploring searching agents and local searching agent, respectively.	2015	[104]
86	Ant Lion Optimizer (ALO)	Mirjalili	The algorithm is inspired by ant lion hunting behaviors and is based on the following steps: random search, trapping, sieging, catching the prey, and trap reconstruction.	2015	[105]
87	Lion Optimization Algorithm (LOA)	Yazdani & Jolai	This algorithm is inspired by the social behavior of lions. Lions live in both resident and nomad types. Adult male lions freely leave the group and move around. Resident lions are modeled as local search agents, while nomad lions are modeled as global search agents for identification and exploration.	2016	[106]
88	Whale Optimization Algorithm (WOA)	Mirjalili & Lewis.	This algorithm is inspired by nature and mimics the social behavior of whales. This algorithm has three main steps: sieging the prey, attacking to prey (i.e. exploitation step) and searching for prey (i.e. exploration step).	2016	[107]
89	Dynamic Virtual Bats Algorithm (DVBA)	Topal & Altun	This algorithm is inspired by bat's ability to generate various wavelengths and frequencies during hunting process.	2016	[108]
90	Tug of War Optimization (TWO)	Kaveh & Zolghadr	This algorithm is inspired by tug of war game and is based on population. In this algorithm, each candidate solution is considered as a team to play the game.	2016	[109]
91	Virus Optimization Algorithm (VOA)	Liang & Cuevas Juarez	This algorithm mimics the behavior of viruses in attacking cells. In this method, the number of viruses in each iteration is controlled by the immune system to prevent unwanted growth of virus population.	2016	[110]

Row	Algorithm	Developer(s)	Brief explanation	Year	Ref.
92	Virus colony search (VCS)	Li et al.	This algorithm mimics the strategy of virus replication and propagation in infecting host cells.	2016	[111]
93	Crow Search Algorithm (CSA)	Askarzadeh	This algorithm is inspired by the intelligent behavior of crows and also is a population-based technique. The basic CSA idea is that crows hide and store their surplus food and find it when needed.	2016	[112]
94	Dragonfly Algorithm (DA)	Mirjalili	This algorithm is inspired by the social behavior of dragonflies when they are searching for food, guiding the group and escaping from enemy.	2016	[113]
95	Camel Algorithm (CA)	Ibrahim & Ali	This algorithm is inspired by the behavior of camel during a desert march. This method considers the factors such as temperature, water supply, stability, visibility, and ground conditions.	2016	[114]
96	Water Evaporation Optimization (WEO)	Kaveh & Bakhshpoori	This algorithm is based on the behavior of evaporation of water molecules from solid surfaces with different characteristics. Water molecules are considered as the members of population and the solid surface is considered as the solution space. Surface wettability with other molecular properties is regarded as the search parameters.	2016	[115]
97	Thermal Exchange Optimization (TEO)	Kaveh & Dadras	This algorithm is based on the Newton's law of cooling, which is simple and straightforward.	2017	[116]
98	Electro-Search Algorithm (ESA)	Tabari & Arshad	This algorithm is inspired by the movement of electrons around the nucleus of atoms.	2017	[117]
99	Grasshopper Optimisation Algorithm (GOA)	Saremi et al.	This algorithm models the optimization problems as a group of grasshoppers. In this method the neonatal stage is modeled the same as adult stage. Young grasshoppers move slowly with small steps, while adults move suddenly with bigger steps.	2017	[118]
100	Sperm Motility Algorithm (SMA)	Raouf & Hezam	This algorithm is based on the human reproductive system. Search agents (i.e. sperms) spread in solution space randomly. In this method, the random sperm motility is modeled to search for ovum. The chemical secretion of ovum attracts the sperm to the optimal solution.	2017	[119]
101	Beetle Swarm Optimization Algorithm (BSOA)	Wang & Yang	This algorithm is proposed by enhancing the performance of swarm optimization through beetle foraging principles.	2018	[120]
102	Chaotic Bird Swarm Optimization Algorithm	Ismail et al.	This algorithm combines the chaotic-based methods with foraging and privilege behaviors to improve exploitation quality.	2018	[121]
103	Butterfly Optimization Algorithm	Arora & Singh	This algorithm mimics food search and mating behavior of butterflies, to solve global optimization.	2019	[122]
104	Chaotic grasshopper Optimization Algorithm (CGOA)	Arora & Anand	This method introduces chaos theory into the optimization process of GOA. The chaotic maps balance the exploration and exploitation efficiently.	2019	[123]

Row	Algorithm	Developer(s)	Brief explanation	Year	Ref.
105	Quantum Dolphin Swarm Algorithm	Qiao & Yang	In this method, quantum search algorithm is introduced into Dolphin Swarm Algorithm to escape the local optimum.	2019	[124]
106	Emperor Penguins Colony	Harifi et al.	This algorithm, inspired by the behavior of Emperor Penguins. It is controlled by the body heat radiation of the Penguins and their spiral-like movement in their colony.	2019	[125]
107	Shell Game Optimization	Dehghani et al.	This method simulates the rules of a game known as shell game to design an algorithm for solving optimization problems.	2020	[126]
108	Darts Game Optimizer (DGO)	Dehghani et al.	This method simulates the rules of Darts game to design an algorithm for solving optimization problems.	2020	[127]
109	Capuchin Search Algorithm (CapSA)	Braik et al.	This algorithm is inspired by the dynamic behavior of capuchin monkeys.	2020	[128]
110	Red deer Algorithm	Fathollahi-Fard et al.	This algorithm mimics the behavior of Scottish red deer. Its main inspiration originates from an unusual mating behavior of Scottish red deer in a breeding season.	2020	[129]

3. Growth and Expansion of Meta-Heuristic Algorithms

Most of meta-heuristic algorithms have been developed in recent years (i.e. after 2000). The growth and development process of these algorithms over time is illustrated in Fig. 3.

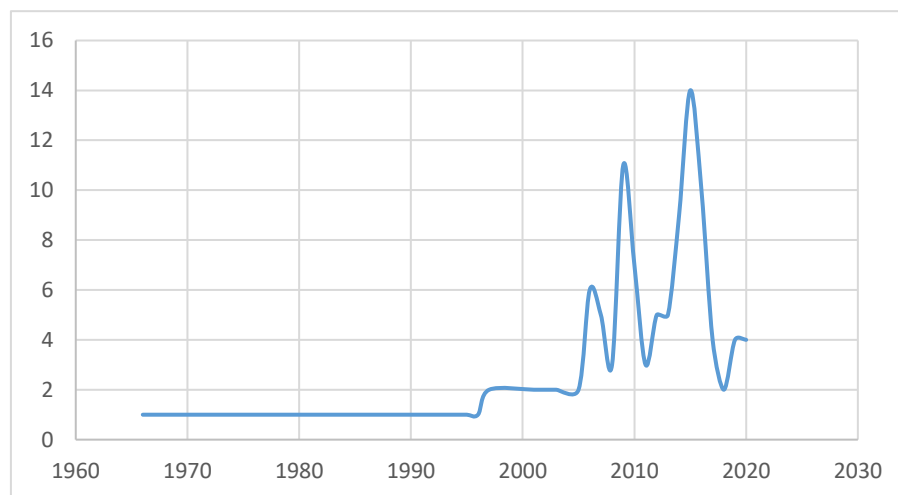


Fig. 3. Growth and development process of meta-heuristic algorithms over time.

4. Classification of Meta-Heuristic Algorithms

According to the features of each algorithm, different classifications are introduced. In this section, the meta-heuristic algorithms are studied and compared from five aspects. Then classifications of algorithms based on these aspects are presented [4], [91], [103], [130], and [131]. These classifications are according to:

- The type of algorithms (swarm-based, evolutionary-based, physics-based and human-based).
- Nature-inspired vs. non-nature-inspired.
- The source of inspiration.
- Population based vs. single solution based.
- Based on the country of origin.

The classification of 110 investigated meta-heuristic algorithms based on the type of algorithms (swarm-based, evolutionary-based, physics-based, human-based), nature-inspired vs. non-nature-inspired, the source of inspiration and population based vs. single solution based is illustrated in *Fig.4*. While *Fig. 5*, *Fig. 6*, *Fig. 7* and *Fig. 8* show the above categories statistically.

The classifications of 110 investigated meta-heuristic algorithm based on the country of origin is

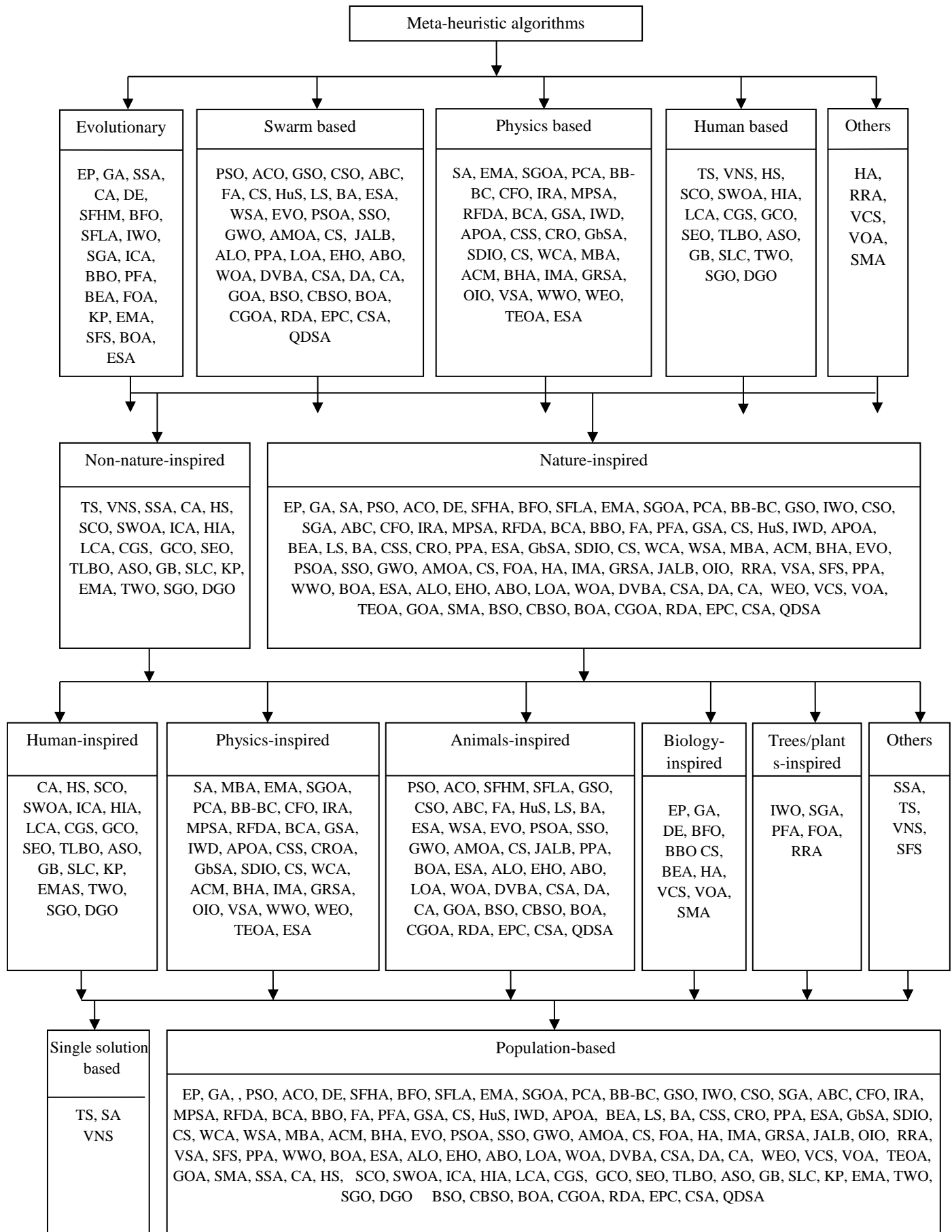


Fig. 4. Classification of 110 investigated meta-heuristic algorithms.

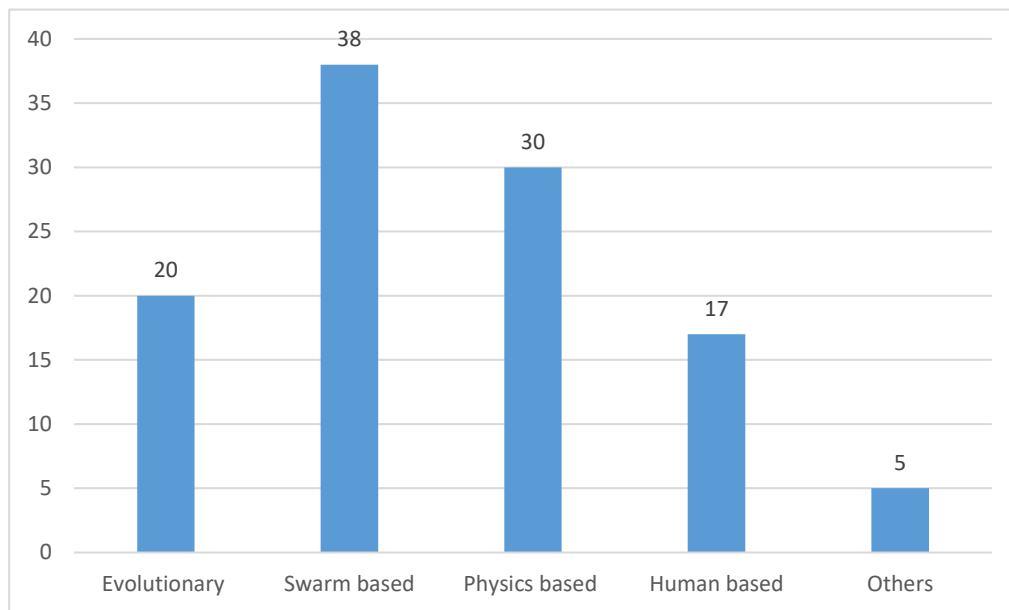


Fig. 5. Classification of meta-heuristic algorithms based on their features statistically.

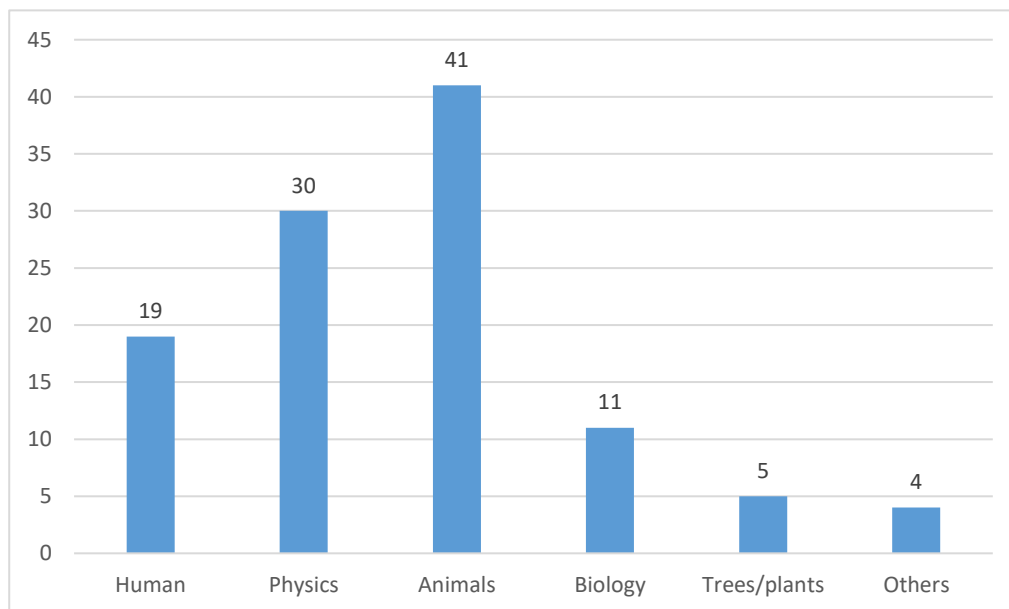


Fig. 6. Classification of meta-heuristic algorithms based on the source of inspiration statistically.

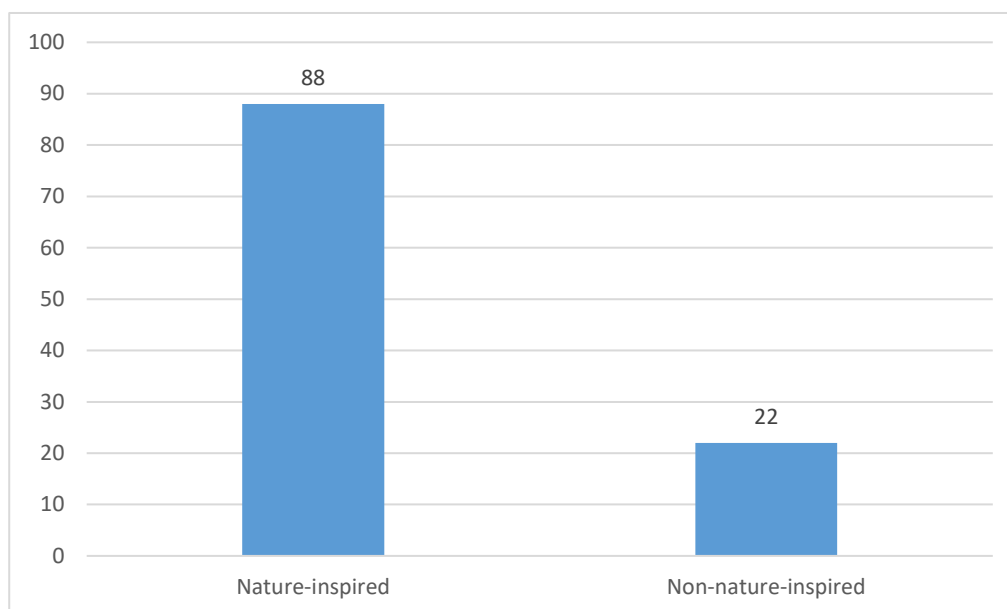


Fig. 7. Classification of meta-heuristic algorithms based on nature/non-nature-inspired statistically.

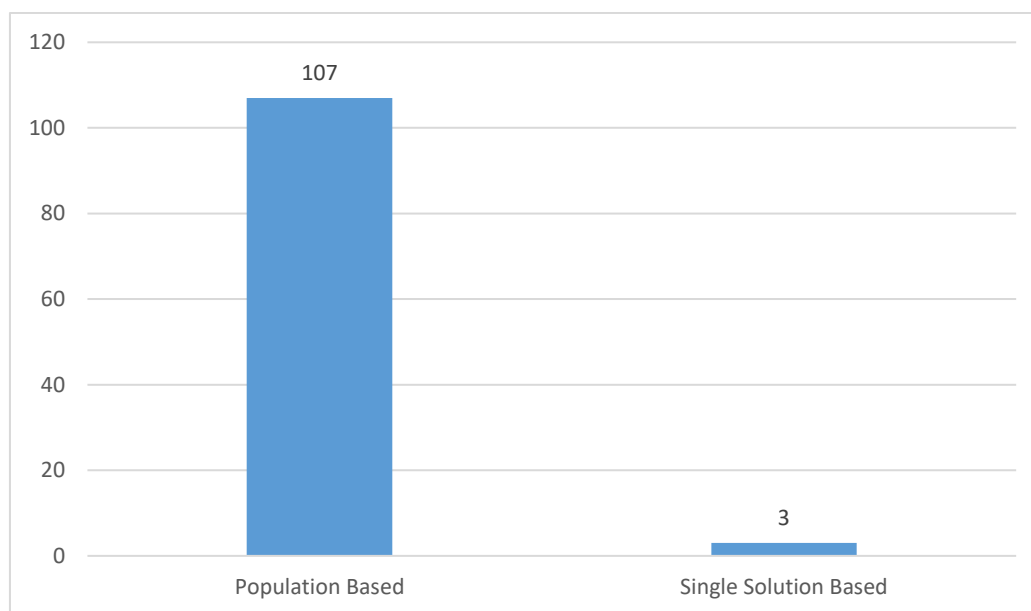


Fig. 8. Classification of meta-heuristic algorithms based on population / single solution based statistically.

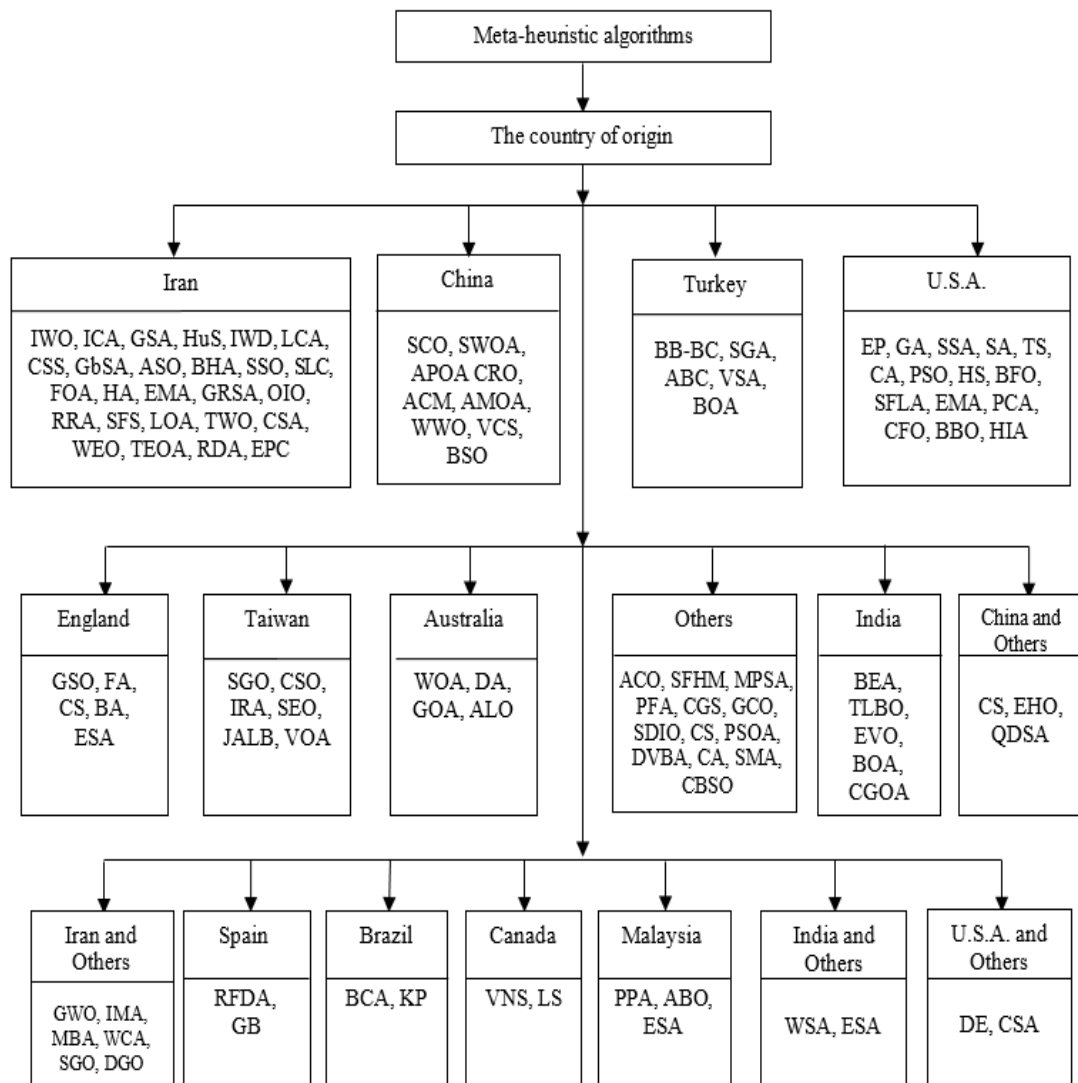


Fig. 9. Classifications of 110 investigated meta-heuristic algorithms based on the country of origin.

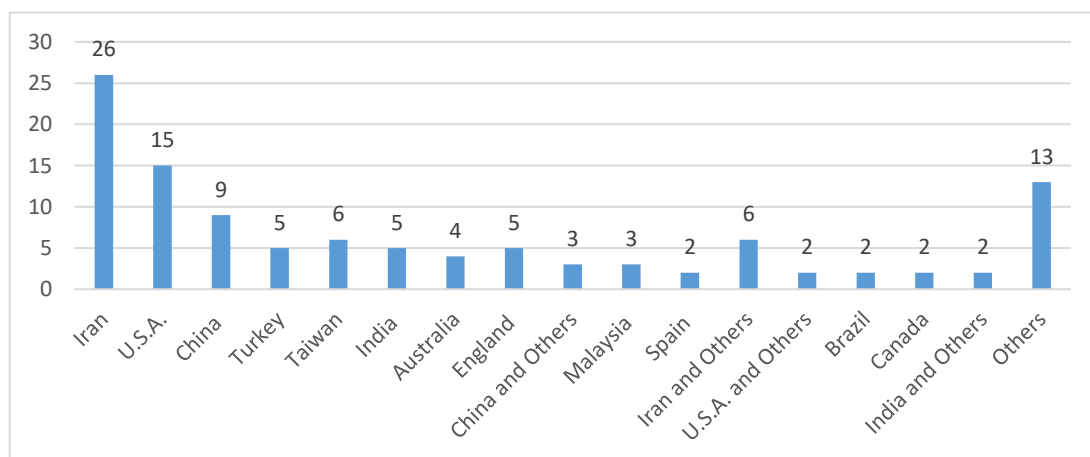


Fig. 10. Classifications of (110 investigated) meta-heuristic algorithm based on the country of origin statistically.

5. Conclusion

One of the main achievements of this paper is to categorize a large number of meta-heuristic algorithms (i.e. 110 algorithms) and give a brief explanation for each of them. Most of meta-heuristic algorithms have been introduced and developed over the last two decades (i.e. 91% of aforementioned algorithms have been introduced since 2000). Also, most of the meta-heuristic algorithms are inspired by nature in such a way that almost 80% of them are in this category. Moreover, 74% of algorithms are inspired by animal's behavior, physics, and biological laws. In addition, Iran is the country of origin for about 24% of algorithms and U.S.A is the country of origin for about 14% of algorithms. It should also be mentioned that, in this research, meta-heuristic algorithms are categorized from different aspects such as: nature-inspired vs. non-nature-inspired based, swarm based, evolutionary based, physics based, human based, source of inspiration, population based vs. single solution based and finally based on the country of origin. For further studies, it is suggested to compare and rank some meta-heuristic algorithms. It is also recommended to present a new meta-heuristic algorithm through being inspired by natural or unnatural phenomena.

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