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REVIEW

A comprehensive study of cuckoo-inspired algorithms

Mohamed Abdel-Basset[1] · Abdel-Naser Hessin[1] · Lila Abdel-Fatah[1]

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Abstract Nature-inspired metaheuristic algorithms are considered as the most effective techniques for solving various optimization problems. This paper provides a briefly review of the key features of the cuckoo-inspired metaheuristics: cuckoo search (CS) and cuckoo optimization algorithm (COA). In addition, it discusses some of their important and emerging studies, investigates their applications in several fields, and finally clarifies the differences between both algorithms so as to remove confusion between them.

Keywords Metaheuristic · Cuckoo search · Cuckoo optimization algorithm

1 Introduction

The adoption of artificial intelligence in solving different optimization problems is one of the most interesting trends in the last years especially for what concerns research on nature-inspired metaheuristics. Glover has introduced the term metaheuristic in 1986 [1] to define not problem-specific heuristic method. There are two major characteristics of metaheuristic [2]: the first one is intensification which tends to search around the current best solution, and the second is diversification which makes sure that the algorithm can explore the search space more efficiently, often by randomization. Metaheuristic will be successful in solving a given optimization problem if it can provide a balance between the search space exploitation and exploration to guarantee to find a high-quality solution for a given problem. The nature-inspired metaheuristic algorithms have simulated natural phenomena or natural forces such as bird flocking, ant or bee colonies, animal herding, water drops, and gravity, for example, genetic algorithm (GA) [3], ant colony optimization (ACO) [4], particle swarm optimization (PSO) [5], water wave optimization (WWO) [6], and gravitational search algorithm (GSA) [7].

One of these fabulous phenomena is the cuckoo bird's proliferation. The other side of the wonderful cuckoo chirp is the aggressive brood parasitism; i.e., the cuckoo uses a cruel deception strategy to lay its own egg in the other birds nest after removing the host bird egg. The cuckoo has the ability to mimic the color and the pattern of the host bird eggs to avoid the detection of its egg. If the host bird exposes the cuckoo's egg dumped in its own nest, it either throw out the exotic egg or abandons the nest to start afresh. After the egg hatches, the chick is cared and fed by the host bird until the chick growing. In addition, the chick instinct motivates it to throw out the host eggs or to propel the eggs out of the nest to ensure the food from the host bird.

The representation of the same phenomena varies according to the developer perspective, i.e., one phenomena can be inspected into various ways. For example, Yang and Deb [8] have introduced a metaheuristic "cuckoo search (CS)." Also, Rajabioun [9] has developed an emerging metaheuristic "cuckoo optimization algorithm (COA)" with a different narration.

In a completely different field, Pagh and Rodler [10] use the cuckoo inspiration to develop an algorithm for creating large hash tables with high space utilization and guaranteed constant access times which was called "cuckoo hashing."

✉ Mohamed Abdel-Basset
analyst_mohamed@yahoo.com

[1] Faculty of Computers and Informatics, Zagazig University, Zagazig, Egypt

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Because this paper interested in the cuckoo-inspired metaheuristic, it focuses on CS and COA. The structure of this paper is as the following: Sect. 2 briefly outlines the main CS mechanism, Sect. 3 presents the main CS variants, and Sect. 4 reviews the major CS applications. Also for COA, Sect. 5 outlines the main COA mechanism followed by the presentation of main COA variants in Sect. 6 then the review of COA applications in Sect. 7. Finally, a comparison between CS and COA is conducted in Sect. 8 followed by conclusion in Sect. 9.

2 Cuckoo search algorithm (CS)

Cuckoo search is among the most widely used algorithms for optimization. Beside the cuckoo's behavior shown before, it based on the technique of Lévy flights rather than the simple isotropic random walks. Lévy flight is characterized by infinite mean and variance which cause much longer step from its current position, so it is more efficient in exploring the search space.

From the CS implementation attitude, each egg is a solution, and only one egg "solution" can be laid by each cuckoo. The aim is to substitute a not-so-good solution by potentially better solution. The CS is based on three basic rules as following:

1. One cuckoo egg is laid at a time and placed in a randomly chosen nest.
2. The best nests with a high quality of eggs "solutions" will be reserved to the next generations.
3. A host bird can detect a dumped egg in his nest with a probability of Pa $\in$ (0, 1).

The CS strength lies in combining a local search "intensification" with a global search "diversification" controlled by a switching parameter pa. The global search is performed when the cuckoo is searching for a nest to replace an egg with a new one "solution," while the local search is performed when the nest with the strange egg has been detected by the host bird and it should be replaced by a new one. If the egg of a cuckoo in the host bird's nest is very similar to the eggs of the host bird, and then, this cuckoo's egg is less likely to be discovered. Thus, the fitness should be related to the difference in solutions. Figure 1 shows how CS works.

Obviously, in the simple view of CS algorithm, there is no difference between cuckoo, egg or nest; all of them represent a potential solution in the search space. Another case of CS can be obtained where each nest has multiple eggs representing a set of solutions. So, CS has many advantages over conventional algorithms as it has been convenient to different problems even the multi-objective problems with less parameter usage.

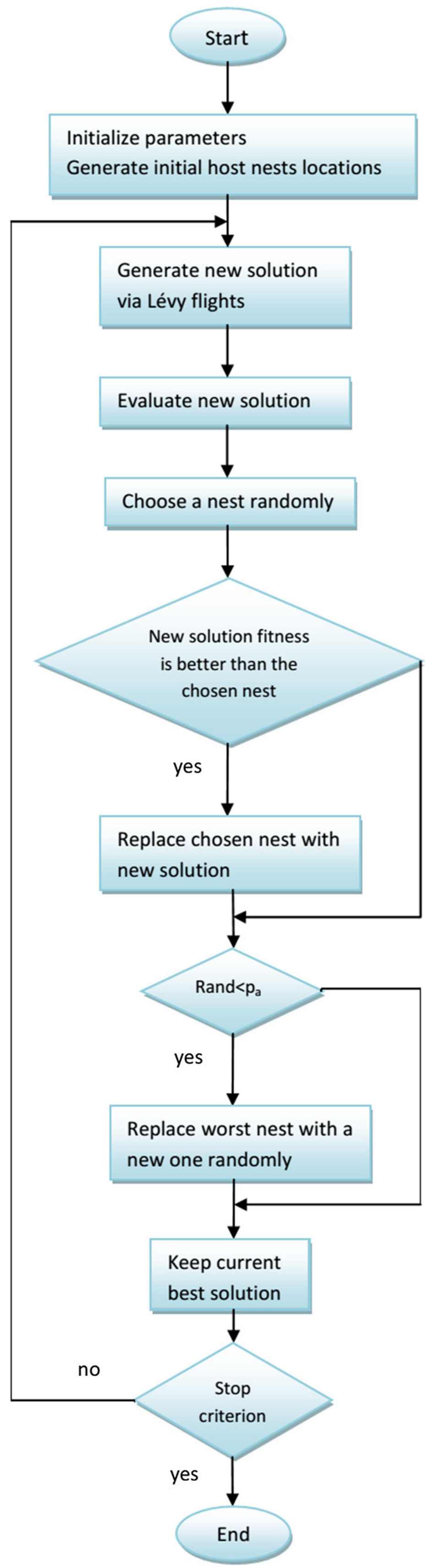


Fig. 1 Cuckoo search flowchart

In order to gain insight into CS search mechanisms, the following formulation has been introduced [11]. The local search can be expressed mathematically, as:

$$x_i^{t+1} = x_i^t + \alpha s \otimes H(p_a - \in) \otimes (x_j^t - x_k^t), \tag{1}$$

where x_j^t and x_k^t are two different solutions selected randomly by random permutation, $H(\mathrm{u})$ is a Heaviside function, $\in$ is a random number drawn from a uniform distribution, and s is the step size. For the global search, it can be formulated as:

$$x_i^{t+1} = x_i^t + \alpha L(s, \lambda), \tag{2}$$

$$L(s, \lambda) \sim \frac{\lambda \Gamma(\lambda) \sin\left(\frac{\pi\lambda}{2}\right)}{\pi} \frac{1}{s^{1+\lambda}}, (s \gg s_0 > 0) \tag{3}$$

where, $\alpha > 0$ is the step size scaling factor that should be related to the scales of the problem. In most cases, $\alpha = O(L/10)$ can be used, where L is the characteristic scale of the problem while in some cases $\alpha = O(L/100)$ can be more effective and avoid flying away. Note that the step size scaling factor has been written as α in Eqs. (3) and (4) regardless the difference in value instead of using two various parameters α_1 and α_2. For simplicity, it has assumed that ($\alpha_1 = \alpha_2 = \alpha$). In addition, "$\sim$" has been written instead of "=" so as to denote drawing random numbers from the distribution; not calculating by using a power law.

3 Cuckoo search variants

Since the original CS appearance in 2009, hundreds of CS studies have been developed. Many researchers have introduced several CS variants which include modification in CS parameters for increasing its efficiency and robust; or hybridization of it with other algorithms to merit different algorithms capabilities. Next, some selected variants will be briefly discussed.

3.1 Modified cuckoo search

3.1.1 Modified cuckoo search (MCS)

Walton et al. [12] have applied two modification to the CS algorithm: the first modification is made to the size of the Lévy flight step size α which has been constant $(\alpha) = O(1)$ has been used by Yang and Deb [8]. The second modification is the information exchanging between the eggs.

In MCS, the eggs are sorted according to their fitness and categorized in two different groups where the high fitness eggs are put into "the top egg group" and the others are put in "the abandoned group". For the abandoned group, α is calculated at each generation by the following formula:

$$\alpha = A/\sqrt{G} \tag{4}$$

where A is the Lévy flight step size (initially $A = 1$) and G is the number of generation.

Obviously, α is inversely related to the number of generations that lead to more local search when getting closer to the solution. For each top egg, another top egg is chosen randomly and a new egg position is generated on the line connecting these two top eggs. This line distance is calculated using the inverse of the golden ratio as:

$$\varphi = (1 + \sqrt{5})/2 \tag{5}$$

If the same egg is picked twice, a local Lévy flight search is done as:

$$\alpha = A/G^2 \tag{6}$$

Also, if the chosen top eggs have the same fitness, the new egg is generated at the midpoint.

3.1.2 Modified adaptive cuckoo search (MACS)

Modified adaptive cuckoo search [13] is another modified version of CS which incorporates the original CS with the following strategies: grouping, parallel, incentive, adaptive, and information sharing. The grouping strategy means that dividing the population into subgroups in order to increase the survival rate of some low-fitness eggs for population diversity, i.e., the grouping strategy prevent some new low-fitness eggs with better gene fragments from easily abandoned in the early stage after their appearance. The grouping strategy can be expressed as:

$$x_j = (x_1, \ldots, x_D)^T \tag{7}$$

$$P_{\mathrm{sk}} = \left\{x_j | 1 \le j \le N_e \text{ and } \quad j \in Z\right\} \tag{8}$$

$$P = \{P_{\mathrm{sk}} | 1 \le k \le N \quad \text{and} \quad k \in Z\} \tag{9}$$

where x_j denotes the jth subgroup member, P_{sk} is the kth subgroup, N_{e} is the subgroup size, and P is the population set.

On each subgroup, cuckoos search the neighborhood space of subgroup for the best solution. If the new solution is better than the worst subgroup solution, cuckoos substitute it with the new one and the successful flight wins a successive flight, until the flight fails to increase the exploitation rate of promising areas "incentive," i.e., there are equal numbers of cuckoos doing a parallel search which enhances the solution space exploration. This strategy searches not only the neighborhoods of the whole population best solution but also the neighborhoods of some worse solutions as well. At the end of each generation, the population is sorted by their fitness value and divided into new subgroups so that the individuals can be exchanged between different subgroups to achieve information sharing. In addition, MACS has used an adaptive Lévy flights step size to adjust search range in different stages.

$$\alpha = \alpha_{\min} + \left(\frac{\mathrm{FE}_{\max} - \mathrm{FE}}{\mathrm{FE}_{\max}}\right)^{m} \cdot (\alpha_{\max} - \alpha_{\min}) \tag{10}$$

$$\alpha_{\min} = \frac{(\mathrm{ub} - \mathrm{lb})}{100} \tag{11}$$

$$\alpha_{\max} = \frac{(\mathrm{ub} - \mathrm{lb})}{4000} \tag{12}$$

where FE is the number of function evaluation, $\mathrm{FE}_{\max}$ is the maximum number of FE, $\alpha_{\max}$ and $\alpha_{\min}$ are maximum and minimum step size, respectively, m is the nonlinear coefficient, and ub and lb are the upper and lower bounds of the selected problem.

3.2 Chaotic cuckoo search

Chaos maps are evolution functions that produce a deterministic bounded sequence of random numbers depending on initial condition. They can have discrete or continuous time domain. There are different types of maps like logistic map, Chebyshev map, tent map (see Table 1).

Chaotic metaheuristics are recently used for more randomness and escaping from local optima. The main idea of integrating chaos maps with the procedures of metaheuristics is availing the chaos maps features. As well, chaos maps can be used instead of the random sequence generator because of being random like, non-period, and non-converging for parameter adaptation.

3.2.1 Emotional chaotic cuckoo search (ECCS)

Lin and Lee [14] have introduced an integration between the Lévy flight and the chaos maps in order to improve the search process. As the Lévy flight has infinite mean and variance, it can lead to a premature search process. To avoid that, the chaotic Lévy flight has used the logistic map to generate a chaotic sequence for the Lévy flight parameter, as:

$$c_s(t+1) = 4.0 \times c_s(t) \times (1 - c_s(t)), \quad 0 \le c_s(0) \le 1 \tag{13}$$

where c_s is the chaotic sequence.

Then, the α parameter in Eq. (1) will be replaced by the generated c_s. Also, a new emotional acceptance criterion is added to prevent getting trapped into local optima. For ECCS, there are two cuckoos' emotions (positive and negative) which correspond to two reactions as follow:

$$e_s = -k \ln\left|\frac{S(F(x_i) - F(x_j))}{S_0}\right|$$

$$\mathrm{IF}(c_s < e_s) \quad \begin{array}{l} \text{THEN positive} \\ \text{ELSE negative} \end{array} \tag{14}$$

where e_s is the cuckoo's emotion, k is a constant factor, S is the stimulus function, S_0 is a stimulus threshold, and F is the fitness function.

3.2.2 Chaotic cuckoo search (CCS)

Like ECCS, the proposed CCS [15] has replaced the value of α, but with 12 different one-dimensional chaotic maps. In addition, an elitism strategy is introduced to protect the best cuckoos from being corrupted by cuckoo updating operator. So, even if cuckoo updating operation destroys its corresponding cuckoo, the best cuckoos can be reverted back if needed. The authors have shown that the performance of CCS is more effective with the sine map and sinusoidal map than others. Regarding these two maps, on average, the sinusoidal map is significantly better than the sine map on most benchmarks. Also, it can provide more information for CS to guide its search while other chaotic maps cannot. When multiple runs are made, it yields a slight difference output with the optimal value. So, it has been selected as the final optimal map to be used for chaotic CS (CCS).

3.3 Improved cuckoo search (ICS)

The main idea behind ICS [16] is adjusting the value of two fixed parameters P_a and α; i.e., in the original CS, the values of P_a and α are fixed which may lead to significant increase in the iteration number if the value of pa is small and the value of α is large. Also, if the value of P_a is large and the value of α is small, it may lead to a premature convergence. The ICS algorithm has identified big enough values of P_a and α in the early generations to increase the diversity of solution vectors. However, these values are decreased in final generations to result in a better fine tuning of solution vectors. The values of P_a and α are dynamically changed with the number of generation as following:

$$P_a(N_G) = P_a^{\max} - \frac{(P_a^{\max} - P_a^{\min})}{N_{\mathrm{iter}}} \times N_G \tag{15}$$

$$\alpha(N_G) = \alpha_{\max} \exp(c N_G) \tag{16}$$

$$c = \frac{\ln(\alpha_{\min}/\alpha_{\max})}{N_{\mathrm{iter}}} \tag{17}$$

where N_{iter} denotes the number of total iterations and N_G is the current iteration.

Table 1 Chaos maps

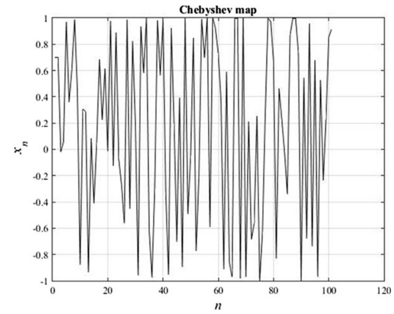
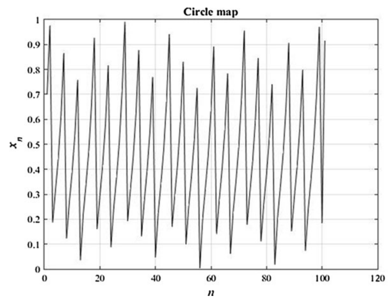
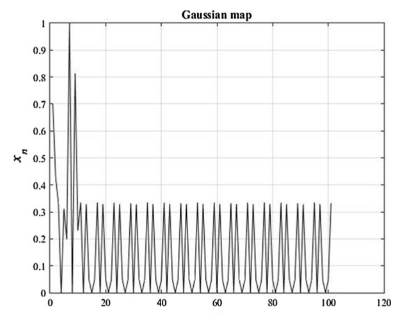
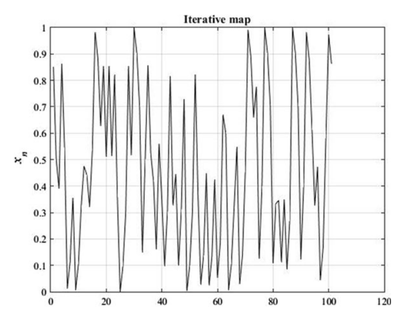
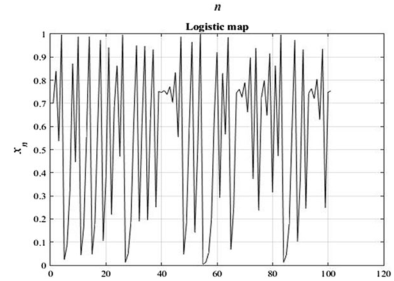
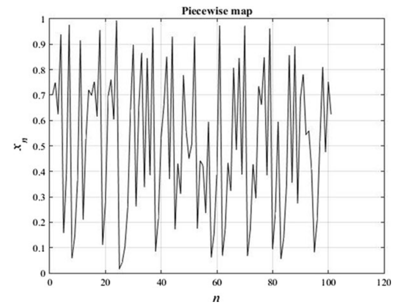
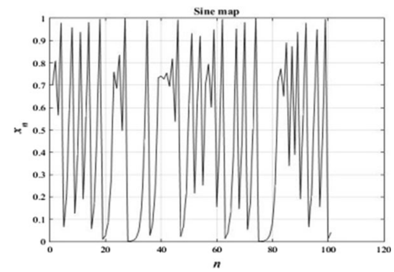
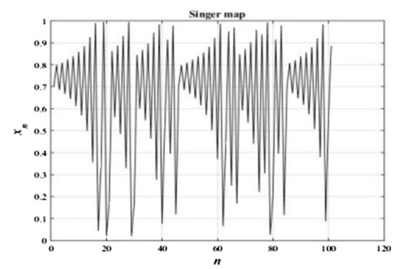
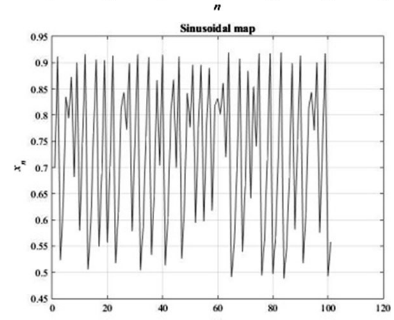
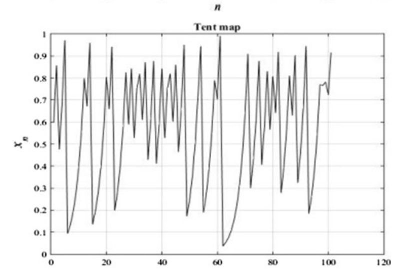
No.	Map name	Definition	Modality
1.	Chebyshev	$x_{n+1} = \cos(k \cos^{-1}(x_n)), \quad x \in (-1, 1)$, where k is a constant	
2.	Circle	$x_{n+1} = x_n + b - (a/2\pi)\sin(2\pi x_n) \bmod (1)$ where $a = 0.5$ and $b = 0.2$, with range (0, 1)	
3.	Gaussian	$x_{n+1} = f\,(x) = \begin{cases} 0, & x_n = 0 \\ \dfrac{1}{x_n} \bmod (1), & \text{otherwise} \end{cases}$	
4.	Iterative	$x_{n+1} = \sin\left(\frac{a\pi}{x_n}\right), \quad a \in (0, 1)$	
5.	Logistic	$x_{n+1} = a x_n (1 - x_n), \quad x \in (0, 1), \quad 0 < a \leq 4$	

Table 1 continued

No.	Map name	Definition	Modality
6.	Piecewise	$x_{n+1} = \begin{cases} \frac{x_n}{p}, & 0 \le x_i < p \\ \frac{x_n - p}{0.5} - p, & p \le x_n < 0.5 \\ \frac{1 - x_n - p}{0.5} - p, & 0.5 \le x_n < 1 - p \\ \frac{1 - x_n}{p}, & 1 - p \le x_n < 1 \end{cases}$	
7.	Sine	$x_{n+1} = \frac{a}{4}\sin(\pi x_n), x \in (0,1), 0 < a \le 4$	
8.	Singer	$x_{n+1} = \mu\left(7.86x_n - 23.31x_n^2 + 28.75x_n^3 - 13.302875x_n^4\right)$, $\mu = 1.07$	
9.	Sinusoidal	$x_{n+1} = ax_n^2 \sin(\pi x_n), \quad a = 2.3$	
10.	Tent	$x_{n+1} = f(x) = \begin{cases} \frac{x_n}{0.7}, & x_n < 0.7 \\ \frac{10}{3}(1 - x_n), & x_n \ge 0.7 \end{cases}$	

3.4 Multi-objectives cuckoo search (MOCS)

The use of traditional single-objective metaheuristics has become insufficient for multiple conflicting objectives of a wide range of optimization problems. Therefore, the need of multi-objective optimization has been raised. Multi-objective optimization can reconcile between a set of alternatives instead of a single/best solution of single-objective metaheuristic "Pareto front" which subject to a set of constraints. Also, it could be also called "vector optimization," "multicriteria optimization," "multiattribute optimization" or "Pareto optimization." The proposed algorithm [17] emulates some of the evolutionary computation concepts which make MOCS more efficient due to diversifying of the search. MOCS based on three main rules:

1. A number K of cuckoo eggs are laid at a time and placed in a randomly chosen nest.
2. The best solutions will be reserved to the next generations "elitism".
3. Each nest will be abandoned with a probability pa, and a new nest with K eggs will be built, according to the similarities or differences of the host eggs. Some random mixing can be used to generate diversity. This implies that n nests are replaced by new nests randomly with the fraction pa. "mutation."

Obviously, the first and last rules should be modified to incorporate multi-objective criteria which has K different objectives. The authors have shown that according to the first rule, the new solutions are generated by performing random walks or Lévy flight. Simultaneously, a form of crossover is performed over solutions through a localized random permutation. For each nest, there can be K solutions which are generated using Eq. (18). In addition, the mutation in the last rule is a vectorized operator that combines Lévy flight and differential quality of the solutions.

$$x_i^{t+1} = x_i^t + \alpha \oplus \text{Le vy}(\beta) \tag{18}$$

$$\alpha = \alpha_0 (x_j^t - x_i^t) \tag{19}$$

$$\text{Lévy} \sim u = t^{-1-\beta}, \quad (0 < \beta \leq 2) \tag{20}$$

where $(x_j^t - x_i^t)$ is the difference between two randomly solutions to denote the difference between solution quality.

Also, the generation of step size s samples is a very important operation which is performed using Lévy flight as:

$$s = \alpha_0 \left(x_j^t - x_i^t\right) \oplus \text{Le vy}(\beta) \sim 0.01 \frac{u}{|v|^{1/\beta}} \left(x_j^t - x_i^t\right) \tag{21}$$

where μ and v follow the normal distribution as:

$$u \sim N(0, \sigma_\mu^2) \quad v \sim N(0, \sigma_v^2) \tag{22}$$

with

$$\sigma_u = \left\{ \frac{\Gamma(1+\beta) \sin\left(\frac{\pi\beta}{2}\right)}{\Gamma\left[\frac{1+\beta}{2}\right] \beta 2^{(\beta-1)/2}} \right\}, \quad \sigma_v = 1 \tag{23}$$

where Γ is the standard gamma function.

3.5 Hybridization of CS

The hybridization of CS with other techniques (optimization algorithms, machine learning techniques, heuristics, etc.,) is a prevailing research area because the high efficiency of these algorithms which makes it possible to apply them for solving a wide range of optimization problems. In each part of CS, the hybridization can be carried out. For example:

3.5.1 CS/PSO algorithm

Ghodrati and Lotfi [18] have proposed hybridization between CS and the particle swarm optimization (PSO) algorithm [5]. The proposed algorithm has mimic PSO swarm intelligence to add a communication between cuckoos to inform each other about their positions and help each other to immigrate to a better place.

3.5.2 CS–GA algorithm

Kanagaraj et al. [19] have hybridized CS with the genetic algorithm (GA) [3]. In each CS–GA generation, every two-parent cuckoos will reproduce two eggs instead of one cuckoo egg at a time; the crossover and mutation are performed, respectively. Also, some form of elitism is applied after each operation. Before the generation end, the best solution in the current population will perform Lévy flight to increase the search space exploration for the next generation. At each generation, the algorithm creates a new population via genetic principles "natural selection."

3.5.3 CS/ACO algorithm

In [20] study, the main disadvantage of ant colony optimization (ACO) [4] has been handled by CS, i.e., the ants deposit chemical trail called pheromone on the ground in order to guide the other ants toward the source food. The pheromone quantity left by one ant relies on the amount of food found and the number of ants using this trail. Moreover, this trail has a decreasing action over time "trail evaporation." To accelerate the search process, CS can perform the local search more efficient and faster. Also, there is only a single parameter apart from the population size in CS.

3.5.4 MKF-Cuckoo algorithm

Binu et al. [21] have introduced a new hybrid algorithm "MKF-Cuckoo" which is the hybridization of cuckoo search algorithm with the multiple kernel-based fuzzy c means algorithm (MKFCM) [22]. The objective of MKF-Cuckoo is to find the best centroid in the search space. The proposed algorithm depends on three main phases: (1) the initial solution encoding process by choosing random centroid taken from the input dataset that has represented as $m * k$ matrix, (2) defining the fitness function as minimization function which makes use of kernel-based distance and fuzzy membership function to find the minimum distance between the data points with its nearest neighbor cluster centroid, (3) applying CS approach.

3.5.5 TLCS algorithm

A new hybrid algorithm named teaching–learning-based cuckoo search (TLCS) is proposed by Huang et al. [23]. TLCS has hybrid CS with teaching–learning-based optimization (TLBO) [24]. The main TLCS idea is dividing the population into two subgroups (top solutions P1 and abandoned solutions P2), then applying TLBO to P1 group and the Lévy flight to P2 group.

3.5.6 CS/ABC algorithm

Singla et al. [25] have introduced a hybridization between CS and artificial bee colony optimization (ABC) [26] algorithms to improve the search strategy of CS by using the ABC global search strategy which depends on filtering the solution from the all the bees (onlooker and Scout bees) to give the quality of the food Nectar.

3.5.7 CSHS algorithm

Sheikholeslami et al. [27] have combined CS with a harmony search algorithm (HS) [28] to introduce a new double stage optimization algorithm (CSHS). The framework of CSHS has been used to get rid of CS drawbacks: premature convergence due to random walk and no communication between individuals; i.e., first CS is used for the initial exploration of the search space then a hybridization of CS and HS approaches is employed in the exploitation phase.

3.5.8 CS–IDE algorithm

Zhang et al. [29] have combined CS with the improved differential evolution (IDE) [30] algorithm to merge CS exploration and IDE exploitation capabilities. IDE is an improved version of the traditional differential evolution (DE) [31] algorithm which has the benefits of evolutionary algorithms (mutation, crossover, selection, and elitism). IDE was chosen instead of DE for the sake of higher accuracy as IDE has an adaptable step size which is updated dynamically according to the various generation results.

3.5.9 CCS based on SFLA

Liu and Fu [32] have proposed a new improved CS that utilizes three enhancement methodologies: (1) chaos maps (the Logistic and Tent maps) have been used for generating initial population for more randomization, (2) inertia weight has been used in the Lévy flight to improve exploration, and (3) a hybridization of CS and the local search technique of shuffled frog leaping algorithms (SFLA) [33] has been used to improve the convergence rate.

3.6 Discretizing of CS

There are numerous optimization problems that cannot be solved by using continuous metaheuristic. Therefore, the researchers have to develop different discretization methods to accommodate discrete and combinatorial problems such as traveling salesman problem, facility location problem, make span scheduling problem, and knapsack problem.

For CS, several discretization methods have been proposed. Table 2 shows the main methods that have been used for discretizing CS.

4 Cuckoo search applications

Due to the CS simplicity and flexibility, it has been applied for solving many optimization problems in various fields. In this section, a small fraction of the relevant applications will be listed in Table 3.

5 Cuckoo optimization algorithm (COA)

The COA basic idea is the survival of cuckoo population (mature cuckoos and eggs) in different societies which lead to the pursuit for immigration to a better environment. As discussed before, cuckoos dump eggs into different host nests. These eggs have the chance to grow up if they are more similar to the host bird's eggs, if not they will be killed. After eggs growing, they become mature cuckoo and begin to make societies. Each society has its habitat

Table 2 Major CS discretization methods

Authors and year	Discretization method	References
Zheng et al. (2012)	Transform a COA continuous search space into a binary one by using the sigmoid function (SF): $x_{ij} = f(x) = \begin{cases} 1, & \text{rand}() \leq \dfrac{1}{1+\exp(-x_{ij})} \\ 0, & \text{otherwise} \end{cases}$	[34]
Burnwal and Deb (2013)	The nearest integer (NI):	[35]
	Real values are converted to NI by rounding or truncation	
Ouaarab et al. (2015)	Random key (RK) encoding scheme:	[36]
	uses a vector of random numbers then assigning a weight to each element in the vector (in ascending order). These weights are used to generate one combination as a solution	
Dasgupta and Das (2015)	The smallest position value (SPV):	[37]
	SPV is similar to RK, but it depends on element permutation; i.e., it places the weight of the lowest valued element as the first item on a permutated solution, the next lowest as the second and so on	
Li and Yin (2013)	The largest ranked value (LRV) rule-based random key:	[38]
	LRV is similar to SPV, but the permutation is carried out according to the largest element value	
Guo et al. (2015)	Redefine Lévy flight operations as:	[39]
	The subtraction is replaced by a comparison strategy	
	The addition is replaced by a number of swap moves	
	The multiplication: For each solution vector, a random number is generated for each element, and then it will be compared with the scalar $\sigma \sim = t^{-\lambda}$ to take the corresponding decision	

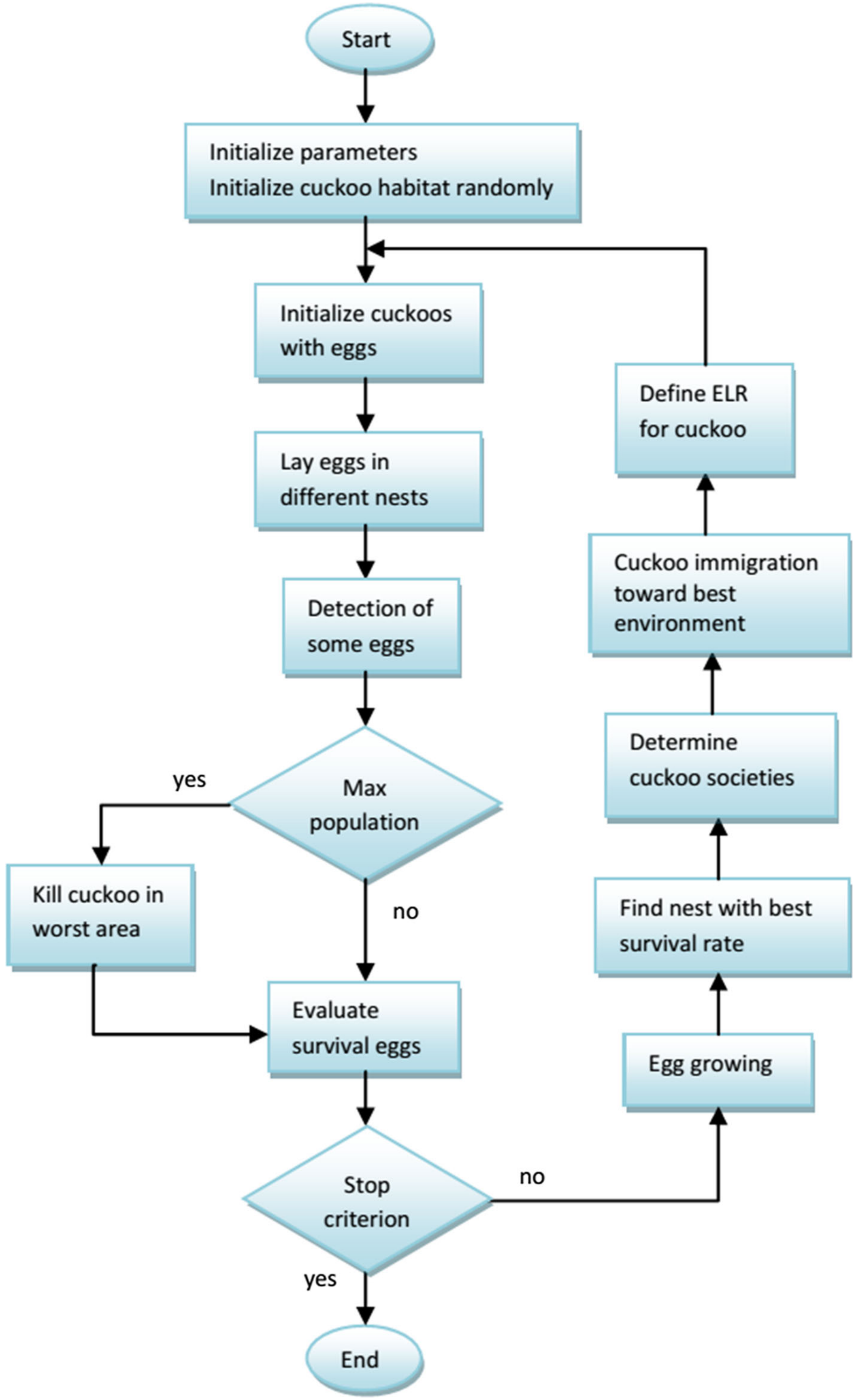
Table 3 CS main applications

Field	Applications
Bioinformatics	Training Artificial Neural Networks [40], Cloud Computing Optimization [41]
Computer Science	Web Document Clustering [42, 43]
Engineering	Structure Designing And Machining Processes [23], Design Of Water Distribution Systems [27], Spectrum Parameter Estimation In Brillouin Scattering Distributed Temperature Sensor [29], Load Frequency Control (LFC) [44], Flexible Single-Link Manipulator [45], Wind Farm Reliability Optimization [46], The Design Process Of Integrated Power Systems For Modern And Energy Self-Sufficient Farms [47], Integrated Circuits (ICS) [48], Network Distribution [49], Performance Analysis [50]
Operations Research	Reliability–Redundancy Allocation Problems [19], Job Scheduling [20], Knapsack Problem [34], Traveling Salesman Problem [36], Scheduling Optimization of Flexible Manufacturing System [35], Flow Shop Scheduling Problems [37] [38], Parallel Machine Scheduling with Step-Deteriorating Jobs and Setup Times [39], Economic Dispatch Problems [51] [52], The Capacitated Vehicle Routing Problem (CVRP) [53], Forecast The Annual Foreign Tourist [54]
Information Science	Image Segmentation [55–57], Satellite Image Classification [25], Noise Suppression and Enhancement of Speech Signal [58], Image Compression [59], Tsallis Entropy Image Processing [60], Face Recognition [61], Cryptanalysis of Vigenere Cipher [62], Optimum Wavelet Based Masking (OWBM) [63]
Geolocation	Mobile Object Tracker [64]
Mathematics	Parameter Estimation of Takagi–Sugeno Fuzzy System [65]

region to live in. Cuckoos are always searching for the best habitat which has more eggs survival rate to be their destination for laying eggs. Then each cuckoo starts to lay an egg inside her egg laying radius (ELR) in some nests randomly. The algorithm stops when all the survived cuckoos converge to the same position (see Fig. 2). To apply COA, the following rules should be considered:

1. The values of any optimization problem variables should be formed as an array called "habitat;" i.e., In a N_{var}—dimension optimization problem, a habitat can be expressed as an array of $1 \times N_{\text{var}}$, which representing the current location of the survival cuckoos.

Fig. 2 COA flowchart



$$\text{Habitat} = [x_1, x_2, \ldots, x_{N_{var}}] \tag{24}$$

2. At different iterations, the lower and upper bounds of cuckoo eggs are 5 and 10, respectively.
3. Each cuckoo lay eggs within a maximum distance from their habitat called "Egg Laying Radius (ELR)." ELR depends on the total number of eggs, number of current cuckoo's eggs, and also variable limits (see Fig. 3).

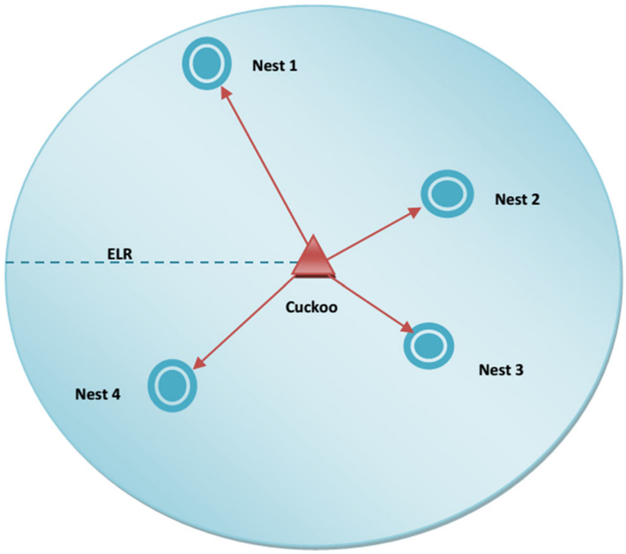


Fig. 3 Random egg laying in ELR

ELR can be defined as:

$$\mathrm{ELR} = \alpha \times \frac{\text{number of current cuckoos eggs}}{\text{total number of eggs}} \times (\mathrm{var}_{\mathrm{hi}} - \mathrm{var}_{\mathrm{low}}) \tag{25}$$

where α is an integer for controlling ELR maximum value and $\mathrm{var}_{\mathrm{hi}}$ and $\mathrm{var}_{\mathrm{low}}$ are variable limits.

4. After egg laying, p % of all eggs (usually 10 %), with less profit (more cost) values, will be killed.
5. The grouping of cuckoos' societies is done with K-means clustering method (a k of 3–5 seems to be sufficient in simulations).
6. For immigration of cuckoos, each cuckoo only flies λ% of all distance toward goal habitat and also has a deviation of φ radians. These two parameters λ and φ help cuckoos search much more positions in all environment (see Fig. 4). For each cuckoo, λ and φ are defined as follows:

$$\lambda \sim U(0, 1) \tag{26}$$

$$\varphi \sim U(-\omega, \omega) \tag{27}$$

where λ is a random number and ω is a parameter for deviation controlling ($\omega = \frac{\pi}{6}$ seems to be enough).

6 COA variants

As COA is less popular than CS, few COA variants have been proposed, for example:

6.1 A modified cuckoo optimization algorithm (MCOA)

Instead of the fixed ELR in the original COA, Kahramanli [66] has used a modified ELR equation to gradually reduce the large ELR value, it can be formulated as:

$$t = \frac{\mathrm{max\_iter}}{c} \tag{28}$$

$$e = \mathrm{var}_{\mathrm{hi}} - \mathrm{var}_{\mathrm{low}} \tag{29}$$

$$a = \lfloor \mathrm{iteration}/t \rfloor + 1 \tag{30}$$

$$e_{\mathrm{new}} = \frac{e_{\mathrm{old}}}{a} \tag{31}$$

$$\mathrm{ELR} = \alpha \times \frac{\text{number of current cuckoo's eggs}}{\text{total number of eggs}} \times e_{\mathrm{new}} \tag{32}$$

where max_iter is the maximum number of iterations defined for the selected problem, c is constant inside the interval (0, 0.20]. (or it can be adjusted to fit the selected problem), and the bracts $\lfloor\,\rfloor$ means the truncation of the output.

6.2 Hybridization of COA

6.2.1 *COA/TS algorithm*

Dejam et al. [67] have combined COA with the tabu search algorithm (TS) [68] concept; i.e., the basic idea of TS is the prohibition "tabu or taboo" of already visited solution space from being visited again to increase diversification, i.e., TS applies any local search procedure intensively to explore the solution space and avoid getting trapped in local optima. During the local search, the best solution in the neighborhood is selected in each iteration as the new current solution by managing a memory of solutions or moves recently applied, called the tabu list to avoid the siege within cycles.

6.2.2 *COGSA algorithm*

Naseri [69] has introduced a hybridization between COA and gravitational search algorithm (GSA) [70]. GSA is a meta-heuristic optimization algorithm motivated by the Newton's laws of gravity and motion. According to GSA, solutions are considered as objects and their performance is measured by their masses which proportional to their value of fitness function. Every object attracts every other object with gravitational force. In the proposed algorithm, the author has used GSA for exploiting and COA for global exploration the search space.

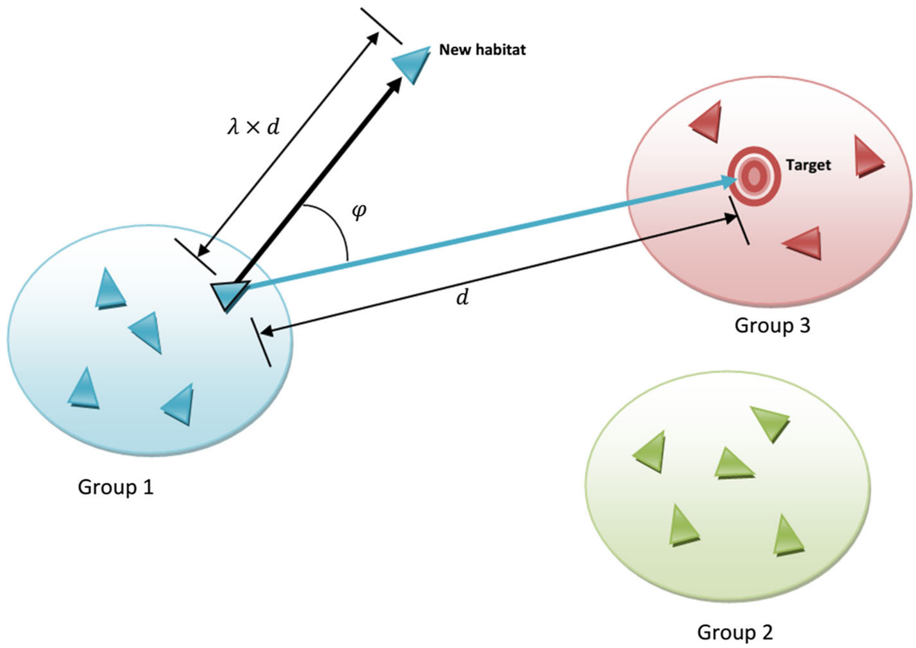


Fig. 4 Explanation of cuckoo Immigration

6.2.3 COA/PSO based on ES

Sarvi et al. [71] have proposed a combination between PSO and COA based on the Eagle strategy (ES) [72] approach; i.e., ES is a two-stage optimization algorithm that is conventional for applying to different purposes with a balanced combination of optimization algorithms. In the first stage, PSO performs initial exploration of the search space and the best solution of the first stage is transmitted to the second stage. In the next stage, COA searches for the global best solution around the first stage best solution.

6.3 Discretizing of COA

Table 3 summarizes the main COA discretization method (Table 4).

7 COA applications

Recently, COA has been applied in many areas of optimization because of the increased awareness about its promising efficiency. For the sake of conciseness, only a sample of COA main applications will be mentioned in Table 5.

8 Comparison between CS and COA

There is some confusion and misunderstanding of CS and COA in the literature, Fister and Yang [113] have provided a brief comparison between CS and COA so as to remove ambiguity and confusion between the concept of both algorithms. Also, Chen et al. [114] have made a comparison between the two algorithms, but this comparison was based on an "artificial neural networks (ANN)" case study. The results show that ANN–COA obtained slightly better results in this case. Table 6 shows the main difference between the two algorithms. In the last 2 years, the awareness of COA effectiveness has reflected on the number of publications that interested in employing COA for solving various problems. Figure 5 shows the percentage of CS and COA publications (forecast).

9 Conclusion

Although the nature-inspired metaheuristics are not well understood regarding why these algorithms work efficiently, they are the most efficient and widely used solution techniques, especially, the evolutionary algorithms such as the previously discussed algorithms CS and COA. However, metaheuristics are not problem specific, choosing the appropriate metaheuristic for the given problem should be considered, i.e., the more adaptation to the given problem, the more efficient metaheuristic. This is, what characterizes CS since it owns a few parameters that need to be adjusted and as shown before CS has many variants which have been applied to numerous application areas. For COA, it has proved its efficiency in solving several problems, especially ANN. But it is still promising and needs more research.

This paper gives an overview of CS and COA main structures, variants, and applications which has been

Table 4 Major COS discretization methods

Authors and year	Discretization method	Reference
Mahmoudi et al. (2013)	transform a COA continuous search space into a binary one by using the sigmoid function $(\mathrm{SF}){:}x_{ij} = f(x) = \begin{cases} 1, & \mathrm{rand}() \leq \dfrac{1}{1+\exp(-x_{ij})} \\ 0, & \text{otherwise} \end{cases}$	[73]
Kazemi and Dejam (2014)	Random-key (RK) encoding scheme: Uses a vector of random numbers then assigning a weight to each element in the vector (in ascending order). These weights are used to generate one combination as a solution. Then, the concepts of distance and geometric rules should be considered by redefining: The new solution generation: Three different operators are defined and for each solution vector, one operator is selected randomly and applied to determine the new position. the three operators are: (1) Permutation: replacing two points selected randomly (2) Sequence order Inversion: several sequential positions are selected and reversed (3) Shifting The migration operator: find the positional Difference between two habitats (the goal point and the current habitat)	[74]
Mousavirad and Ebrahimpour-Komleh (2014)	The nearest integer (NI): A real values are converted to NI by rounding or truncation	[75]

Table 5 CS main applications

Field	Applications
Bioinformatics	Artificial Neural Networks [76–78], Cloud Computing Optimization [79], Feature Selection [80]
Computer Science	Soft Sensor [81], Clustering [82, 83], The Graph Coloring Problem (GCP) [84]
Engineering	Connecting Rod [85], Liquid Level Control [86], Energy Management [87], The Crack Detection Problem [88], Circular Antenna Arrays Design [89], The Selective Harmonic Elimination (She) Problem [90], Design A Hybrid Wind Turbines/Solar Arrays/Fuel Cells System [91], Machining [92], Power Point Control [71, 93], Optimal Power Flow (OPF) Problem [94], Optimal Synchronization Of Teleoperation Systems [95], Optimum Operation Of Reservoir [96], Estimation Of Induction Motor Efficiency Value [97], Inverse Kinematics In Robotics [98]
Operations Research	Quadratic Assignment Problem [67, 74], Production Planning Problem [99], Urban Bus Terminal Location Problem [100], Economic Dispatch [101, 102], Optimal Replacement of Dependability Activities [103], Job Scheduling [104], Coordination of Overcurrent and Distance Relays Optimization [105], Facility Layout Problem (FLP) [106]
Geophysics	Gravity Method [107, 108]
Information Science	Image Segmentation [109, 110], Image Enhancement [111], Image Compression [112]

Table 6 Major difference between CS and COA

Concept	CS	COA
Candidate solution representation	Nest and Egg position	Cuckoo position in habitat
Number of eggs laid	1	5–10
Movement	Lévy flights	ELR
Local search	Random walk	Variable neighborhood search (VNS) [115]
Global search	Redefining the worst solutions	Migration
grouping	No grouping involved	K-means clustering method
Replacement	One-to-one	Replace worst

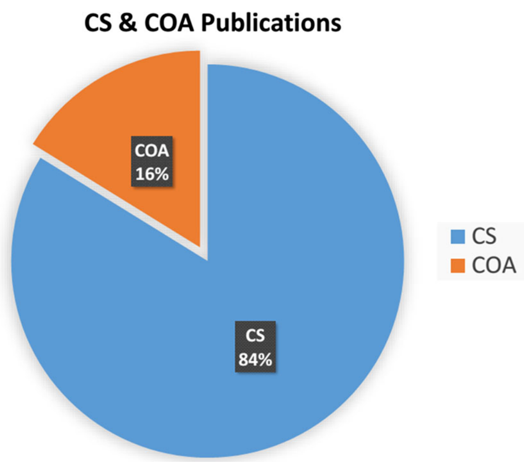


Fig. 5 Percentages of CS and COA publications

supported by a comparison between both algorithms to help the researchers deeply understand the difference between CS and COA algorithms in a simple way.

For future works, there are many applications that can be solved potentially by CS and COA, such as robotics and geographic information system (GIS). Hybridization of cuckoo-inspired algorithms and variants with other methods can be also useful.

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