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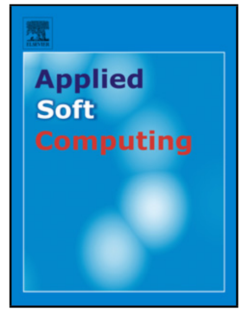

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A survey on applications and variants of the cuckoo search algorithm

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Abstract

This paper introduces a comprehensive and exhaustive overview of the cuckoo search algorithm (CSA). CSA is a metaheuristic swarm-based approach established by Yang and Deb in 2009 to emulate the cuckoo breeding behavior. Owing to the successful application of CSA for a wide variety of optimization problems, since then, researchers have developed several new algorithms in this field. This article displays a comprehensive review of all conducting intensive research survey into the pros and cons, main architecture, and extended versions of this algorithm.

It is worth mentioning that the materials of this survey paper are categorized in accordance with the structure of the CSA in which the materials are divided into the CSA versions and modification, publication years, the CSA applications areas, and the hybridization of CSA. The survey paper ends with solid conclusions about the current research on CSA and the possible future directions for the relevant audience and readers.

The researchers and practitioners on CSA belong to a wide range of audiences from the domains of optimization, engineering, medical, data mining, clustering, etc., who will benefit from this study.

Keywords:
Cuckoo Search Algorithm, Metaheuristic, Swarm-based approach, Nature-inspired Algorithms, Optimization

1. Introduction

Optimization resides in many domains, such as engineering, energy, economics, medical, and computer science. It is mainly concerned with finding the optimal values for several decision variables to form a solution to an optimization problem . An optimization problem is the minimization or maximization of a suitable decision-making algorithm normally adapted to the approximation methods. The principle of decision making entails choosing between several alternatives. The result of this choice is the selection of

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the "best" [1] decision from all choices.

Optimization algorithms developed based on nature-inspired ideas deal with selecting the best alternative in the sense of the given objective function. The optimization algorithm can be either be a heuristic or a metaheuristic approach. Heuristic approaches are problem-designed approaches where each optimization problem has its own heuristic methods that are not applicable for other kinds of optimization problems. The metaheuristic-based algorithm is also a general solver template that can be adapted for various kinds of optimization problems by properly tweaking its operators and configuring its parameters. To elaborate, each optimization algorithm can be categorized into three classes: evolutionary algorithms (EAs), swarm-based algorithms, and trajectory-based algorithms [1]. EAs mimic the evolutionary principle of survival of the fittest. It normally begins with a set of individuals (i.e., solutions) called population. At each generation, the EA algorithms recombine the preferable characteristics of the current population to come up with a new population that will be selected based on the natural selection principle. Examples of EAs include genetic algorithms (GAs) [2], genetic programming (GP) [3], differential evolution (DE) [4], and a harmony search (HS) algorithm [5]. On the other hand, swarm-based algorithms mimic the behavior of a group of animals when searching for food. At each iteration, the solutions are normally constructed based on historical information gained by previous generations [6]. Examples of swarm-based algorithms include the artificial bee colony (ABC) [7], the particle swarm optimization (PSO) [8], the firefly algorithm (FA) [9], and the cuckoo search algorithm (CSA) [10]. Trajectory-based algorithms start with a single provisional solution. At each iteration, that solution will be moved to its neighboring solution, which resides in the same search space region, using a specific neighborhood structure. Examples of trajectory-based algorithms includes tabu search (TS) [11], simulated annealing (SA) [12], hill climbing [13], and β-hill climbing [14](see Figure 1 for a general overview).

The main focus of this survey paper, the CSA, was developed by Yang and Deb (2009) to emulate the brood parasitism behavior of cuckoos. Cuckoos have an aggressive breeding behavior, which inspired the optimization algorithm. Brood parasitism is a primary mechanism of cuckoos. This bird lays eggs in the hosts nest and carefully matches its eggs through mimicking the pattern and color of the hosts eggs [15]. In case the host recognizes the cuckoos eggs in its own nest, it will either throw the eggs out or simply leave its nest and build a new one. Therefore, a cuckoo must be accurate in its mimicry of the host eggs, whereas the host must improve its skills in determining the parasitic egg; therein lies the struggle for survival. In the optimization context, each egg in the nest represents a solution, and the cuckoos egg represents a new solution. The aim is to serve the new and potentially better solutions to replace a not-so-good solution in the nests. The algorithm can be extended to more complicated cases where each nest has multiple eggs representing a set of solutions. Fraction $P\alpha$ with a probability [0,1] checks if a host discovers the eggs are not its own.

The main merits of the CSA over other optimization algorithms are as follows: the number of parameters needed to be configured in the initial search is very little, and the inexperienced user can easily interact with it. CSA has the strength points of TAs in exploitation through random walk and of EAs in exploration through *Lévy* flights. It is

[1]the idiom "best" here may refers to the satisfactory solution to the optimization problem. Also nonoptimal solutions may be considered as satisfactory

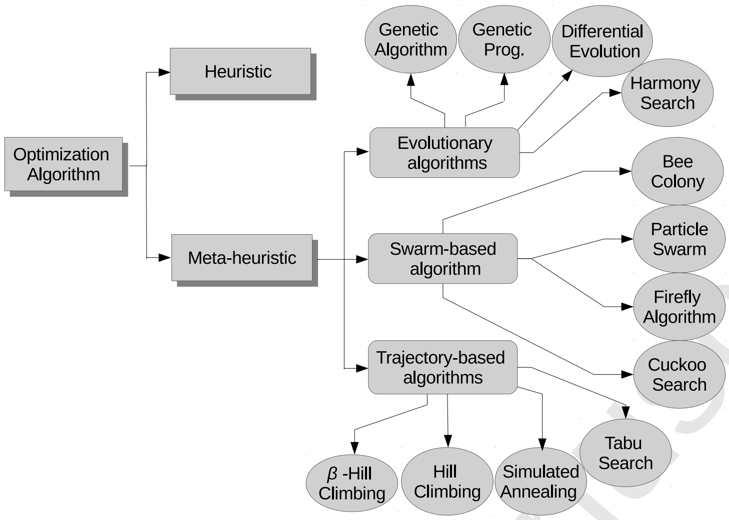

Figure 1: Optimization Algorithms

an efficient metaheuristic algorithm that balances between the local search strategy (exploitation) and the whole space (exploration) [16], deals with multi-criteria optimization problem, and aims for convergence speed and easy implementation. Owing to these merits, the CSA has been successfully tailored to a wide variety of optimization problems, such as image processing [17, 18, 19, 20, 21, 22], in the medical field [23, 24, 25], clustering and data mining [26, 27, 28], economic dispatch problems [29, 30, 31, 32, 33], engineering design [34, 35, 36, 37, 38, 39, 40], and power and energy [41, 42, 43, 44, 45, 46, 47].

The CSA is also modified and hybridized for the convenience of some combinatorial optimization problems because of the complex nature of some optimization problems [48, 49, 50, 51, 52, 53, 54, 55]. The parameter setting of the CSA is also addressed by several researchers [56, 57, 58, 59].

This survey paper provides the new CSA-based user a comprehensive and exhaustive overview of the theoretical aspects of CSA and presents the readers with sufficient materials for the previous adaptation, modification, and hybridization of the CSA. Previous studies on the adaptive parameters of CSA are also discussed. This paper focuses on the principles of CSA, its developments and variants to the original CSA, and a detailed report of recent applications and associated developments attained during the last few years. At the end of this review, the reader will be able to understand the design and working principle of CSA, as well as distinguish the developmental stages and diverse fields that used CSA to optimize solutions. Finally, the paper concludes with the main pros and cons of CSA and suggests possible future work for interested researchers.It is noted that the types of the optimization problem considered are generally minimization. However, some problems discussed in this survey paper are to be maximized. The author will frankly mention that when deemed necessary.

This survey paper is organized as follows. Section 2 introduces the CSA by highlighting its framework. Section 3 discusses the procedures of basic CSA. Then, the growth of

CSA illustrated in Section 4. Section 5 presented an overview of CSA variants and modifications. The application areas and improvements to each particular field is discussed in Section 6. Section 7 discusses three types of the CSA Hybridizations . Finally, Section 8 draws some concluding remarks and outlines several future research lines of interest.

2. Cuckoo Search Algorithm

There are more than 1,000 species of birds in nature, which are common in behaviors and features [60]. For example, all mother birds lay eggs that have different shapes of eggs from one another. Moreover, different nests are built by many birds in secured places to increase safety from predators [61].

Birds that resort to cunning for reproduction, specifically in building nests, are called brood parasites. These kinds of birds do not build their own nests but rather lay their eggs in the nest of another species, leaving the host to care for its young. The most famous of the brood parasites is the cuckoo. It has a fantastic way in the art of deception. Its strategy involves permeation by removing one egg laid by the host and laying her own. It then carefully matches its egg through mimicking the pattern and color of the hosts eggs, a skill that requires high accuracy to ensure its success. The timing of egg-laying is also an amazing way of selecting the nest where the host bird just laid its own eggs [62]. This process will reap benefits after a while; the cuckoo egg will hatch before the host eggs, and the first instinctive action of the host will be to evict its own eggs out of the nest by blind propelling, thus increasing the care and food provided for the cuckoos chicks. Cunning is inherited by the chicks; this trait is shown when the chicks mimic the call of host chicks to gain access to more feeding opportunity [63].

On the other hand, in case the host recognizes the cuckoo's egg in its nest, they either throw out the strange egg or simply leave their own nest and build a new one. The cuckoo must therefore be more accurate in mimicking the host eggs, whereas the host must improve its skills in determining the parasitic egg. Therein lies the so-called struggle for survival.

The use of CSA in the optimization context was proposed by Yang and Deb in 2009. To date, work on this algorithm has significantly increased, and the CSA has succeeded in having its rightful place among other optimization methodologies [64] [10]. This algorithm is based on the obligate brood parasitic behavior found in some cuckoo species, in combination with the *Lévy* flight , which is a type of random walk which has a power law step length distribution with a heavy tail. It is inspired from the behavior discovered from some birds and fruit flies. Also,it has been found [65] [66] that *Lévy* flights is an oft-observed random walk in real life [67] [68]. The CSA is an efficient metaheuristic swarm-based algorithm that efficiently strikes a balance between the local nearby exploitation and global-wide exploration in the search space of the problem [69].

The cuckoo has a specific way of laying its eggs to distinguish it from the rest of the birds [70]. The following three idealized rules clarify and describe the standard cuckoo search:

- Each cuckoo lays one egg at a time and dumps it in a randomly chosen nest.
- The best nests with high-quality eggs will be carried over to the next generations.

- The number of available host nests is fixed, and the egg laid by a cuckoo is discovered by the host bird with a probability $P\alpha \in (0, 1)$. In this case, the host bird can either get rid of the egg or simply abandon the nest and build a completely new nest. In addition, probability $P\alpha$ can be used by the n host nests to replace the new nests, if better.

Based on these three rules, the basic steps of the Cuckoo Search (CS) can be summarized as the pseudo code shown in Algorithm 1.

Algorithm 1 Cuckoo Search algorithm

```
Objective function f(X), X = (x_1, ...x_d)^T
Generate initial population of n host nests Xi(i = 1, 2, ..., n)
while t < Max_iterations do
    (t < MaxGeneration) or (stop criterion)
    Get a cuckoo randomly by Levy flights
    evaluate its quality fitnessF_i
    Choose α nest among n (say, j) randomly
    if F_i > F_j then
        replace j by the new solution;
    end if
    A fraction (Pα) of worse nests are abandoned and new ones are built;
    Keep the best solutions (or nests with quality solutions);
    Rank the solutions and find the current best
end while
Postprocess results and visualization
```

One of the most advantages of CSA, it used of fewer control parameters compared to many other search techniques[4,2,14]. Table 1, summarize the parameters, values, ranges and the commonly used values. The details collected from Yang and Dep [10].

Table 1: Summary Of Parameters Setting Of CSA

parameter	**symbol**	**range**	**commonly used**
Nest	N	[15 , 50]	N = 15 [69]
Fraction	$P\alpha$	[0,1]	$P\alpha = 0.25$ [56]
Step size	α	$\alpha > 0$	$\alpha = 1$ [10]

3. The procedure of basic cuckoo search algorithm

In this section, two CSA procedures are discussed. The first procedure is established by Yang and Deb [10], the founders of CSA. Figure 2 shows a flowchart of the CSA. Similar to other swarm-based algorithms, the CSA starts with an initial population of n host nests. These initial host nests will be randomly attracted by the cuckoos with eggs and also by random *Lévy* flights to lay the eggs. Thereafter, nest quality will be evaluated and compared with another random host nest. In case the host nest is better, it will replace the old host nests. This new solution has the egg laid by a cuckoo. If the host bird discovers the egg with a probability $P\alpha \in (0, 1)$, the host either throws out the egg, or abandons it and builds a new nest. This step is done by replacing the abundant solutions with the new random solutions.

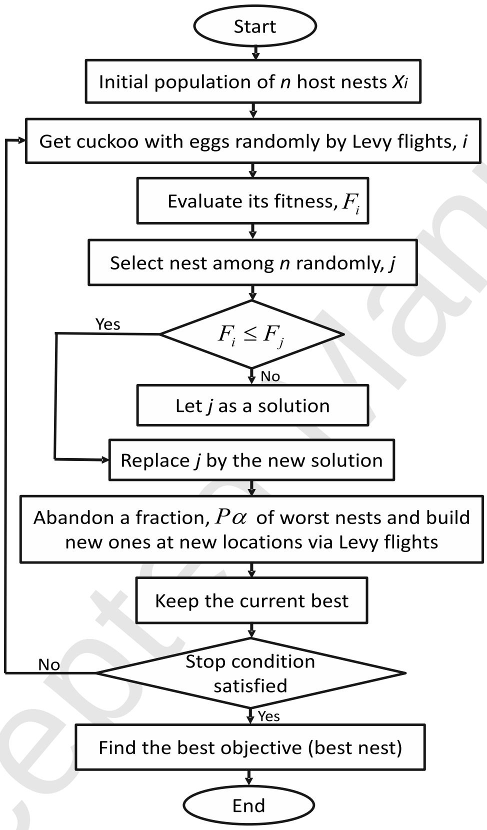

Figure 2: Flowchart of Cuckoo Search Algorithm

Yang and Deb used a certain and simple representation for the implementation, with each ***egg*** representing a solution. As the ***cuckoo*** lays only one egg, it also represents one solution. The purpose is to increase the diversity of new, and probably better, cuckoos (solutions) and replace them instead with the worst solutions. By contrast, the CSA can be more complicated by using multiple eggs in each nest to represent a set of solutions.

The CSA, as a bat algorithm [71] and an FA [72], uses a balance between exploration and exploitation. The CSA is equiponderant to the integration of a *Lévy* flights. When generating new solutions x^{t+1} for, say, a cuckoo i,a *Lévy* flight is performed

$$x_i^{t+1} = x_i^t + \alpha \bigoplus Le'vy(\lambda) \tag{1}$$

where $\alpha > 0$ is the step size which should be related to the scales of the problem of interests. In most cases, we can use $\alpha = 1$. The x_i^t in the above equation represents the current location, which is the only way to determine the next location x_i^{t+1}. This is called the random walk and the Markov chain. The product $\bigoplus$ means entrywise multiplications. This entrywise product is similar to those used in PSO, but here the random walk via *Lévy* flight is more efficient in exploring the search space as its step length is much longer in the long run. A global explorative random walk by using *Lévy* flights can be expressed as follows:

$$L\grave{e}vy \sim u = t^{-\lambda}, \quad 1 < \lambda \leqslant 3 \tag{2}$$

where λ is a parameter which is the mean or expectation of the occurrence of the event during a unit interval. Here the steps essentially form a random walk process with a power law step-length distribution with a heavy tail. Some of the new solutions should be generated by *Lévy* walk around the best solution obtained so far, this will speed up the local search. However, a substantial fraction of the new solutions should be generated by far field randomization and whose locations should be far enough from the current best solution, this will make sure the system will not be trapped in a local optimum.

The second procedure proposed by [60] is more focused on clearly expressing the optimization to the reader, similar to previous structure frameworks (cuckoos, eggs, and nests) but with different representation, as shown in Figure 3. The proposed algorithm starts with an initial population of cuckoos with its eggs; these eggs are randomly laid in different nests. The egg having high similarity with the host eggs will get a chance to survive; the other eggs will be killed by the nest's host. The eggs will be kept until hatching, and the chicks will grow knowing that the eggs in the nest have profit values. The generated cuckoos will then seek for new host nests with the best survival rate to determine the cuckoo societies (select the goal habitat). Finally, the new cuckoo population will emigrate toward its goal habitat by determining the laying distance for each cuckoo.

Rajabioun et al. [60] used a different presentation from Yang and Deb by adopting an optimization problem and using an array of values for problem variables. The proposed algorithm used a habitat and formed an array-like GA using chromosome and PSO in particle positioning. The habitat represents the current position of the cuckoo by N_{var}. The steps to define the N_{var} array are as follows:

- Habitat $= [x_1, x_2, ..., x_{N_{var}}]$.
  The value of each variable of $(x_1, x_2, ..., x_{N_{var}})$ is floating point number

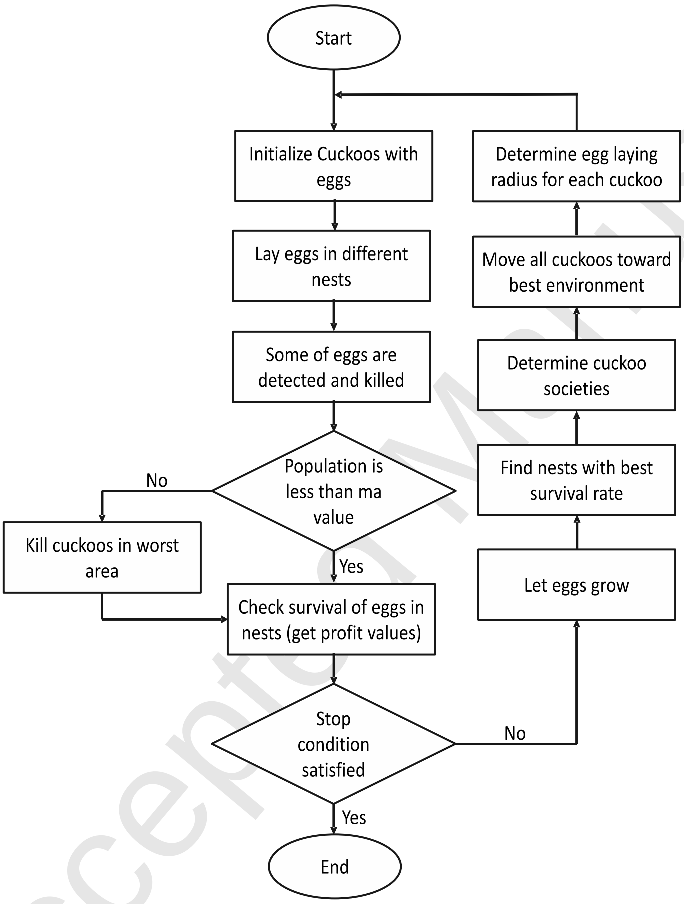

Figure 3: A flowchart of Optimization of Cuckoo Search [73, 60]

- The profit of the habitat is determined by evaluating the profit function f_p as: $f_p(habitat) = f_p(x_1, x_2, ..., x_{N_{var}})$
- In general, the proposed cuckoo optimization algorithm defines the maximized profit function. It is a simple way to define the minimization that maximizes the profit function by: $-Cost(habitat) = -f_c(x_1, x_2, ..., x_{N_{var}}) = profit$
- Each cuckoo lays between 5 and 20 eggs. This number of eggs is used to determine the lower and upper limits of laying egg. Each cuckoo must also lay the eggs within the maximum range from its habitat. This maximum distance is called the egg-laying radius (ELR). ELR is defined as follows: $ELR = \alpha \times \frac{Number of current cuckoo's eggs}{Total number of eggs} \times (var_{hi} - var_{low})$
  Where var_{hi} and var_{low} are upper and lower variable limits, α is an integer, controlling the maximum rate of ELR.

The mission of the cuckoo mother is performed after the cuckoo lays eggs in the host nest, and the host birds mission starts by checking all the eggs in its own nest. A cuckoo egg discovered by the host bird will be thrown out of the nest; this also happens to the eggs with less profit, which will not have a chance to grow in the nest and will be killed. In contrast, the rest of the eggs in the host nest complement the stages of growth. Actually, the cuckoo only laid one egg in the host nest to ensure its survival because the host bird throws out the egg after the first group hatches and the chicks come out; thus, the cuckoo chicks will get care from the host. Additionally, the cuckoo chicks will have more chances of survival because of the food given to them by the host bird, regardless of whether they hatch earlier or later than the host chicks. Given the aforementioned reasons, the body size of cuckoo chicks is three times bigger than the host chicks. This also results in the death of host chicks because the cuckoo chicks consume all the food. Finally, cuckoo chicks remain in the host nest.

The cuckoo chicks mature after a while and remain in the same society and in their own habitat until the time of egg-laying. Here, the immigrants start to find new habitats. Two main conditions influence the immigration to these habitats: the shape of the cuckoo eggs should be similar to the host bird eggs and the abundance of food for the next generation. The immigration principle of cuckoos is based on grouping cuckoos in different areas. The goal is to immigrate to a society with the highest profit value. After a while, all cuckoos will meet in the same environment. This makes distinguishing and determining which cuckoo is from which group very difficult. K-means clustering of cuckoo grouping is used to solve the distinguishing problem by grouping and calculating the profit value of cuckoos. It will then select the group with a maximum profit value as the goal group, which will become the destination habitat for immigrant cuckoos.

However, not all cuckoos move to the destination habitat because several deviations are encountered along the way. In other words, two parameters help the cuckoos fly and find more locations in environment λ and ϕ, which defined by the following equations:

$$\lambda \sim U(0,1) \quad and \quad \phi \sim U(-w, w) \tag{3}$$

where λ is a random number (U) between 0 and 1, and ϕ is the radius of destination and w is the control parameter of the deviation calculated by $\pi/6(rad)$ [74].

Finally, each cuckoo is not specified to belong to either goal point or new habitats. Some eggs also have a determined ERL. The process repeats for the newly laid eggs. At the end, the cuckoo with a better profit value will survive. Because it managed to pass many difficulties such as, failure to determine a suitable nest for eggs, or being killed by predators.

To summarize this section, the cuckoo search principle depends on three components as mentioned by the procedure of Yang as follows:

- Exploration by integration with *Lévy* flights globally and gets very efficient solutions.
- Exploitation by local random walk.
- Selection of the best solutions and keep it, this is like a genetic algorithm for access to the elitist.

Rajabioun focused on the optimization context of cuckoo search, which is shown in case the eggs survive and become mature cuckoos. Immigrating to the best habitat is the main purpose because the immigration process benefits the population in more areas but does not move in a straight line. All cuckoos will get the area's best position after some immigration process. The main steps of the cuckoo search optimization are presented in Algorithm 2 as a pseudo code.

Algorithm 2 Optimization Cuckoo Search Algorithm

```
Initialize cuckoo habitats with some random points on the profit fuction
Dedicate some eggs to each cuckoo
Define ELR for each cuckoo
Let cuckoos to lay eggs inside their corresponding ELR
Kill those eggs that are recognized by host birds
Let eggs hatch and chicks grow
Evaluate the habitat of each newly grown cuckoo
Limit cuckoos' maximum number in environment and kill those who live in worst habitats
Cluster cuckoos and find best group and select goal habitat
Let new cuckoo population immigrate toward goal habitat
If stop condition is satisfied stop, if not go to 2
```

4. The growth of cuckoo search algorithm in the literature

Several papers have been widely published on the cuckoo search algorithm. In this review paper, the materials have been collected based on using the CSA as a keyword through two stages. Firstly, the published CSA papers are obtained from the highly-reputed publishers such as Elsevier, Springer, and IEEE as well, from other journals which were searched using Google Scholar. Second, the search results are classified based on the year of publication as shown in this section, and the subject as shown in the application section and theoretical section.

In 2009, CSA was developed and evaluated using multimodal objective functions and then compared with GA and PSO [10, 75]. In 2011, it gradually started to develop, with the enhancement of the convergence rate and the accuracy of the standard CSA utilized for training the feedforward neural networks [76]. Subsequently, in 2011, [56, 48] implemented a modified CSA by determining the step size from the sorted rather than only the permuted fitness matrix and by adding information exchange between the best solutions, respectively.

In 2012, CSA began to be used in many problems. Durgun and Yildiz [77] proposed CSA for solving structural vehicle design optimization problems, which improves fuel efficiency and cost. In addition, Xiang-Tao and Ming-Hao [78] applied CSA in combination with orthogonal learning to estimate the parameters of chaotic systems. In the same year, the same authors applied the binary version of CSA. The same binary versions are used to solve $0-1$ knapsack problems [79]. For evaluation purposes, the performance of the CSA binary version is superior compared with the binary PSO.

In 2013, CSA was also used for the optimization design of truss structure problems [34] and the optimization of machining parameters in milling operations [80]. Both works obtained very effective and robust outcomes compared with GA, ant colony optimization (ACO), and PSO. The problem of optimum synthesis of a six-bar double-dwell linkage was successfully tackled using CSA in mechanical engineering [81]. CSA has likewise been successfully tailored for structural engineering optimization problems, where the obtained solutions are better than the best solutions obtained by the existing methods by a large gap [82].

Major studies on CSA were conducted in 2014 across different disciplines, where different hybridizations and modifications were attempted by different researchers [83, 84, 85] to solve various problems in major areas, such as power energy savings [86], engineering [87, 37, 88, 89, 90, 91], digital image processing [19, 20], medical applications [27, 24], and clustering and data mining [28, 92].

In 2015, CSA underwent remarkable development in different areas in various fields. For instance, in the field of power and energy, [93] used CSA to control the load frequency for a nonlinear interconnected of power system, which achieved better performance in settling times and various indices. The design of an optimum superconducting magnetic energy storage (SMES) system for automatic generation control of a two-area thermal power system using CSA proved the effectiveness of fast-acting energy storage devices, such as SMES [94]. Moreover, CSA contributes to energy and cost savings, distributed generation [95], plate fin heat exchangers [96], short-term hydrothermal scheduling problem [97], optimal operation of the multi-reservoir system [98], and solving economic load dispatch problems [99]. In the telecommunications and network area, [100] proposed a design for an adaptive routing protocol using CSA to provide secure and reliable routers between source and destination node, as well as determine an optimal distance and low routing overhead. CSA was used by [101] to distribute a network reconfiguration for power loss minimization and voltage profile improvement. It was also used by [102] to discover the transition rules for cellular automata. CSA was also used in the image processing field in [103, 104, 105, 106, 107]. Some researchers modified and adapted CSA to enhance performance [108, 109, 110], increase efficiency [111, 112, 29, 113, 114], and reduce time requirement [115].

The CSA is still undergoing remarkable development until now. In 2016, more than 50 articles used the CSA in various fields. The economic problems of inflation and unfair energy use continue to draw attention toward searching for ways to save energy and money.CSA has a strong chance because of its distinctive characteristics; for example, in harnessing wind power through optimal allocation of wind-based distributed generators [116] and reactive power optimization in wind power plants [117], and benefitting from water reservation [118, 119, 120] and the optimal design of the power systems [121,

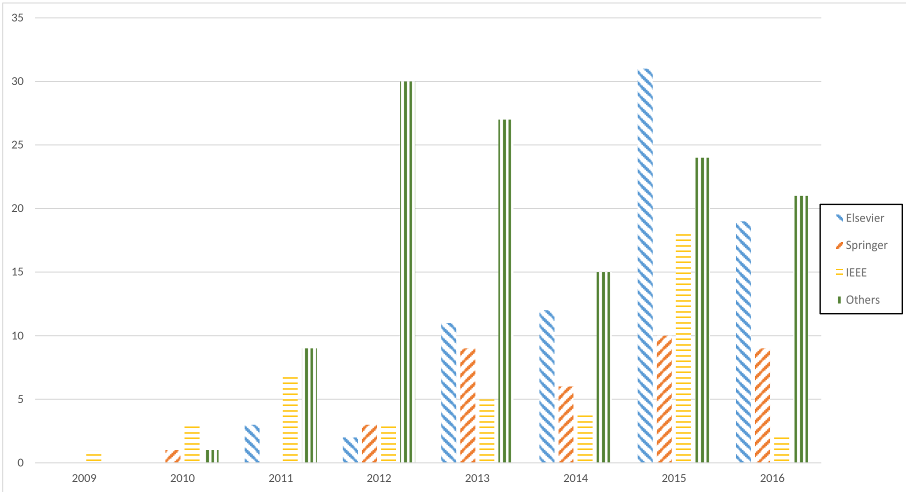

Figure 4: Number Of CSA Published Papers By Elsevier, Springer, IEEE And Others, Per Annum (2009 To 2016).

122, 44, 43]. Furthermore, CSA was used in power systems to increase the load ability [123, 124, 125]. In engineering, a decline is noticeable compared with last year. CSA has been used in robotic cell scheduling [126], engineering structure solving [127, 128, 129] , and electrical engineering [130]. The use of CSA was normal for the rest of the fields, such as economic load dispatch [29, 33, 32], image processing [131, 17, 22, 132], clustering [133, 133] and medical applications [134].

Figure 4 shows the number of published papers by various researchers from 2009 to 2016 on CSA and its variants based on the different databases where these are reported; Elsevier, Springer, IEEE, and others [2]. The distribution of published research articles on CSA with respect to applications, hybridizations, and modifications is shown in Figure 5.

5. Cuckoo search algorithm variants

The CSA proposed in 2009 is a recent swarm-based algorithm in comparison with the firefly, bee colony, PSO, and ant colony algorithms proposed in 2008, 2005, 1995, and 1992, respectively. However, the CSA has been updated for several variants developed by researchers to cope with the nature of the search space of the optimization problem. Most of these variants will be extensively but not exhaustively described.

5.1. Binary Cuckoo Search Algorithm

Gherboudj et al. [79] proposed a discrete binary cuckoo search (BCS) algorithm for binary optimization problems. The solutions are represented in the optimization

[2] This is based on the search conducted by the authors using CSA as the keyword till September, 2016

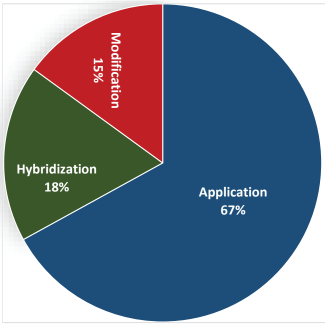

Figure 5: The Distribution Of Published Research Articles On CSA

problems either by a set of real numbers (called continuous optimization) or by a set of integer numbers (called discrete optimization). The discrete optimization problem class has some subclasses, such as discrete binary optimization problems, and its solutions are represented by a set of bits, including routing [135], job shop scheduling [136], and flowshop scheduling problems [137]. This BCS variation uses a sigmoid function to create a bridge between the discrete/the continuous and the binary values.

As aforementioned, the CSA is based on *Lévy* flights. Therefore, the solutions present as a set of real numbers working in a continuous search space. The solutions must be converted to binary values to extend the CSA to discrete binary areas. The BCS is designed to contain two basic modules:

- Main binary cuckoo dynamics: this module includes two operations:
  - *Lévy* flights: it used to obtain a new cuckoo.
  - Binary solution representation (BSR) to compute the flipping chances for each cuckoo by using the sigmoid function. After that, the flipping chance of each cuckoo to calculate the binary value is used.
- Objective function and the selection operator: the selection operator principles presented here is the same as presented for genetic algorithms

To convert from the continuous area to the binary area, assume x_i is a solution of continuous nature in the interval [0, 1] and $x_i^{'}$ is a BSR, the sigmoid function will convert the values as follows:

$$S(x_i) = \frac{1}{1 + e^{-x_i}} \tag{4}$$

where $S(x_i)$ is the flipping chance of bit $x_i^{'}$. To obtain the binary solution $x_i^{'}$, $S(x_i)$ is compared to the result of the generated random number from the [0, 1] interval for each dimension i of solution x as shown in following equation:

$$x_i^{'} = \leftarrow \begin{cases} 1 & \gamma < S(x_i) \\ 0 & otherwise \end{cases}$$

where γ is a random number between [0,1]. In case the flipping chance of bit $x_i^{'}$ is bigger than the random number then the value is 1, otherwise the value is 0.

5.2. Discrete Cuckoo Search Algorithm

The TSP is a classical optimization problem used to evaluate any new development. The TSP principle is that the salesman must visit each city once, starting and finishing from a certain one with a minimum total length of the trip. Ouyang *et al.* [138] proposed the discrete CSA (DCSA) for solving spherical TSP, where all points are on the surface of a sphere. DCSA was applied on the A and 3-opt operators to speed up the convergence. The DCSA operators were applied to search around for the current city. The experimental results showed that the DCSA achieved better and faster solution by solving an instance HA30 from TSPLIB and different size problems.

Ouaarab *et al.* introduced a DCSA for the TSP [139]. The author improved and developed the CSA through rebuilding the population and proposing a new category of cuckoos. Thus, DCSA efficiency was increased with less iterations. The DSCA can also solve the continuous and combinatorial problems. It increases the protection of local optima in the case of TSP from stagnation. This supports the DCSA to have more control over the diversification and intensification with less parameters. The experimental analysis of the results showed that the performance of the proposed DCSA algorithm was highly effective compared with genetic simulated annealing ant colony system with particle swarm optimization techniques (GSA-ACS-PSOT) [140] and discrete PSO [141].

In another study, DCSA was proposed to solve TSP [142]. The authors proposed two phases and called them schemes. The first scheme proposed, discrete step size, refers to the distance between the cuckoo and the best cuckoo in its generation. The second scheme is where the cuckoos were updated using a step size α and a random step length drawn from the *Lévy* distribution called *Lévy* flight. The results proved the performance of DCSA with simple TSP. However, it could not achieve the optimal solution for complex TSP. Gherboudj *et al.* proposed a discrete binary CSA (DBCSA) to solve 0-1 knapsack problems [79]. The authors used a sigmoid function to obtain binary solutions, which are the same as those used in binary PSO. This work has two objectives. The first objective copes with the binary optimization problems, where the basic CSA solution consists of a set of real numbers. On the other hand, the DBCSA solution consists of a set of bits by using a sigmoid function and a probability model to generate binary values. The second objective proves the effectiveness of the basic CSA dealing with binary combinatorial optimization problems. The experimental results on both the multidimensional knapsack problem instances showed the effectiveness of the BDCSA and its ability to obtain good quality solutions compared with the quantum-inspired CSA (QICSA), HS, and binary PSO [143].

5.3. Modified Cuckoo Search Algorithm

Tuba *et al.* [56] proposed modified CSA (MCSA) for unconstrained optimization problems. The authors modified the basic CSA by determining the step size from the sorted rather than only the permuted fitness matrix. For example, if the similarity between the cuckoos egg and the hosts eggs was very high, the likelihood of discovery was reduced; therefore, fitness should be linked to the variation in solutions. The authors used a random walk in a biased way with some random step sizes by applying a different function set to calculate this step size. MCSA has been compared with the original CSA by applying a set of standard benchmark functions. The results showed that the performance of MCSA was slightly better in seven of eight benchmark functions.

MCSA with rough sets was introduced to deal with high-dimensional data through feature selection [144]. MCSA is utilized to build the fitness function based on two factors. The first factor is the number of features in a reduced set, which means that reducing the number of learning parameters leads to a decrease of the consumed time and an increase of speed convergence. The second factor is the classification quality. MCSA is validated using several public datasets. The experimental results showed that MCSA is highly efficient for classification performance and more stable in comparison with ACO, PSO, BA, and GA.

Abdul *et al.* [57] proposed MCSA for side lobe suppression in a symmetric linear antenna array. MCSA was integrated with the roulette wheel and the inertia weight to control the search ability for synthesizing symmetric linear array geometry with the minimum side lobe level. The authors concentrated on the four internal parameters: α, number of population, distribution type, and fraction probability $P\alpha$. In MCSA, when the value of $\alpha = 2.0$, the side lobe level will be lower than the other three counterparts. By contrast, when the value of $\alpha = 1.0$, the side lobe level will approximately have similar performance with the basic CSA of $\alpha = 2.0$. Interpreting these results due to finding the global minimum values require greater probability in the fixed search space. In the distribution type within the direction angle domains of [20°, 75°] and [105°, 160°] , MCSA has the best side lobe suppression. The fourth parameter is that the MCSA obtained the best performance with the lowest value of $P\alpha$ ($P\alpha = 0.05$). By contrast, MCSA achieved the worst results when $P\alpha$ had the largest value ($P\alpha = 0.95$). In this work, MCSA was proven to be slightly better than PSO and GA.

The multi-objective analytical aspects of the distribution systems with multiple multi-type compensators solved by MCSA were analyzed [49]. The authors used MCSA to enhance the convergence rate and quality of the solution as well in basic CSA. However, the *Lévy* flight in basic CSA can dominate the exploration of the solutions. MCSA used the crossover operation to try and balance the exploration and exploitation search aspects. This leads to the decrease in diversity, and hence the final best solution with less iterations are achieved. MCSA also generates the initial population with uniform control variables rather than random ones. The effectiveness of MCSA by applying the standard 15-, 33-, and 69-node radial distribution systems seems superior. The obtained results were compared with existing literature methods and achieved more effective performance.

Tawfik et al. utilized one-rank CSA to optimize algorithmic trading systems [58]. The authors combined the exploration and exploitation phases to generate new solutions. In addition, in basic CSA, exploring new solutions is achieved based on the *Lévy* flights to avoid large moves. Thus, the solutions will skip outside the search space because step size determination depends on the scale of the problem. MCSA used the optimal utilization of the *Lévy* flight in optimization and the typical step size $\alpha = 0.01$. MCSA also eliminated the invalid solutions with randomly selected solutions among the current best solutions. MCS was tested on a set of 10 standard benchmark functions and applied to a real-world problem of algorithmic trading systems optimization with clear success. The results showed that the MCSA improved the performance in almost all benchmark functions and other considered problems.

Short-term hydrothermal scheduling (ST-HTS) problem takes the reservoir volume constraint into account. Many algorithms, such as SA, have tried to solve the problem. However, despite resolving the drawbacks, SA has not been widely applied because it takes a long simulation time but obtains a low-quality solution. For this purpose, Dinh *et al.* [145] proposed an MCSA for the ST-HTS problem by taking into account the existence of important elements, such as reservoir volume, fuel cost function thermal unit, and power losses in transmission line. In their work, the MCSA was focused on generating a new CSA solution and keeping the solution generation based on an alien egg discovery. They partitioned all eggs to high or low quality based on the value of their fitness function. The best egg selected will be employed to obtain the increased value. The MCSA performance was validated by testing on two power systems and comparing it with the performance of the basic CSA and other methods in the literature. The results showed that MCSA achieved better and faster solutions than the other existing methods.

Over seven years have passed since the initial CSA by Yang and Deb. SA has proven its worth as a powerful, robust, and efficient tool in yielding global optima. The accuracy of CSA primarily depends on the initial solution and its place from the target value. Thus, it may cover many generations. Given that the evolutionary operators were used in each generation, CSA could lead to a delay in the convergence rate. Therefore, Rao and Venkaiah [146] proposed MCSA to improve the performance of CSA and optimize the wire-EDM process while machining Inconel-690. The authors utilized the two-stage initialization process to increase the probability of finding the optimal solution. In the first stage, the population is divided into subpopulations, with each subpopulation represented as a vector. The subpopulation vector contains the evaluation of the value of the objective function for each string. Then, the best string is selected based on its fitness function value. Finally, the previous procedures are repeated for all subpopulation vectors. In the second stage, all the best strings are combined to form a new subpopulation vector, and then the operations of the evolutionary are applied on the newly formed population vector. The robust and accurate performance of the MCSAs is maintained by testing it on standard benchmark problems. MCSA was likewise applied to wire electrical discharge machining (WEDM) process. It was found to be fast and accurate in comparison with the basic CSA, PSO, GA, and response surface methodology (RSM).

Indeed, CSA is introduced to try and converge to the global optima [75]. However, the fast convergence rate cannot be guaranteed because it depends on random walks. Walton *et al.* MCSA as a new robust optimization algorithm [48] by introducing two modifications. The first modification considered the *Lévy* flight step size α to increase a wide range of applications and maintain the attractive features of the original method to be closer to the solution. The second modification realized the addition of exchange information between the eggs in an attempt to slow down the convergence to a minimum. In basic CSA, no information exchange occurs between individuals. This modification grouped the top eggs, with the second egg in the group to be chosen in random. Thereafter, it generates the new egg based on these two eggs. The results showed better resulting solutions compared with the basic CSA, PSO, and DE using standard optimization benchmark functions. MCSA also proved its efficiency on the engineering problem [147]. A modified cuckoo search for unconstrained optimization problems to determine the step size from the sorted rather than only the permuted fitness matrix was implemented by [56].

5.4. Other Variants of Cuckoo Search Algorithm

The improved CSA (ICSA)was introduced to solve planar graph coloring problem [148]. The authors improve the basic CSA by modifying the step length (heavy tailed) through utilizing the walking one strategy, swap and inversion strategy, and greedy transform algorithm. The walking one strategy depends on the node and adjacent nodes of the number of the conflicts. Swapping and inversion strategy finds the maximum conflict node. In this work, the ICSA performance was compared with the basic CSA and the improved POS (IPSO) proposed by [149]. The results showed that ICSA has a fastest convergent velocity and better global search capability in terms of solving the same problem in a more accurate and efficient manner.

Lin and Lee [150] proposed a new CSA variation for the reconstruction of chaotic dynamics, which includes the psychology model effects of emotion and chaotic dynamics. This approach contains a couple of systems; a primary chaotic systems with unknown parameters to generate a time series is used to drive a secondary chaotic systems.

The back propagation neural network algorithm is a widely used technique to train artificial neural networks. The Levenberg –Marquardt training algorithm using traditional back propagation optimization has several defects, such as getting stuck in local minima and network stagnation . An improved Levenberg –Marquardt back propagation algorithm integrated and trained with CSA to avoid the local minima problem and achieve fast convergence was proposed by [151].

Zheng and Zhou [152] proposed a new CSA variation based on a complex-valued encoding system. In this algorithm, the term plurality indicates the individual bird's nest. Therefore, a diploid swarm is structured by a sequence plurality, which means that the bird's nest can express the space dimension more than the real-coded one. Thus, the bird's nest contains more information that improves the search capabilities of the pure CSA. Zheng and Zhou [152] also used the Gauss distribution with cuckoo search optimization algorithm as a new CSA variation to solve the standard test functions and engineering design optimization problems, called the Gauss cuckoo search (GCS). It achieved better results and a higher convergence rate than CSA alone. A brief summary of the main modified features of the modified CSA versions are reported in Table 2.

6. Application of cuckoo search algorithm by area of discipline.

Many applications of CSA to real-world and benchmark optimization problems have been reported [153]. Substantial portions of the publications have also compared the performance of CSA with other optimization algorithms. In the following subsections, some areas in which CSA was applied are discussed in detail, including benchmark optimization, medical applications, clustering and mining applications, image processing applications, economic load dispatch problems, engineering design and applications, and power and energy.

6.1. Benchmarking optimization

Benchmark functions are groups of functions that can be used to test the performance of any optimization problem, such as constrained and unconstrained, continuous

Table 2: Summary Of Recent Modifications To CSA versions

Algorithm Name	**Description of Modifications**	**Problem**	**References**
ICSA	modifying the step length (heavy-tailed)	planar graph coloring problem	[148]
MCSA	used two modifications: size of the Lvy flight step size α and add information exchange between the eggs in an attempt	a new robust optimization algorithm	[48]
CSA	determining the step size from the sorted rather than only permuted fitness matrix	Unconstrained optimization problems	[56]
MCSRS	build the fitness function based on two factors: the number of features and classification quality	High dimensionality data through feature selection	[144]
MCSA	concentrated on the four internal parameters: α, number of population, distribution type and fraction probability $P\alpha$	Side lobe suppression in a symmetric linear antenna array	[57]
MCSA	used the crossover operation to balance exploration and exploitation processes	Analyzing the multi-objective analytical aspects of distribution systems with multiple multi-type compensators	[49]
ORCS	combined exploration and exploitation phases to generate the new solutions	Algorithmic trading systems optimization	[58]
ACSA	focused on generating a new solution of the CSA and keep the solution generation based on an alien egg discovery	Short-term hydrothermal scheduling (ST-HTS) problem	[145]
CSA	utilized two-stage initialization process: The population divided into subpopulation and combined all the best strings form to a new form of the subpopulation	optimize Wire.EDM process while machining Inconel.690	[146]
DCSA	proposed discrete CSA by applying two operators to speed up the convergence	for solving spherical the traveling salesman problem (TSP)	[138]
DCSA	Used discrete CSA to improve and develop the CSA through rebuilding the population and proposing a new category of cuckoos	for solving spherical the traveling salesman problem (TSP)	[139]
DCSA	Used discrete CSA through two phases dealing with the step size	for solving spherical the traveling salesman problem (TSP)	[142]
DBCSA	Utilized a discrete binary CSA by using a sigmoid function to get binary solutions	for solving spherical the 0-1 knapsack problems	[79]
CSA	contains a couple of systems: a primary chaotic systems to generate a time series is used to drive a secondary chaotic system	for the reconstruction of chaotic dynamics	[150]
CSA	Levenberg - Marquardt back propagation algorithm integrated and trained with CSA to avoid the local minima and achieve fast convergence	to train artificial neural networks	[151]
GCS	Interested of the bird's nest which can provide a lot of information to improve the search capability	to solve the standard test functions and engineering design optimization problems,	[152]

and discrete variables, and unimodal and multimodal problems. The original CSA was evaluated by Yang and Deb in 2009 using unimodal and multimodal problems; other developed CSA variations were evaluated using different benchmark optimization problems [152, 154, 155].

Gherboudj *et.al.,* [79] evaluated the performance of the BCSA on some multidimensional knapsack problem (MKP) by using benchmarks taken from the OR-Library. They tested the binary CSA by two stages. First, they used small-size MKP instances taken from seven benchmarks, namely, mknap1. Second, they used big-size MKP instances taken from benchmarks, namely, mknapcb1 and mknapcb4. Both stages were applied to binary CSA, binary PSO, and HSA. Binary CSA was noted to produce better results and prove the feasibility and effectiveness of binary CSA.

To verify the performance of the enhanced version of the CSA using orthogonal learning method, Xiangtao *et al.* [156] used 23 benchmark functions divided into unimodal and multimodal functions to solve the global optimization problems. Xueying and Meiling [157] also used the unimodal functions defined by large numbers of local optimal solutions. Furthermore, the multimodal problem was employed to test the local search capability of the algorithm.

Pinar and Erkan [158] conducted a study comparing CSA, PSO, DE, and ABC on a larger set of numerical test functions. The results showed that CSA performance is mostly better than all of the comparative algorithms.

Recently, five constrained optimization problems (i.e., g01, g04, g05, g06, and g07) were used to show the effect of the improved CSA (ICSA) to solve constrained optimization problems. The results demonstrated that the ICSA provides better performance than the CSA, BA, fish swarm optimization (FSO) algorithm, hybrid cuckoo search algorithm (HCS-LSAL), hybrid Nelder–Mead simplex search and particle swarm optimization (NMPSO), and co-evolutionary PSO (CPSO) [40].

6.2. Medical applications

The features of CSA also make it suitable for application in the medical domain. For example, a CSA-based approach hybridized with the support vector machine (SVM) for parameter optimization was developed to find better initial parameters of the kernel function. After that, PSO was applied to find the best SVM parameters. The results of the CSA-PSO-SVM model achieved better classification accuracy than PSO-SVM and GA-SVM in heart disease and breast cancer datasets [24].

In 2012, diabetes and high blood glucose were the direct cause of 1.5 and 2.2 million deaths respectively. In 2014, 8.5% of adults aged 18 years and older had diabetes [25]. The importance of early screening for diabetes is to protect and reduce complications. Hence, Giveki *et. al.,* [23] investigated a novel automatic approach to diagnose diabetes based on feature-weighted support vector machines (FW-SVMs) and MCSA. They used the UCI Diabetes diseases dataset introduced by Black [159]. The proposed method obtained 93.58% accuracy on the CI dataset.

6.3. Clustering and data mining applications

In general, clustering is the unsupervised classification of patterns into groups. The main concentration of clustering is to split a group of datasets into clusters based on the relationship between the elements within the same cluster. For decades, data clustering problems have been identified in various applications, for example, computer vision, pattern recognition, networks, databases and computing, statistical physics, and mechanics.

Despite its importance, there are some defects when using the traditional mechanisms [160]. In the medical image segmentation, for example, the configuration defects of the initial centroid and the optimal number of clusters using the fuzzy c-means are the most effective clustering methods. In this regard, the PSO optimization and cuckoo search techniques using a hybrid method have been used to increase the cover of the c-means defects [161]. This combination achieved better results compared with the traditional methods by reducing computation time and achieving quick convergence in a few iterations regardless of the initial number of clusters [27].

The clustering of web search engine results has considerable importance in academic and scientific communities involved in the information retrieval domain. Web clustering engines try to provide services for the user by increasing the convergence of documents presented to review and reduce the time spent reviewing them. This work has already been carried out by several clustering web search engine algorithms. However, the results took more time than expected. This problem was solved by using hybridization among CSA, k-means algorithm, and balanced Bayesian information criterion. The objective of using CSA provides a combined global and local search strategy in the search space, which provides diversity and prevents the nests population from converging too quickly [28]. One of the major challenges in the information retrieval domain, which is related to web document clustering, lies in the process of finding relevant information. Zaw and Mon [162] proposed a cuckoo search clustering algorithm based on *Lévy* flight to help users effectively navigate, summarize, and organize the the wealth of information. Using CSA in the web document clustering area helps locate the optimal centroids of the cluster and find the global solution of the clustering algorithm. This work was experimented on a benchmark dataset and it performed well in web document clustering.

Modification of k-means clustering algorithm with CSA is a new partitioning cluster method [92]. This work proposed on finding methods for efficient and effective cluster analysis in a large database. Accordingly, it does not need to enter the value of cluster points to obtain the best clustering by using clustering validity.

A novel strategy of biomimicry that combines the CSA with an unsupervised classification method has been proposed and has yielded good results on a benchmark dataset [26]. The proposed algorithm was validated on a relatively complex problem: two real-time remote sensing satellite–image datasets for extraction of the water body. It introduced a CSA strategy for generating new cuckoos and achieved results of high accuracy after some parameter tuning.

6.4. Image processing

Image processing extracts useful information from the image to enhance its view by converting it into a digital form and performing some operations. The research on image processing domains gradually grew due to their important applications in various aspects of the business area. Image processing forms a core research area in the engineering and computer science domains as well.

The ability to recognize faces is crucial to many aspects of life. Face recognition helps identify anonymous individuals who could be dangerous. However, some challenges are faced by this process, such as noisy and redundant data, which decrease the accuracy of the face recognition process. Tiwari [18] applied CSA to an array of feature vectors extracted by a 2-D discrete cosine transform of an image. Interestingly, he found the most matched images from the database using Euclidean distance. CSA achieved a better solution compared with the PSO and ACO optimization algorithms when applied to the image recognition domain.

A satellite image is an image of the whole or part of the earth taken using artificial satellites. A high and expensive computation is needed to extract meaningful parts of satellite images because it extends to multilevel thresholding, which is efficient for bilevel thresholding. To overcome this problem, Bhandari *et al.* [19] proposed a new approach by combining CSA and wind-driven optimization (WDO) using Kapur's entropy for optimal multilevel thresholding. In this combined algorithm, selecting the best fitness value of the best solution is achieved through initial random threshold values. The correlation function is used to evaluate the quality of a solution. Experimental results revealed that CSA combined with WDO using Kapur's entropy criterion can be efficiently used in multilevel thresholding and, therefore, improves the extraction of meaningful parts of a satellite image. In another study of the same authors, the integration of discrete wavelet transform (DWT) and CSA was performed in [20] for quality improvement of low-contrast satellite images. DWT is responsible for analyzing the image of four frequency sub-bands. CSA is used to optimize each sub-band and select the singular value matrix of the drop thresholded sub-band image. The last step enhances the image by reconstructing it using IDWT. The results showed the effectiveness and efficiency of the proposed combined algorithm. This algorithm is useful for detecting surface features of various visible areas and for remote-sensing applications.

Another study that deals with optimal thresholds for multilevel thresholding was conducted in [21], where Tsallis entropy was maximized using CSA. The results of the proposed algorithm achieved better solution than bacteria foraging optimization, ABC, GA, and PSO. Furthermore, it required less computational time compared with other techniques.

In [22], the optimal segmentation of RGB image was studied by maximizing the entropy value in Kapur's method using the CSA-based image multithresholding. The objective of the proposed algorithm was to find an optimized threshold value for image segmentation where the fitness function was designed based on entropy measures of the same image. The obtained results were compared with the firefly and PSO algorithms using the universal images and showed that better CSA performance was achieved through offering fast convergence with comparatively less computational time.

6.5. Engineering design and applications

The highest percentage of CSA publications can be found in the engineering field. CSA has been broadly utilized in complex optimization problems arising in most engineering applications, such as network reconfiguration, electronic, construction and engineering structures problems, and mechanical applications.

Engineering design is a general term that covers multiple engineering disciplines, such as mechanical, chemical, electrical, and structural of building (architectural). The main objectives of engineering design are optimizing energy consumption, reducing financial costs, and minimizing environmental impacts. Kaveh *et al.* [163] used CSA to minimize the self-weight of real-size structures, yielding acceptable convergence performance from early iterations. CSA has been selected by the American Institute of Steel Construction because of its complex constraints, such as displacement constraints and geometric limitations. The results showed that the effect of their proposed method in optimizing practical structures is significant. Numerous authors have introduced CSA to solve structural optimization problems. For example, Gandomi *et al.* [38] started by verifying CSA using a benchmark of a nonlinear constrained optimization problem. Then, validation was conducted through its application to 13 design problems, such as pressure vessel design, parameter identification of structures, and three-bar truss design. The performance of the proposed algorithm is far better than GA and slightly better than PSO, DE, and FA. Qu and He [128] used the improved CSA to solve engineering structural optimization problems. The performance also started with the standard test functions and two engineering designs: tensioncompression spring and pressure vessel design problems. The results showed the efficiency of the proposed algorithm, which can obtain better solutions in comparison with FSO, BA, CPSO, and hybrid Nelder–Mead simplex search and particle swarm optimization.

A multi-objective optimization problem, also called the reliable embedded system, is tackled by CSA. The objective of this problem is to design a reliable embedded system to determine the optimal solutions in terms of performance, reliability, cost, and availability, among others. The practical systems require long processing and reveal high complexity. CSA is proposed to solve the scheduling problems of a reliable embedded system. The results achieved high-quality solutions that were built stably based on good solutions and were less sensitive to the variation of tuning parameters [164]. Furthermore, an efficient multi-objective CSA for design optimization was proposed to solve structural design problems, such as disc brake and beam designs [165]. Finding widespread solutions with good coverage and convergence is also easy [40]. A truss is a structure composed of slender members joined together at their end points. CSA proposed the design optimization of truss structures [34, 39]. The aim of using CSA is to determine the minimum weight design of truss structures. The results show that CSA achieved better solutions in comparison with the best solutions obtained by the other comparative algorithms, such as PSO, GA, ACO, and HS.

The use of renewable resources has become the optimal orientation because of its great features, such as availability, easy accessibility, and environmental friendliness. Wind energy uses wind turbines (modern windmills) to produce electricity. In using wind for power supply in remote locations, a serious consideration is needed because establishing such a system is not cheap. In this regard, CSA is proposed to solve the problem of wind power system design optimization [166]. It allows electrical power components with different parameters to be appropriate for electrical power systems. The CSA solutions are either optimal or very close to the optimal solution. Furthermore, water energy is used to produce electricity and has various uses. Abrasive water jet (AWJ) utilized CSA to predict the surface roughness of AWJ [167]. The results showed the capability of CSA to provide an improved surface roughness that exceeds the results of two established computational techniques, namely, support vector machine and artificial neural network.

Cutting optimization is a nonlinear and constrained optimization that features reduced costs with increased productivity. Madic *et al.* [168] applied CSA for surface roughness optimization in CO2 laser cutting. The authors integrated the neural networks and CSA to offer a simple and effective method to search for the optimal solution. The output produced by CSA and neural networks was found to be better than those produced by other existing techniques. Esfandiari [37] used another way in his work by applying CSA, GA, and SA to five test functions and then used it to optimize the cutting conditions. The results showed the superiority of CSA with faster convergence, high accuracy, and better global optimum achievement than others.

CSA was also used to solve manufacturing optimization problems, such as a milling optimization problem [80]. The results showed the effectiveness and robustness of CSA by comparing it with GA, ACO, hybrid particle swarm algorithm, hybrid immune algorithm, immune algorithm, feasible direction method, and handbook recommendation. In the electrical field, CSA was used in the maximum power point Tracking (MPPT) for the price of photovoltaic (PV) systems [35]. In this work, there are three main points for evaluating the system, temperature changes and control gradual irradiance, the irradiance changing and quick change in both temperature and irradiance. It likewise provided the CSA the capability to deal with the partial shading condition.

Printed circuit board (PCB) is an example of the drill path. As PCB takes a long time in the drilling path, using the combined CSA and PCB reduces the time and production costs and increases the quality of the productivity, as mentioned in [169, 90]. Bhargava *et al.* [36] utilized CSA with its modified version to solve the challenging stability, equilibrium, and reactive phases of equilibrium problems in both reactive and nonreactive systems. The CSA performance was compared with the FA, integrated DE, and covariant matrix adaptation. The CSA results showed that the CSA offers reliable and better performance for solving these thermodynamic calculations compared with others.

6.6. Energy and economic load dispatch problems

Another area of discipline that has been tackled by CSA is power and energy. Numerous optimization problems have been addressed in this area, such as the optimal allocation of capacitors, power economic dispatch, power transmission network, optimal allocation of wind-based distributed generators, and optimization of reservoir operation.

CSA has been proposed to improve voltage profile and reduce power loss of the distribution network. Distributed generation (DG) is an approach that employs small-scale technologies to produce electricity close to the end-users of power. The main criterion for power quality improvement is the voltage profile determined by the minimum of voltage deviations and the maximum of voltage variations. The results illustrated that the performance of CSA is better than PSO and GA. Additionally, the convergence rate of the CSA is not affected by the parameters used, which means that it can deal with any given problem without the need of prior knowledge [170]. Buaklee *et al.* [42] also used CSA in a smart distribution grid environment, which is an application of DG for optimal sizing and siting of DG to reduce power loss. The effectiveness of the CSA was demonstrated through a nine-bus radial distribution system of the Provincial Electricity Authority of Thailand (PEA) and DIgSILENT software. On the other hand, increasing the energy demand with limited resources opens the door to search for renewable energy. For the purpose of optimally locating the renewable-based DG, Sudabattula *et al.* [116] utilized CSA to reduce the power loss of the distribution system. CSA was tested on an IEEE 69 bus-test system and showed better CSA performance in comparison with GA and PSO.

The PV system is a power system designed to supply usable solar power. This technology has been used to power homes for many years because it is clean, quiet, and visually unobtrusive in an unused space on rooftops of existing buildings. The novel approach to locate the maximum power point (MPP) in the PV system by CSA was proposed by

Ahmed and Salam in [41]. They randomly generated three samples of voltage through the span of the PV voltage. The proposed method achieved the best solutions compared with Perturb and Observe [45]. It showed very fast convergence with zero steady-state oscillation and rapid changes of atmospheric condition. A new CSA-based parameter was proposed to elicit the parameters of single-diode models for commercial PV generators [46]. The author compared the results generated by the proposed algorithm with existing algorithms in the literature and implemented an exhaustive search method to derive optimal solutions. The results from CSA showed its capability to obtain all parameters with high accuracy. CSA was also used to optimize the gains of the PI controller for a PV-connected micro grid [171]. The optimized PI controller reduced the peak values and had better stability in a short time subjected to various fault conditions. A comparative study was made between the conventional PI and optimized PI controller by CSA. The results showed that the optimized PI controller by CSA achieved better stability and less peak values.

The scheduling problem is the mapping of jobs to machines where the objective is to minimize the processing time as much as possible. Many studies look for solving the short-term schedule, which is characterized by being brief and precise [i.e., short-term fixed-head hydrothermal scheduling (HTS) problem]. However, power loss in the transmission systems and valve point causes an increase in fuel cost function of thermal units. For this purpose, Nguyen *et al.* [172, 120] proposed CSA to solve this problem through few control parameters and effective optimization problems with complicated constraints. The obtained results were compared with the other methods in the literature and showed better performance with the high quality of the proposed algorithm. The same authors [119] used the MCSA to solve the short-term cascaded hydrothermal scheduling (ST-CHTS) problem by defining the optimal operation of thermal plants and the cascaded reservoir system. The two systems with the thermal plants with nonconvex fuel cost function and the cascaded reservoir system were used to validate the MCSA. The results showed the efficiency of MCSA to solve the ST-CHTS problem.

A new feature selection method, called BCSA, was proposed to develop the recognition rates and also accelerate the extraction feature [173]. Two datasets obtained from a Brazilian electrical power company were used. The results showed increasing theft recognition at 40% for selecting the proper set of features. This makes the BCSA suitable for feature selection.

Recently, many engineers have benefited from the ability to develop flexible power chains in significantly less time and low cost. Piechocki *et al.* [86] proposed MCSA to deal with the issues of computer-aided design of energy systems, which influenced the performance of the power system, such as the structure of walls and water preparation systems. The results illustrated that the features of MCSA, which gave the closest results to the desired cost minimization, clearly outperformed the other values. It was also particularly useful in the design of such systems. In addition, Manesh and Ameryan utilized CSA to find the optimum design of a solar hybrid cogeneration cycle [122]. The authors used the CSA features on solar power tower technology, which is applied to extract the fired fossil, where. temperatures higher than 1,000° are needed. The prescribed simple cogeneration (CGAM) problem has been tackled by CSA. The results indicated that CSA is effective in optimizing thermodynamic cycles and saves cost and time compared with GA.

Power system stabilizers (PSSs) are generator control equipment used in feedback to enhance the damping of rotor oscillation caused by small signal disturbance [47]. The PSS parameter tuning problem is formulated as an optimization problem. In this regard, CSA was utilized to seek optimal parameters [44]. An eigenvalue-based objective function showing the collection of damping ratio and damping factor was optimized for different operating conditions. The authors compared CSAPSSs with GAPSSs using conventional PSSs under different operating conditions and disturbances. CSAPSSs obtained the optimal solution for the deployment problem, and quality of solution obtained showed that the approach is good and robust.

The optimal location and sizing significantly help save energy, cost, and time. Devabalaji *et al.* presented the CSA by defining the optimal size of the capacitor to implement a voltage stability index [43]. The feasibility of the proposed method was checked by testing the IEEE 34- and 69-bus radial distribution systems with different load factors. The simulated results obtained using CSA were compared with other existing techniques in the literature. The results showed the distinguished performance of CSA for power loss and voltage profile minimization and net savings maximization. Moreover, Sanajaoba *et al.* [121] used CSA for optimal sizing of a remote hybrid renewable energy system in the Almora district of Uttarakhand, India. The authors tailored the CSA to three system schemes, PVwindbattery system, windbattery, and PV battery, to reduce the total system cost and control the seasonal load variation. The CSA performance was compared with PSO and a GA. The results elucidated the reliable and economical system scheme of the CSA for the study area.

A power system has many power industries (energy productions), and each one has many generation units. At any point in time, the aggregate load in the system is achieved by generating each unit in different power industries. The economic dispatch problem (EDP) control determines the power output of each power industry, where the operation and planning of a power system are required. The main objective of EDP is to minimize the overall cost of fuel needed to serve the system load. The CSA has been applied to solve both convex and nonconvex EDPs in generating the fossil fuel-fired, such as multiple fuels, transmission losses, and valve-point loading [30]. The effectiveness of CSA has been verified through testing on different systems. The results have proven its ability to converge to a better quality solution. Vo *et al.* [31] used the same steps but focused only on the nonconvex economic dispatch version.

Pham *et al.* [32] utilized the adaptive cuckoo search algorithm (ACSA) to solve EDP. For this purpose, the author used ACSA, which includes some adaptations, such as evaluating the initial eggs and then dividing into two categories, good and bad. Initially, the updating step is utilized with the *Lévy* flight at each iteration. The ACSA performance was tested on two power systems with different load cases, such as multiple fuel options and valve point. The obtained ACSA experimental results were compared with other methods, revealing that ACSA is efficient for EDP application.

Another recent study proposed the enhanced cuckoo search algorithm (ECSA) for contingency constrained economic load dispatch (CCELD) to decrease overloading on the transmission line [33]. The secure and insecure operating states were defined by the power system security. Generation rescheduling could reduce the distress on the overloaded lines. ECSA was used to improve the dynamic variable parameters. The probability values were used in the solution vectors. The efficiency of the technique was demonstrated using the IEEE 30-bus systems. The results obtained with CCELD and ECSA proved that the algorithm produces better results than BA and PSO, showing minimum fuel cost and the minimum severity index - that's used to measure the severity of overloaded lines through the index - in less computational time. Thus, ECSA was nominated to be efficient in obtaining the solution of the CCELD problem. The main CSA features across different disciplines are summarized in Table 3.

Table 3: Summary Of Applications Of CSA Across Field Of Discipline

Application	**Publications**
Benchmarking optimization	[154, 158, 79, 40, 156, 157, 155, 152]
Medical	[23, 24, 25]
Clustering and mining	[92, 27, 28, 26, 162]
Image processing	[21, 20, 19, 22, 18]
Economic dispatch problems	[30, 32, 33, 31]
Engineering design and applications	[35, 36, 37, 34, 38, 39, 40, 163, 164] [169, 90, 168, 166, 167, 128, 165, 80]
Power and energy	[41, 42, 43, 44, 45, 46, 47, 171, 122] [170, 119, 120, 172, 86, 173, 121, 116]

7. Hybridization of cuckoo search algorithm

Since its introduction in 2009, CSA has continued to attract the interest of investigators from diverse disciplines across the globe. This has resulted in various hybridizations to the basic CSA. In the following subsections, the hybrid versions of CSA are presented, together with algorithms and other search techniques.

7.1. Hybridized versions of Cuckoo Search Algorithm

A hybrid algorithm is an algorithm that combines two or more other algorithms that solves the same problem. Numerous features of hybridization exist, such as enhancing the weaknesses of the algorithm and improving in terms of either computational speed or accuracy. The researchers improved the CSA performance by integrating the other popular rules and metaheuristic algorithms, such as s selection, mutation, and crossover of GA, and DE. The following subsections present the hybridization of CSA to other component metaheuristic techniques

7.1.1. Hybridization of cuckoo search algorithm with population -based algorithms

A wide range of population-based algorithms, such as DE, PSO, GA, and EA, have been developed to tackle the hard optimization algorithms. In the population-based algorithm behavior, deeply searching in each region of the problem search space is mostly insufficient. Therefore, the search normally does not reach the local optima in that region, especially for the problem of ragged search space. Several suggestions have been proposed to empower the capability of the population based on exploiting the search space region in which it is searching. As commonly known, the operators of the population-based algorithm behaves differently in navigating the search space. Some operators are powerful in exploiting the search space (such as selection in GA), while some others are powerful in exploration (such as random consideration in HS). To this end, hybridizing some powerful operators in a population-based search algorithm may help with striking the right balance between exploration and exploitation through the search.

GA is a search strategy that uses random choice to prove a highly exploitative search by attempting to achieve the balance between exploration and exploitation [174]. Kanagaraj *et al.* proposed a hybridization of CSA with GA (CSA-GA) to solve reliability and redundancy allocation problems [175]. The solution is achieved through integrating the genetic operators in the basic CSA. CSA-GA can achieve the balance between exploration and exploitation; therefore, the performance of the algorithm in the search is improved. The crossover preserves the partial identity of the parent cuckoo bird while allowing for the diversity in the solution space. Mutation has been used in the local search of the solution space by making small but logical changes in the genes. There are four classical reliability redundancy allocation problems in the literature that have been applied to confirm the validity of CSA-GA. The results showed that CSA-GA is extremely effective and efficient at locating optimal solutions. Furthermore, it greatly avoids the possibility of trapping in a premature convergence situation.

Kanagaraj *et al.* [176] proved the efficiency of hybrid CSA and a GA (HCSAGA) for solving engineering design optimization problems. In HCSAGA, it begins with randomly generating the initial solution; thus, it was distributed throughout the solution space. Then, they applied selection, crossover, and mutation, respectively, in each generation. After that, the best solutions were selected by applying some form of elitism. Next, they performed the *Lévy* flight operation for the best solution space. Finally, they replaced the solutions in the current population with better solutions by genetic principles. The previous processes were repeated to guide the search toward the global optimum. To validate the HCSAGA, the authors started with testing 13 standard benchmark functions. Thereafter, they experimented with three well-known design problems reported in the literature. The results proved the performance of HCSAGA compared with the existing approaches for constrained design optimization problems.

The drilling path optimization problem is an example of an NP-hard optimization problem. It becomes an interesting research problem for many researchers because of the complex nature of its search space. The CSGA was proposed to solve the path optimization problem of the drilling process for PCB holes [83]. The authors used genetic principles and replaced it with the CSA components, such as replacing the crossover with the *Lévy* flights and the mutation with the random walks. CSGA saved the high-quality eggs, while the poor-quality eggs were neglected; this is called the elitism strategy. The experiments showed the efficiency and robustness of the CSGA and its ability to find the optimal path for the PCB holes drilling path optimization problem.

Lim *et al.* proposed a hybrid CSA and a GA for optimizing the hole-making operation (CSAGAHM) [52], knowing that a hole takes time, cost, and effort before obtaining the final size. CSAGAHM minimized the total time of noncutting, tool positioning, and tool switching at the machine. The authors used the same hybridization mechanism used for PCB. CSAGAHM was verified by testing on a set of benchmark problems; the results showed that CSAGAHM is superior in comparison to PSO, immune-based algorithm, ACO, and basic CSA.

Two hybrid schemes using CSA and a GA were proposed by [177]. There are two phases in both hybrid schemes (i.e., GA-CS and CS-GA). In the first phase, GA or CSA explores the search space to identify the most promising regions of the search space and find a set of promising solutions. In the second phase, the solution is improved by either

GA or CSA, which did not operate in the first phase. The performances of the GA-CS and CS-GA were tested using 15 benchmark functions carefully selected from the literature. The results illustrated the effectiveness of the proposed algorithms compared with basic CSA and a GA.

Wang *et al.* [178] proposed a hybrid metaheuristic DE and a CSA (DE/CSA) for the uninhabited combat air vehicle (UCAV) path planning problem and UCAV three-dimension path planning problem [179]. The authors hybridized DE to empower the CSA capability by embedding the advantages of DE in CSA. Note that the DE has the skill at exploring the search space and determining the region of global optimal value. Through this DE feature, it can solve the drawback of the basic CSA, which lies in the speed of exploiting the solution. In addition, DE can add diversity of the population to improve the search efficiency. The performance of the DE/CSA was proved by comparing it with the basic CSA. The results showed the efficiency and feasibility of DE/CSA to solve both the UCAV path planning problem and UCAV three-dimension path planning problem.

The network operation is decentralized where the nodes implement the networks organization. A mobile ad hoc network (MANET) can connect large networks in a standalone manner. These networks, either connected or standalone, do not need an infrastructure but causes some challenges. The central infrastructure must likewise be ensured by mobile nodes in the new environment. For this purpose, Nancharaiah and Chandra [85] proposed a hybrid optimization technique, i.e., ACO and a CSA (ACO-CSA), to optimize MANET routing. ACO-CSA starts to run with ACO to update the pheromone. Then, CSA is initialized to perform as the local search. The proposed algorithm optimizes the ad hoc on-demand distance vector routing (AODV) based on delay and cost. The results showed that the performance of the proposed algorithm is better than the basic ACO.

Babukartik and Dhavachelvan [50] proposed a hybrid ACS with ACO for the job scheduling problem. In their work, they combined CSA with some features of ACO. The experimental analysis showed that using the proposed algorithm leads to an increased in the number of tasks. In addition, the time required for task creation and result retrieval is increased.

The optimal design of water distribution systems was solved by using a hybrid optimization method, which combined the CSA and a HS (CSAHS) [180]. In the CSAHS, the explorative stages of searching and finding the promising regions of the search space were conducted by CSA. Then, the hybridization between CSA and HS algorithms was utilized in the exploitation phase. CSAHS was improved through harmony memory (HM), which consists of information extracted online through a search and the addition of the pitch-adjusting operation of HS through the evolution process. Thus, HM vectors become the CSA population, and an evolving process is performed in the CSA. In addition, CSAHS was improved by utilizing a self-adaptive strategy for the dynamic adaption of the control parameters using a learning mechanism. The performance of the CSHS was demonstrated by employing four water distribution system design problems with increased scales and complexity. The results illustrated that the CSHS method overtook the basic CSA, proved its efficiency to obtain optimal solutions, and enhanced the convergence rate.

Wang *et al.* [51] proposed a hybrid algorithm that combined CSA and a HS (HS/CSA) for continuous optimization problems. In the HS/CSA method, the pitch adjustment of

HS was used to update the process of the CSA, which leads to the increase of population diversity. The improved elitism scheme was used to retain the best individuals in the cuckoo population as well. The performance of HS/CSA was evaluated by means of testing the set of benchmark functions. The obtained results showed that the HS/CSA achieved better outcomes in comparison with ACO, PSO, GA, HS, DE, and basic CSA.

An early diagnosis of a disease is an important issue in life science and is effective in avoiding the risk to human health. Liu *et al.* [24] proposed a disease diagnosis model based on cuckoo search, PSO, and support vector machine (CSA-POS-SVM) [24]. The authors used SVM to solve classification and regression problem on a dataset that is nonlinearly separable and handle data that are not fully linearly separable [181]. Additionally, the PSO was used to make use of particles moving in the n-dimensional space to search for solutions to the functions of n-variables. This allows the particles to distribute in the problem space by attracting the particles of the best solutions [182]. Thus, it is initialized with a group of random particles (solutions) and then searches for optima by updating each generation [183]. CSA discovered that the random-walk style search has better performance for *Lévy* flights rather than the simple random walk. CSA with its random-walk style is also simple in comparison with other algorithms. Experimental results showed that the CS-PSO-SVM realized better classification accuracy and F-measure than GASVM and PSO-SVM; thus, it is efficient in disease diagnosis.

7.1.2. Hybridization of cuckoo search algorithm with local search -based algorithm

Population-based search algorithm is normally very powerful in exploring several regions of the problem search space. However, it has difficulty in determining the local optima in each region. By contrast, deep searching of the local search-based algorithm is very efficient in a single search space region but not for several search space regions [184]. Thus, sometimes, it is very beneficial to hybridize a local and a population search-based method to complement their advantages in a single optimization framework. Based on the above suggestion and through hybridization, the search can strike a balance between the wide range of exploration and nearby exploitation of the problem search space. In this context, CSA has been hybridized with other population-based algorithms to improve its performance in tackling complex optimization problems. This section summarizes an overview of the attempts made to hybridize CSA with other population-based algorithms.

Quadratic assignment problems (QAPs) are considered to be NP-hard problems, which cannot be easily solved by exact methods. Therefore, Dejam *et al.* [185] proposed a hybrid algorithm combined with the CSA of TS (i.e., CSA-TS) to solve QAPs. In their research, the QAPs were initially tackled using CSA. Thereafter, these were combined with TS, which focused on the local search to increase the optimization precision. The experimental results indicated that the proposed algorithm performs better than ABC and GA.

Quantum computing (QC) is a new research field that covers investigations on quantum computers and quantum algorithms [186]. QC can simultaneously deal with huge numbers of quantum states in parallel, enhancing both the efficiency and speed of classical evolutionary algorithms. In this paper, a new inspired algorithm, called the QICSA, for knapsack problem was proposed [187]. QICSA was developed to enhance the basic CSA for successful application on combinatorial optimization problems on some quantum computing principles. In addition, it provides a large exploration of the search space during diversification and intensification stages. The experimental results showed the effectiveness and successful performance of the QICSA on the knapsack problem. Furthermore, it has the ability to achieve good quality solutions. Layeb and Boussalia [53] used QICSA to solve one-dimensional bin packing problem (1-BPP). In their work, QICSA aimed to determine a suitable quantum representation for the bin packing solutions. A new hybrid quantum measure operation (i.e., using the first-fit heuristic to pack non-filled objects by the standard measure operation) was introduced. The obtained results showed the effectiveness and feasibility of QICSA.

The integration of the Nelder–Mead simplex method with CSA, named NMA-CSA, was proposed by [84] to optimize the performance of multi-cell solar systems. In this work, a simplex was used instead of single solutions as nests for the CSA. In this way, it can replace the Nelder–Mead algorithm instead of the *Lévy*. Thus, NMA-CSA becomes more robust and less sensitive to parameter tuning. However, a difficulty in evaluating the complex function exists. The performance of NMA-CSA has been applied on both solar cell optimization and standard benchmark functions. The obtained results achieved better solutions with higher speed of convergence compared with other methods presented in the literature. Once again, Ali and Tawhid [188] proposed a hybrid algorithm, which includes the CSA and Nelder–Mead method (HCSANM), to solve the integer and minimax optimization problems. HCSANM started with a basic CSA for a number of iterations, chose the best results achieved, and then passed it to Nelder–Mead, similar to an intensification for increasing the search and eliminating the slow convergence struggle of the basic CSA. Therefore, HCSANM controls the balance using the basic CSA for global exploration, and NM method is utilized for deep exploitation. The validation of the performance was determined by applying the HCSANM on 7 integer programming and 10 minimax problems. The results showed the efficiency of HCSANM and its ability to deal with minimax optimization problems in a reasonable time.

The linear least squares problem solved by hybridization algorithm between Newton method (NM) and CSA is called CSANM [189]. The authors benefited from CSA for fast convergence and global search as well as from NM for the ability of strong local search. The experimental results showed the convergence efficiency and computational accuracy of the CSANM in comparison with the basic CSA and HS based on NM (HSNM) .

7.1.3. Hybridization of cuckoo search algorithm with other techniques

A novel CSA base on the Gauss distribution (GCSA) was proposed by [190]. In the basic CSA, although it finds the optimum solution, the search entirely depends on random walks. By contrast, fast convergence and precision cannot be guaranteed. For this purpose, GCSA was introduced to solve the low convergence rate of the basic CSA. GCSA has been applied to solve the standard test functions and engineering design optimization problems. The obtained results showed that the GCSA proved its efficiency through achieving better solutions compared with basic CSA.

Chandrasekaran and Simon proposed a hybrid algorithm, which integrated CSA with the fuzzy system to solve the multi-objective unit commitment problem [191]. In general, the successful power system needs reliable operation and environment and economic preservation. However, these three points are conflicting because fuel cost is not compatible with the emission and reliability level of the system. The authors used fuzzy set theory to build the fuzzy membership search domain for all possible solutions. They also used CSA to look for the best solution inside the fuzzy search domain. The proposed method started with the basic CSA through initializing a fixed number of host nests; each nest includes a cuckoo's egg. The size of the host nest is increased at the end of each generation. Afterward, the fuzzy fitness starts to pick up the best solution, and then the host bird destroys the alien egg, which is far away from the best solution. Otherwise, the egg grows up alive for the next generation based on the fitness function. The validation of the proposed method is measured using the benchmark test systems for single and multi-objective optimization problems. The results of the proposed method showed its superiority over other methods reported in the literature. It also has the ability to solve non-smooth multi-objective problems in a power system.

Centroidal Voronoi tessellations (CVT) is a Voronoi tessellation of a set where the generators of the Voronoi groups the centers of the same mass where all of them work at the same time (parallel). An integration of CSA and CVT was proposed to improve the basic CSA (CSA with CVT) [54]. The CVT presented the problem space in an equally distributed manner. For this, the authors utilized CVT as the starting points for the nests. Then, the CSA was used for the generated Voronoi points. The results of the experiment, when compared with the basic CSA, showed the effectiveness, robustness, and feasibility of the CSA with CVT. A summary of the main features of the hybridized CSA with components of other metaheuristic algorithms is shown in Table 4.

Table 4: Summary Of Hybridization Of CSA With Component Of Population-Based, Local Search-Based And Other Heuristic Algorithms

Algorithm Name	**Problem**	**References**
GA-CSA & CSA-GA	for Optimization Problems	[177]
DE/CSA	to solve the uninhabited combat air vehicle (UCAV) path planning problem	[178]
DE/CSA	to solve the uninhabited combat air vehicle (UCAV) three-dimension path planning problem	[179]
ACO-CSA	for the Mobile Ad hoc Network (MANET) routing	[85]
ACO & CSA	for job scheduling	[50]
CSAHS	to solve the optimal design of water distribution systems	[180]
HS/CSA	to address the optimization problems	[51]
CSA-POS-SVM	early diagnosis of disease	[24]
CSA-TS	for solving Quadratic Assignment Problems (QAPs)	[185]
QICSA	for solving spherical the knapsack problems	[187]
NMA-CSA	to optimize the performance of multi-cell solar systems	[84]
HCSANM	to solve the integer and minimax optimization problems	[188]
CSANM	to solve linear least squares problem	[189]
GCSA	for solving multi-objective unit commitment problem	[190]
CSA with fuzzy	for solving multi-objective unit commitment problem	[191]
CSA with CVT	to improve the basic CSA	[54]

8. Conclusion and Possible Future Directions

In this survey paper, over 150 research articles were studied and analyzed in an attempt to make a robust conclusion for the researchers interested in working on CSA. The survey exhaustively and comprehensively summarized the references published from 2009 until the second half of 2016. The papers, which were collected in this work, observed that the largest share went to CSA applications in various fields, such as medical, image processing, economic load dispatch, engineering design, and data clustering. This result shows the high popularity of CSA because of its successful characteristics and features. The modification and three categories of hybridizations were introduced in this paper to enhance the performance of CSA and maintain its applicability in the problems or a rugged search space.

CSA remains a promising and interesting algorithm and will continue to be widely used by researchers across different fields. Its advantages over other optimization algorithms include its simplicity, fewer parameters compared with other algorithms, and ease of hybridization with other optimization algorithms. However, CSA lacks the mathematical analysis. It does not have a theoretical analysis similar to other algorithms, such as PSO [192] and GA [193]. This difference can be observed with the difficulty of understanding when and why the algorithm works . Additionally, how does the performance of the algorithm improve compared to other search techniques Parameter tuning is also considered an important part of research [194], where the values and settings of the parameters govern the CSA performance.

All these reasons make CSA robustly viable for continued utilization to the community. This paper could also guide the researchers who are currently working or will work in this area by leading them toward how the CSA algorithm can be employed to solve the problems, point out its weaknesses and strengths, and prove its effectiveness. Thus, important research can still be solved through the utilization of CSA.

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Authors' Biographies

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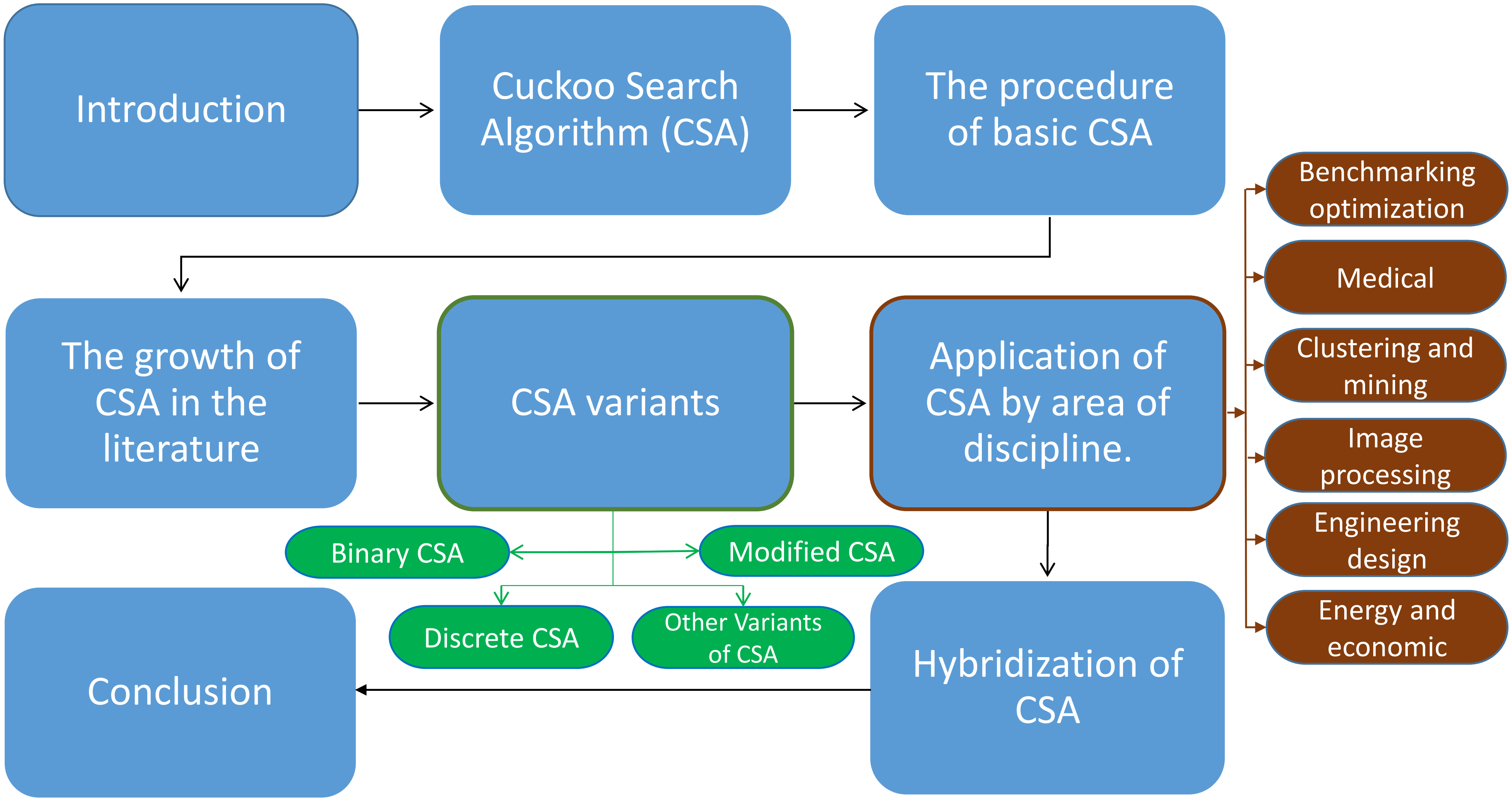
Highlights

- We introduce a literature review considering articles on Cuckoo Search Algorithm.
- Around 150 suitable articles are identified and classified according to defined methodology.
- We focus on the growth, variants, applications and modifications of the Cuckoo search algorithm.
- We mention on the possible ways to use the cuckoo search in the future work.


Introduction
Cuckoo Search Algorithm (CSA)
The procedure of basic CSA
Benchmarking optimization
Medical
Clustering and mining
Image processing
Engineering design
Energy and economic
The growth of CSA in the literature
CSA variants
Application of CSA by area of discipline.
Binary CSA
Modified CSA
Discrete CSA
Other Variants of CSA
Conclusion
Hybridization of CSA