A comprehensive review of cuckoo search: variants and hybrids

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Abstract: Cuckoo search (CS) is an efficient swarm-intelligence-based algorithm and significant developments have been made since its introduction in 2009. CS has many advantages due to its simplicity and efficiency in solving highly non-linear optimisation problems with real-world engineering applications. This paper provides a timely review of all the state-of-the-art developments in the last five years, including the discussions of theoretical background and research directions for future development of this powerful algorithm.

Keywords: cuckoo search; swarm intelligence; optimisation; nature; algorithm.

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1 Introduction

Swarm intelligence (SI) concerns the collective behaviour of multi-agent systems, which can serve an efficient methodology for solving real-world optimisation problems. These multiple interacting agents usually follow simple local rules, but can show some collective, emerging and self-organising characteristics. While each agent may be considered as unintelligent and only capable of carrying out simple activities, the whole system of multiple agents may show some complex, self-organisation behaviour, leading to the so-called collective intelligence, or SI (Yang, 2013a, 2013b).

A class of SI-based algorithms for optimisation have been developed in recent years, including particle swarm optimisation, ant colony optimisation, firefly algorithm, cuckoo search (CS) and others. These algorithms have been found to be effective in solving even non-deterministic polynomial time (NP) hard, simply NP-hard, problems (Yang and Deb, 2013a). In fact, many real-world problem are NP-hard (Garey and Johnson, 1979), where a solution cannot be found in polynomial time. Therefore, many researchers have been trying to solve these hard problems by using approximate methods, heuristic methods and hybrid methods.

Recent studies suggest that SI-based algorithms are among the most promising ones. In the last 20 years, nature-inspired algorithms have drawn much attention with rapid developments. A taxonomy of these algorithms was collected by Fister et al. (2013e). In their review, algorithms were classified into four groups, as follows:

- SI
- bio-inspired without SI
- physics and chemistry based
- others.

SI algorithms represent a subset of bio-inspired algorithms. A prominent example of bio-inspired algorithm is genetic algorithms (GA), but GA cannot be considered as SI-based. Recently, artificial immune systems have been emerged (e.g., in Ljubič et al., 2013). Obviously, not all algorithms are bio-inspired, some meta-heuristic algorithms take their sources of inspiration often from physics and chemistry. This kind of algorithms mimics certain physical and/or chemical laws, including electrical charges, gravity, river systems, etc. Some examples of these algorithms are: harmony search (Geem et al., 2001), simulated annealing (SA) (Kirkpatrick et al., 1983) and others.

It is not easy to touch all algorithms in one paper, but the above three groups (SI-based, bio-inspired, physics/chemistry-based) include about 95% of all the nature-inspired algorithms. The remainder 5% of the algorithms are based on the history, emotions, and social behaviour, and some of these were even inspired by philosophy. An example of this group is the so-called anarchic society optimisation (Shayeghi and Dadashpour, 2012).

This paper is fully devoted to the comprehensive review of the CS algorithm, its variants and hybrids. In fact, this work is an extension of the paper by Fister et al. (2014) that deepens already clear knowledge about this algorithm and extends it with the new facts covered in recent papers. The structure of this paper is as follows: In Section 2, the biological basics of the cuckoos are presented. Section 3 deals with the fundamentals of the CS with the emphasis on historical notes. In order to present this overview as systematical as possible, this review is further subdivided into three parts (Section 4 to Section 6) that deal with the following areas, respectively:

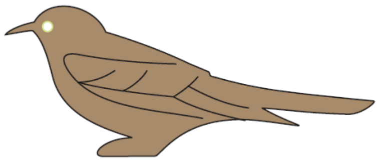
- CS variants and hybrids
- CS in engineering
- CS in applications.

Then, the theoretical analysis and implementation details are presented in Section 7, while the directions for further development of CS are discussed in Section 8, then followed by the summary of this work.

2 Biological foundations

Cuckoos (scientific name: Cuculiformes) have three big families: Musophagidae, Cuculidae and Opisthocomidae (Figure 1). There are more than 100 species of cuckoos, but only one family of cuckoos lives in Europe, i.e., Cuculidae. Cuckoos are widespread in almost all areas in the world from Africa to Europe. They often feed on insects, especially caterpillars (Gooders, 1998).

Figure 1 Cuckoo (see online version for colours)



In fact, the CS has been inspired by the brooding parasitism of some cuckoo species. This aggressive reproduction brooding parasitism acts as follows. A female cuckoo typically lays 16 to 22 eggs that can be different in colour and can match the eggs of the host. Different species may produce different colours, and they often target at different host birds. On the grey, yellow, green and red surface, eggs are often dotted with spots, also found in monochromatic or milky-white. Eggs size may vary from about 21.9 to 16.3 mm in radius. Approximately half of cuckoo birds do not hatch their own eggs, but resort to such parasitism. A hidden female awaits nearby the appropriate host nest for a chance of dumping its eggs in the host nest. Usually, newborn cuckoo chick can engage aggressive eviction of host birds' eggs (Wikipedia, 2013; Davies and Brooke, 1989; Kilner et al., 1999). Biological classification of cuckoos is summarised in Table 1.

Table 1 Classification of cuckoos

Biological classification	
Kingdom	Animalia
Phylum	Chordata
Class	Aves
Order	Cuculiformes
Family	Cuculidae

3 CS algorithm

CS is a swarm-intelligence-based algorithm that has been developed by Yang and Deb (2009), inspired by natural behaviour of cuckoos, especially, the obligate brood parasitisms of some cuckoo species by laying their eggs in the nests of other host birds. Authors defined the CS algorithm by setting three rules that idealise behaviour of cuckoos in order to become appropriate for implementation as an computer algorithm:

- 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 may be discovered by the host bird with a probability $p_a \in (0, 1)$. In this case, the host bird can either get rid of the egg, or simply abandon the nest and build a completely new nest.

Regarding the mentioned rules, the CS was implemented as follows. Each egg in a nest represents a candidate solution. Thus, each cuckoo can lay only one egg into a nest in original form although each nest can has multiple eggs representing a set of solutions, in general. The task of CS is to generate the new and potentially better solutions that will replace the worse solutions in the current nest population. The quality of solutions is evaluated with the objective function of the problem to be solved. Normally, this function needs to be maximised. However, there are also real-world problems where we are interested about their minimum values of the particular objective function. Mathematically, these kinds of problems are trivial to transform from minimisation to maximisation problems regarding equation $\min(f(x)) = \max(-f(x))$. In contrast to objective function, such transformed function is now named as a fitness function.

Furthermore, the last rule is approximated by an additional parameter p_a named the switching probability that determine when the worst of the n host nests is replaced by a new randomly generated nest. In fact, this parameter balances two components of the CS process, i.e., exploration and exploitation as identified by Črepinšek et al. (2013), where too much exploitation induces premature convergence, while too much exploration slows down the convergence.

The pseudo-code of CS algorithm can be seen in Algorithm 1 from which it can be seen that the first step of algorithm generates an initial population, where host nests are positioned in the search space randomly (line 1). In the main loop that follows, the algorithm obtains a new position of i^{th} cuckoo randomly by Lévy flight (line 5) and evaluates its fitness (line 6). Then, some random solution j is selected that can be replaced when the i^{th} solution is better (lines 9 to 11). The worst nests can be abandoned and the new ones are built (lines 12 to 14). However, maintaining the best solution is performed in lines 15 to 17.

As can be seen from Algorithm 1, the local random walk intended for exploitation of the search space is implemented in *init_nest* function and is mathematically expressed, as

$$\boldsymbol{x}_i^{t+1} = \boldsymbol{x}_i^t + \alpha s \otimes H\left(p_a - \epsilon\right) \otimes \left(\boldsymbol{x}_j^t - \boldsymbol{x}_k^t\right), \tag{1}$$

where $\boldsymbol{x}_j^t$ and $\boldsymbol{x}_k^t$ are two different solutions selected randomly, $H(u)$ is a Heaviside function, ϵ is a random number drawn from a uniform distribution, and s is the step size. On the other hand, the global random walk (implemented in *generate_new_solution*) intended for exploration of the search space is carried out by using Lévy flights expressed, as

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

where

$$L(s, \lambda) = \frac{\lambda \Gamma(\lambda) \sin(\pi\lambda / 2)}{\pi} \frac{1}{s^{1+\lambda}}, \quad (s \gg s_0 > 0). \tag{3}$$

In equation (2), the term $L(s, \lambda)$ determines the characteristic scale and $\alpha > 0$ denotes a scaling factor of the step size s. The characteristic scale L depends on the problem to be solved. For instance, the $\alpha = O(L/10)$ is suitable when the dimensionality of the problem is small. In contrast, when the dimensionality of the problem is large, the $\alpha = O(L/100)$ is more appropriate. In this case, modifications are smaller and therefore, prevailing the cuckoos to move too far in the search space.

Algorithm 1 Original CS algorithm

Input: Population of nests $\mathbf{x_i} = (x_{i1}, \dots, x_{iD})^T$ for $i = 1 \dots Np$, *MAX_FE*.
Output: The best solution xbest and its corresponding value $f_{\min} = \min(f(\mathbf{x}))$.
generate initial host nest locations();
eval = 0;
while termination condition not meet **do**
  for $i = 1$ **to** Np **do**
    $\mathbf{x}_i$ = generate_new_solution($\mathbf{x}_i$);
    f_i = evaluate_the_new_solution($\mathbf{x}_i$);
    eval = *eval* + 1;
    $j = \lfloor \text{rand}(0, 1) * Np + 1 \rfloor$;
    if $f_i < f_j$ **then**
      $\mathbf{x}_j = \mathbf{x}_i; f_j = f_i$;   // replace j-th solution
    end if
    if rand(0, 1) $< p_a$ **then**
      init_nest($\mathbf{x}_{worst}$);
    end if
    if $f_i < f_{\min}$ **then**
      $\mathbf{x}_{best} = \mathbf{x}_i; f_{\min} = f_i$;   // save the local best sol.
    end if
  end for
end while

In fact, equation (2) represents the stochastic equation describing a random walk. A sequence of random walks during generations forms a Markov chain, where the next cuckoo position depends on the current position x_i^t and the transition probability captured in the second term $L(s, \lambda)$. If the algorithm will not be trapped in a local optimum it depends on this second term. Therefore, the specific parameter setting of the

CS algorithm should be found in order to ensure that the generated solutions are far enough from the current best solution. However, this parameter setting also depends on the problem to be solved.

3.1 Special cases of CS

CS as a meta-heuristic algorithm has surprisingly rich characteristics. Taking care at the updating equations (1) and (2) more closely, we can discover such subtle richness. From (1), we can group some factors together by setting $Q = \alpha s \otimes H(p_a - \epsilon)$, then we have $Q > 0$. As a result, equation (1) becomes the major updating equation of differential evolution (DE). Furthermore, we further replace $\boldsymbol{x}_j^t$ by the current best $\boldsymbol{g}^*$ and set $k = i$, we have

$$\boldsymbol{x}_i^{t+1} = \boldsymbol{x}_i^t + Q\left(\boldsymbol{x}^* - \boldsymbol{x}_i^t\right), \tag{4}$$

which is essential a variant of the particle swarm optimisation without individual historical best. In this case, the above case is very similar to the accelerated particle swarm optimisation (APSO) developed by (Yang and Deb, 2013a). On the other hand, from (2), this random walk is in fact the SA with a Lévy-flight transition probability. In this case, we have SA with a stochastic cooling scheduling controlled by p_a.

Therefore, DE, particle swarm optimisation and SA can be considered as the special cases of CS. Conversely, we can say that CS is a solid and efficient combination of DE, PSO and SA in one algorithm. Therefore, it is not surprisingly that CS is very efficient.

3.2 Advantages of the CS

In addition to the analysis of the previous section showing that performances of the CS are comparable with performances of DE, particle swarm optimisation and SA, recent theoretical studies by Wang et al. (2012a) also indicate that CS exposes the global convergence abilities. In summary, CS can be characterised by the following three features:

- it satisfies the global convergence requirements
- it supports local and global search capabilities
- it uses Lévy flights as a global search strategy.

Study of Wang et al. (2012a) proved that CS has characteristics of the global optimiser with ability for converging to the true global optimum. On the other hand, the theoretical studies of particle swarm optimisation showed that this algorithm looses a diversity of population very fast. That is, all the solutions become similar to the current best solution. In other words, all solutions are crowded around the current best solution in small region of a search space. In such situations, the particle swarm optimisation algorithm converges prematurely being the global optimum cannot be found. Typically, this phenomenon can be detected by multimodal optimisation, where the particle swarm optimisation algorithm converges fast to the local optimum, while the CS can find a way to the global optimum.

CS process consists of two components, i.e., local and global. The former is intended for improving the best solution via directed random walk, while the latter for maintaining the diversity of population via Lévy flights. The switching probability p_a controls a balancing between both components of the stochastic search. Studies in Subsection 3.1 showed that the optimal setting for this parameter is $p_a = 0.25$. In this way, the global search is preferred because of demanding the 75% of the search time, while the rest of this, i.e., 25% is intended to the local search. This setting ensures that the search space is explored more efficiently and thus, the diversity of population is maintained effectively. On the other hand, enough time has also been left for exploitation process that directs the search process towards the global optimum.

A final feature of CS is using the Lévy flights by a global search instead of standard random walk using Gaussian processes. Normally, the standard Gaussian process allows only small changes in magnitude or direction from the current position. In contrast, Lévy flights with infinite mean and variance allows larger changes from its current position in the search space. These larger changes in magnitude and direction are also characteristics by moving some animals and insects in nature. This feature enables CS to discover the global optimum so efficiently. In summary, the efficiency CS has been demonstrated by various studies and applications (e.g., Yang and Deb, 2013a; Gandomi et al., 2012, 2013).

4 CS: variants and hybrids

Since the development of CS in 2009, much attention and efforts have been dedicated to this algorithm and significant progress has been made. In fact, there are about 20 different variants and hybrids in the literature. We will briefly review them in this section.

4.1 Variants

The original CS was firstly tested using numerical function optimisation benchmarks. Usually, this kind of problems presents a test bed for new developed algorithms. In line with this, standard benchmark function suites (Yang and Deb, 2010) have been developed in order to make comparison between algorithms as fair as possible. As a result, some original studies in this area are presented in Table 2.

Table 2 Original studies

Name	*Reference*
Cuckoo search via Lévy flights	Yang and Deb (2009)
An efficient cuckoo search algorithm for numerical function optimisation	Ong and Zainuddin (2013)
Multimodal function optimisation	Jamil and Zepernick (2013)

CS can deal with multimodal problems naturally and efficiently. However, researchers have also attempted to improve its efficiency further so as to obtain better solutions or comparable results to those in the literature (Eiben and Smith, 2003), and one such study that is worth mentioning is by Jamil and Zepernick (2013).

Since the first appearance of CS in 2009, many variants of the CS algorithm have been developed by many researchers. The major variants are summarised in Figure 2 and Table 3.

Figure 2 Variants of CS

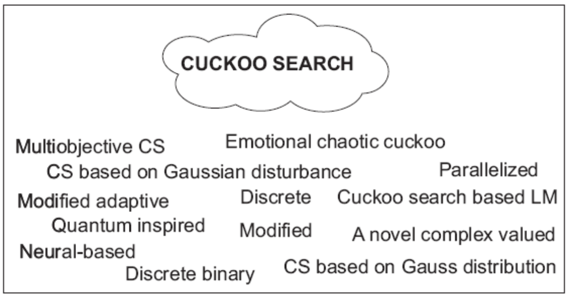


Table 3 List of CS variants

Name	*Author*	*Ref.*
Discrete binary CS	Gherboudj et al.	Gherboudj et al. (2012)
Discrete CS	Jati and Manurung	Jati et al. (2012)
Discrete CS for TSP	Ouaarab et al.	Ouaarab et al. (2013)
Binary CS	Rodrigues et al.	Rodrigues et al. (2013)
Neural-based CS	Khan and Sahai	Khan and Sahai (2013)
Quantum inspired CS	Layeb	Layeb (2011)
Emotional chaotic cuckoo	Lin et al.	Lin et al. (2012)
Cooperative coevolutionary	Zheng and Zhou	Zheng and Zhou (2013)
Cuckoo search-based LM	Nawi et al.	Nawi et al. (2013b)
Parallelised CS	Subotic et al.	Subotic et al. (2012)
Modified CS	Tuba et al.	Tuba et al. (2011)
Modified CS	Walton et al.	Walton et al. (2011)
Modified adaptive CS	Zhang et al.	Zhang et al. (2012)
A novel complex valued	Zhou and Zheng	Zhou and Zheng (2013)
CS-based on Gauss distribution	Zheng and Zhou	Zheng and Zhou (2012)
CS-based on Gaussian disturbance	Wang et al.	Wang et al. (2011b)

4.2 Hybrid algorithms

For many continuous optimisation problems, CS can find the desired solutions very efficiently. However, sometimes, some difficulty may arise, when the appropriate solutions could not be found for some other optimisation problems. This is consistent with the so-called no-free-lunch theorem (Wolpert and Macready, 1997). To circumvent this theorem, hybridisation has been applied to optimisation algorithms for solving a given set of problems. In line with this, CS has been hybridised with other optimisation algorithms, machine learning techniques, heuristics, etc. Hybridisation can take place in almost every component of the CS. For example, initialisation procedure, evaluation function, moving function and others have all been attempted. Some papers tackling the hybrid variants are summarised in Table 4.

Table 4 Hybrid CS

Name	*Author*	*Reference*
Hybrid CS/GA	Ghodrati and Lotfi	Ghodrati and Lotfi (2012a, 2012b)
Hybrid CS	Li and Yin	Li and Yin (2013)

4.3 Multi-objective optimisation

Multi-objective optimisation consists of optimising the more than one objective, and these objectives may even be conflicting each another. Many real-world optimisation problems require design solutions according to many criteria. While a single objective optimisation algorithm searches for a single optimal solution, multi-objective optimisation algorithms demand a set of many (potentially infinite), optimal solutions, namely the Pareto front in Robič and Filipič (2005), and Veldhuizen and Lamont (2000). Obviously, there are many issues and approaches for multi-objective optimisation; however, two goals in multi-objective optimisation are worth noting:

- to obtain solutions as close to the true Pareto front as possible
- to generate solutions as diversely as possible in the non-dominated front.

Various variants have been developed to extend the standard CS into multi-objective CS. Table 5 presents some main variants on multi-objective optimisation using CS.

Table 5 Multi-objective CS

Name	*Author*	*Reference*
Multi-objective CS	Yang and Deb	Yang and Deb (2013b)
Multi-objective scheduling problem	Chandra. et al	Chandrasekaran and Simon (2012)
Multi-objective cuckoo search algorithm for Jiles-Atherton vector hysteresis parameters estimation	Coelho et al.	Coelho et al. (2013)
Pareto archived cuckoo search	Hanoun et al.	Hanoun et al. (2012)
Hybrid multi-objective optimisation using modified cuckoo search algorithm in linear array synthesis	Rani et al.	Rani et al. (2012a)
Multi-objective cuckoo search for water distribution systems	Wang et al.	Wang et al. (2012d)

5 Engineering optimisation

Rising the power of digital computers has caused that an optimisation became popular also in engineering. Thus, we apply algorithms to solve specific problem in engineering, e.g., design of sky-scrappers, houses, highways, antennas, sport equipment, photo-voltaic and many more (Figure 3).

Figure 3 Engineering optimisation

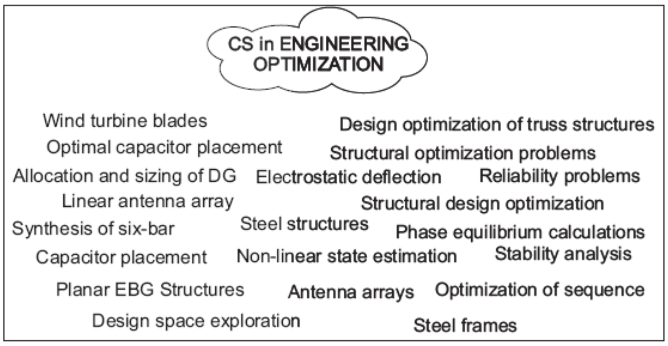


Table 6 CS in engineering optimisation

Problem	*Author*	*Reference*
Engineering optimisation	Yang and Deb	Yang and Deb (2010)
Capacitor placement	Arcanjo et al.	Arcanjo et al. (2012)
Synthesis of six-bar	Bulatovič et al.	Bulatovič et al. (2013)
Wind turbine blades	Ernst et al.	Ernst et al. (2012)
Design optimisation of truss structures	Gandomi et al.	Gandomi et al. (2012)
Structural optimisation problems	Gandomi et al.	Gandomi et al. (2013)
Electrostatic deflection	Goghrehabadi et al.	Goghrehabadi et al. (2011)
Steel frames	Kaveh and Bakhspoori	Kaveh and Bakhshpoori (2013)
Steel structures	Kaveh et al.	Kaveh et al. (2012)
Antenna arrays	Khodier	Khodier (2013)
Design space exploration	Kumar and Chakarverty	Kumar and Chakarverty (2011a, 2011b)
Optimisation of sequence	Lim et al.	Lim et al. (2012)
Planar EBG structures	Pain et al.	Pani et al. (2013)
Stability analysis	Rangasamy and Manickam	Rangasamy and Manickam (2013)
Linear antenna array	Rani and Malek	Rani and Malek (2011), Rani et al. (2012b)
Optimal capacitor placement	Reddy and Manohar	Reddy and Manohar (2013)
Allocation and sizing of DG	Tan et al.	Tan et al. (2012)
Photovoltaic models	Ma et al.	Ma et al. (2013)
Integrated power systems	Piechocki et al.	Piechocki et al. (2013)
Reliability problems	Valian et al.	Valian et al. (2013), Valian and Valian (2012)
Non-linear state estimation	Walia and Kapoor	Walia and Kapoor (2013)
Phase equilibrium calculations	Bhargava et al.	Bhargava et al. (2013)
Structural design optimisation	Durgun and Yildiz	Durgun and Yildiz (2012)
Antenna arrays synthesis	Ahmed and Abdelhafid	Ahmed and Abdelhafid (2013)
Constrained engineering tasks	Kanagaraj et al.	Kanagaraj et al. (2013b)

In the last decade, evolutionary algorithms and SI became very effective tools in engineering optimisation (e.g., Fister, 2013; Fister et al., 2013a). Table 6 collects the more prominent papers that tackle solving the problems in engineering optimisations with CS. Note that a lot of papers address a domain of antenna optimisations.

6 Applications

Computer applications are special programmes that are written in programming language and are intended to perform some useful task. Generally, each programme running on digital computer represents a kind of application. Obviously, this programme implements an algorithm for solving some problem. In this sense, also programmes for solving problems in engineering optimisation are applications. In this section, we are interested about applications that are not directly devoted for solving the problems in engineering optimisation, but can serve as a general tools applied to each application domain (also engineering optimisation). In line with this, CS was used in many real-world applications (Figure 4).

Table 7 presents a comprehensive collection of papers tackling the applications using the CS. As can be seen from the table, a lot of papers describe applications using CS for clustering. Clustering groups is a task of grouping the set of objects into group in such a way that objects in the same group is more similar to each other according to the some characteristic than with objects in the other group. This group of objects is named a cluster. Note that clustering is a data mining method that becomes more important with emergence of the big data connected with internet. With internet, it is also connected domain of web service composition, where CS plays an increasingly important role. Web service composition is a complex problem. The main task of it is to arrange multiple services into work-flows that supply the complex user needs (e.g., in Bartalos and Bieliková, 2012).

Figure 4 CS applications

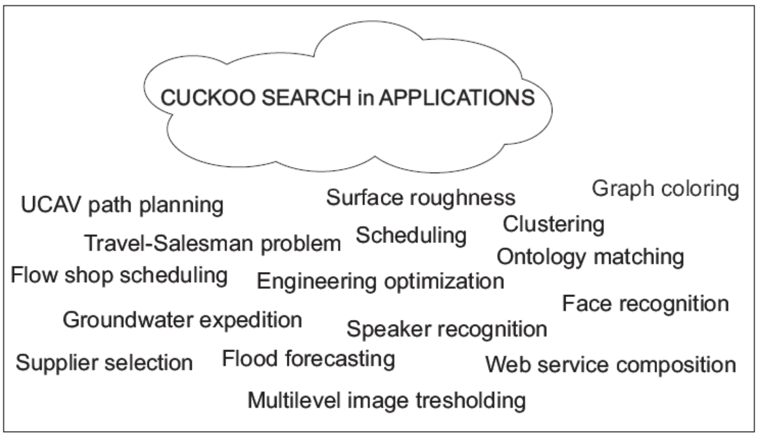


Table 7 CS in applications

Application	*Author*	*Reference*
Multilevel image thresholding	Brajevic et al.	Brajevic et al. (2012)
Flood forecasting	Chaowanawatee and Heednacram	Chaowanawatee and Heednacram (2012)
Wireless sensor networks	Dhivya and Sundarambal	Dhivya and Sundarambal (2011)
Data fusion	Dhivya et al.	Dhivya et al. (2011a)
Data clustering	Saida et al.	Saida et al. (2014)
Cluster in wireless networks	Dhivya et al.	Dhivya et al. (2011b)
Clustering	Goel et al.	Goel et al. (2011)
Clustering	Senthilnath et al.	Senthilnath et al. (2013)
Groundwater expedition	Gupta et al.	Gupta et al. (2013)
Supplier selection	Kanagaraj et al.	Kanagaraj et al. (2012)
Load forecasting	Kavousi-Fard and Kavousi-Fard	Kavousi-Fard and Kavousi-Fard (2013)
Surface roughness	Madic et al.	Madić and Radovanović (2013)
Flow shop scheduling	Marichelvam	Marichelvam (2012)
Optimal replacement	Mellal et al.	Mellal et al. (2012)
DG allocation in network	Moravej and Akhlaghi	Moravej and Akhlaghi (2013)
Optimisation of bloom filter	Natarajan et al.	Natarajan et al. (2012a, 2012b), Natarajan and Subramanian (2012)
BPNN Neural Network	Nawi et al.	Nawi et al. (2013a)
Travelling salesman problem	Ouaarab et al.	Ouaarab et al. (2013)
Web service composition	Pop et al.	Pop et al. (2011)
Web service composition	Chifu et al.	Chifu et al. (2011, 2012)
Ontology matching	Ritze and Paulheim	Ritze and Paulheim (2011)
Speaker recognition	Sood and Kaur	Sood and Kaur (2013)
Planar graph colouring	Zhou et al.	Zhou et al. (2013)
Road networks	Baskan	Baskan (2013)
Automated software testing	Srivastava et al.	Srivastava et al. (2012a, 2012b, 2012c)
Manufacturing optimisation	Syberfeldt and Lidberg	Syberfeldt and Lidberg (2012)
Face recognition	Tiwari	Tiwari (2012)
Reliability-redundancy allocation	Kanagaraj et al.	Kanagaraj et al. (2013a)
Training neural models	Vázquez	Vázquez (2011)
Non-convex economic dispatch	Vo et al.	Vo et al. (2013)
UCAV path planning	Wang et al.	Wang et al. (2012b, 2012c)
Business optimisation	Yang et al.	Yang et al. (2012)
Machining parameter selection	Yildiz	Yildiz (2013)
Job scheduling in grid	Prakash et al.	Prakash et al. (2012)

Table 7 CS in applications (continued)

Application	*Author*	*Reference*
Quadratic assignment	Dejam et al.	Dejam et al. (2012)
Sheet nesting problem	Elkeran	Elkeran (2013)
Query optimisation	Joshi and Srivastava	Joshi and Srivastava (2013)
n-queens puzzle	Sharma and Keswani	Sharma and Keswani (2013)
Scheduling optimisation	Burnwal and Deb	Burnwal and Deb (2013)
Computer games	Speed	Speed (2010, 2011)

The CS is also appropriate for solving many NP-hard problems (Garey and Johnson, 1979) that present a real tough nut to crack. Therefore, many of these problems are used as a test-bed for developing the new heuristics. For instance, travelling salesman problem was tried to cope with this algorithm. Thus, Ouaarab et al. (2013) achieved excellent results. On the other hand, graph colouring is one of the more famous problems from the class of NP-hard. Zhou et al. (2013) have successfully undertaken the colouring of planar graphs with the CS. Moreover, Marichelvam (2012) was also applied this algorithm to flow shop scheduling that is well-known NP-hard problem.

In this context, reader is invited to check the complete list of papers tackling the other applications in Table 7.

7 Theoretical analysis and implementation

As we have seen, the applications of CS are very diverse. In contrast, theoretical studies are very limited. This brief summary may highlight the need for further research in theoretical aspects of CS.

7.1 Theory and algorithm analysis

It may be difficult to classify a study into a theoretical category or not because the contents may sometime include both simulations and some analysis of the algorithm. So the following categorisation may not be rigorous. Even so, some theoretical studies about CS in the current literature can be summarised, as follows:

- A conceptual comparison of the CS, particle swarm optimisation, DE and artificial bee colony algorithms by Civicioglu and Besdok (2013).
- Enhancing the performance of CS algorithm using orthogonal learning method by Li et al. (2013).
- Starting configuration of CS algorithm using centroidal Voronoi tessellations by Shatnawi and Nasrudin (2011).
- Reduced order mesh optimisation using proper orthogonal decomposition and a modified CS by Walton et al. (2013a, 2013b).
- Bat algorithm and CS: a tutorial by Yang (2013a).

- Meta-heuristic algorithms for inverse problems by Yang (2012, 2013b), and Yang and Deb (2012).
- Markov model and convergence analysis of CS by Wang et al. (2012a).
- Towards the improvement of CS algorithm by Soneji and Sanghvi (2012).

7.2 Improvements and other studies

Sometimes, some researchers applied CS as operators, combined with other search techniques, or even incorporated into other meta-heuristics. These studies can be summarised as follows:

- Tsallis entropy by Agrawal et al. (2013).
- Improved scatter search using CS by Al-Obaidi (2013).
- CS via Lévy flights for optimisation of a physically-based runoff-erosion model by Freire et al. (2012).
- Improved DE via CS operator by Musigawan et al. (2012).
- CS with the conjugate gradient method by Salimi et al. (2012).
- CS with PSO by Wang et al. (2011a).

7.3 Implementations

As its popularity increases, CS has been implemented in many different programming languages. The first DEMO version was released in 2009 by Yang[1]. Not all researchers use MATLAB, researchers have developed their versions in different programming languages. A quick current literature survey suggests that CS has been implemented also in Java, C/C++ and in Python. Currently, some object-oriented approach and implementations were carried out in studies of Bacanin (2011, 2012). Moreover, paralelisation was also provided by Tuba et al. (2013).

8 Future directions of CS

Up to now, we have summarised the main developments about CS in previous sections. As we can see that CS has been applied into many areas such as engineering optimisation and diverse applications. In addition, many industries also used CS for their optimisation tasks and improvement of their industrial processes. However, there is still plenty of room for improvement. From our survey and observations, we expect that further research in the following areas using CS will be very useful:

- large-scale global optimisation, like in Fister et al. (2012)
- combinatorial optimisation, e.g., graph colouring (Fister et al., 2013b), scheduling, and travelling salesmen problem
- hybridisation with other algorithms, e.g., Krill herd by Gandomi and Alavi (2012)

- systematical theoretical analysis
- self-adaptation, like in firefly algorithm by Fister et al. (2013c)
- working with ensemble strategies
- various representations, e.g., like quaternion representation of individuals in Fister et al. (2013d)
- parameter tuning and control
- more industrial applications.

9 Conclusions

In this paper, a review of the CS algorithm and its variants has been carried out. Almost all major studies that we can find (e.g., Google Scholar, Scopus and Web of Science) on CS have been briefly included in this review. Currently, CS is a very hot topic and it can be expected that more papers on this topic will appear in the near future.

It is highly needed to gain more insight by carrying out more theoretical analysis with mathematical proof about the performance, parameter tuning and control of CS and other algorithms. Moreover, there remain many open questions for improving CS, including how to design self-adaptive CS, how at much efficiently to tune the parameters, and how to control these to achieve the best performance. It will be very useful to carry out large-scale real-world applications in engineering and industry.

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Notes

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