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A Review on Research Trends in using Cuckoo Search Algorithm: Applications and Open Research Challenges

***Abstract**. This paper provides an exclusive understanding of the Cuckoo Search Algorithm (CSA) using a comprehensive review for various optimization problems. CSA is a swarm-based nature inspired, intelligent and metaheuristic approach, which is used to solve complex, single or multi objective optimization problems to provide better solutions with maximum or minimum parameters. It was developed in 2009 by Yang and Deb to emulate the breeding behaviour of cuckoos. Since CSA provides promising solutions to solve real world optimization problems, in recent years there have been introduced several new modified and hybridized CSAs using for different applications. In this regard this article provides a comprehensive survey including recent trends, modifications, open research challenges, applications, and related taxonomies for various optimization problems. The literature of this reviewed paper belongs to the domains of engineering, optimization, and pattern recognition. The aim of this review paper is to provide a detailed overview regarding CSA for possible future directions using the recent contributions.*

Streszczenie.** Ten artykuł zapewnia wyłączne zrozumienie algorytmu przeszukiwania kukułki (CSA) za pomocą kompleksowego przeglądu różnych problemów optymalizacyjnych. CSA to oparte na roju, inteligentne i metaheurystyczne podejście inspirowane naturą, które służy do rozwiązywania złożonych, jedno- lub wielocelowych problemów optymalizacyjnych w celu zapewnienia lepszych rozwiązań z maksymalnymi lub minimalnymi parametrami. Został opracowany w 2009 roku przez Yang i Deb, aby naśladować zachowanie hodowlane kukułek. Ponieważ CSA zapewnia obiecujące rozwiązania do rozwiązywania rzeczywistych problemów optymalizacyjnych, w ostatnich latach wprowadzono kilka nowych zmodyfikowanych i hybrydowych CSA używanych do różnych zastosowań. Pod tym względem ten artykuł zawiera obszerną ankietę, w tym najnowsze trendy, modyfikacje, otwarte wyzwania badawcze, aplikacje i powiązane taksonomie dla różnych problemów optymalizacyjnych. Literatura tego recenzowanego artykułu należy do dziedzin inżynierii, optymalizacji i rozpoznawania wzorców. Celem tego artykułu przeglądowego jest przedstawienie szczegółowego przeglądu dotyczącego CSA dla możliwych przyszłych kierunków z wykorzystaniem ostatnich wkładów.* (Przegląd trendów badawczych w używaniu algorytmu cuckpooz: aplikacje i otwarte wyzwania badawcze***)

Keywords: Cuckoo Search Algorithm, Swarm Intelligence Algorithms, Metaheuristics, Optimization Problems, Local Trap Problems;
Słowa kluczowe: algorytm cuckoo, optymalizacja

Introduction

In recent years, the nature inspired metaheuristic algorithms are active in literature to solve different problems including optimization and computational intelligence because the conventional methods were based on complex numerical solutions [1-3]. For most real-world optimization problems, resource utilization, time consumption, efficiency, global optimization, and optimal solutions are the major requirements. Furthermore, it is quite difficult to find the best optimal solution for various engineering and related applications, such as artificial intelligence (AI), machine learning (ML), and data mining (DM) [4-6]. Subsequently, most of the heuristic algorithms were based on trial-and-error strategies to find best optima, while other methods include selection and previous information for search process. However, optimality is the major concern, which needs to be reachable [7, 8].

In the last decades, there are many metaheuristic algorithms have been applied to different optimization problems [9-15] and one of them is Cuckoo Search Algorithm (CSA). CSA is an efficient nature inspired metaheuristic and evolutionary algorithm (EA), which is proposed by Xin-She Yang and Suash Deb in 2009 [12] inspired by cuckoos' reproduction strategy. Cuckoos are bird species that are being mimicked by CSA specifically in their eggs laying behaviour. Cuckoos lay their ages in the host or other species nest in order to sustain. The phenomena of natural imitation consist of certain rules and randomness occurred in EAs, such as Differential Evolution (DE) [16], Evolutionary Algorithm (EA) [17] and Genetic Algorithm (GA) [18], algorithms using animal behaviour includes Ant Colony Algorithm (ACA) [19], Tabu Search Algorithm (TBA) [20] and Particle Swarm Optimization (PSO) [21], similarly the imitation process of physical annealing in Simulated Annealing (SA) [22].

Though, CSA provides far better optimal solutions as compared to certain other swarm intelligence (SI) algorithms [23]. This paper provides state of the art review of CSA including all the recent trends, applications, challenges, and future directions. This paper helps the researcher to gain a detailed overview regarding CSA.

Standard Cuckoo Search Algorithm

CSA has gained the researchers' attentions because of its promising results, which provides better optimal solutions for real world applications and facing optimization problems [8, 24, 25]. The behaviour of standard CSA as shown in Fig. 1 can be described using following rules. First, cuckoos in the algorithm can lay one egg at a time and then this egg should be placed in a randomly selected nest. Second, only those nests can carry cuckoos' next generation, which contains high quality of eggs.

Third, there are fixed number of host nests available and the worst-case probability of egg discovery by host nest is $P_a \in [0,1]$ in this worst-case scenario the host bird can abandon the nest and reconstruct the new one or it can destroy the cuckoos' discovered egg as in Algorithm 1.

Algo. 1. Standard Cuckoo Search Algorithm [4]

begin
  Objective function $f(x), x = (x_1, x_2, x_3, \dots, x_d)^T$
  Generate initial population of n host nests,
  $X_i\ (i = 1,2,3, \dots, n))$
  while $t <$ *max generation or stopping criterion*
    Get a cuckoo randomly by Lévy flights.
    Evaluate its quality/fitness F_i
    Choose a nest among n (say, j) randomly.
    if $(F_i \le F_j)$
      Replace j by new solution.

end if
A fraction (P_a) of worst nests are abandoned and new ones are reconstructed.
Keep the best solutions (or nests with quality solutions).
Rank the solutions and find the current best
end while
Postprocess results and visualization
end

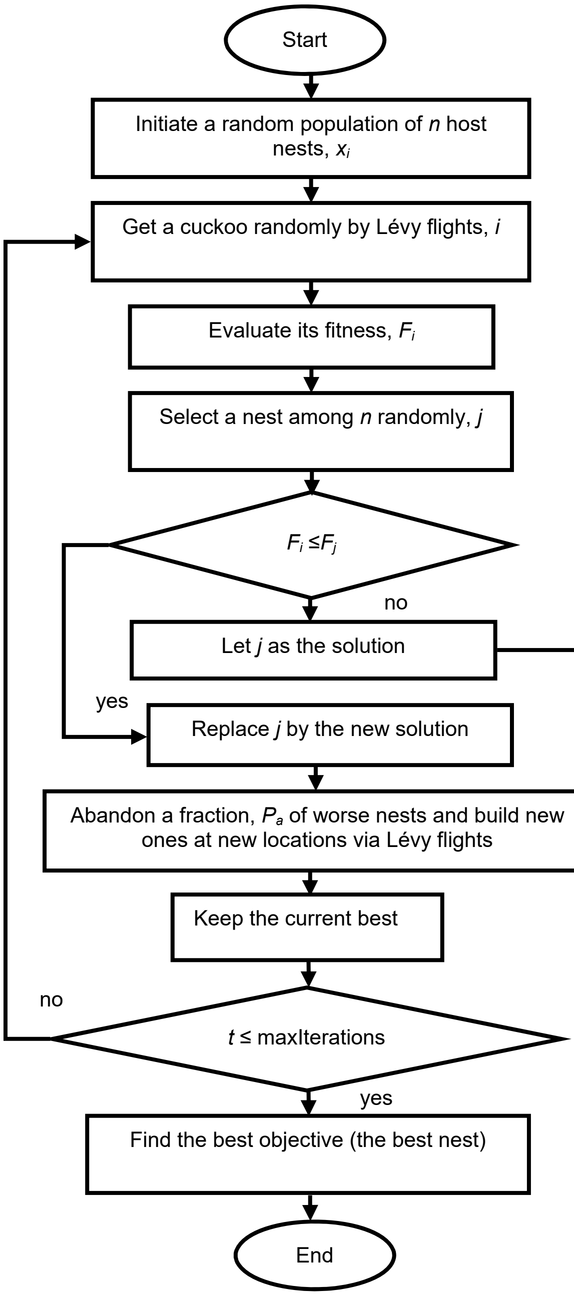

Fig.1. Flowchart of Standard Cuckoo Search Algorithm [20].

Standard Cuckoo Search Algorithm is based on parasitic brood behaviour of cuckoo species along flight mode, which represents step wise distribution using a heavy tail for random walk. This swarm-based metaheuristic behaviour of random walk imitates the real-life walking behaviour of fruit flies and birds such as Lévy flight. Moreover, CSA provides an efficient balance between the local exploitation and global exploration within the given search space problem area [26, 27]. Furthermore, the main strategy of swarm based CSA starts with *n* host nests, as an initial population. Initially the host nests will randomly attract towards cuckoos to lay eggs using Lévy flight. Afterwards, quality of the nests will be compared and evaluated with randomly chosen nests. In the best case scenario, the old host nest will be replaced with the new ones where cuckoos will lay their eggs in it. Alongside, there is a possibility of discovery, $P_\alpha \in (0, 1)$, where the host bird will build a new nest or abandon the old nest or throw out the discovered eggs of suspicious cuckoo in the current nest [27]. This host nest replacement process will be randomly done until a better solution (best host nest) is obtained[28].

$$x_i^{t+1} = x_i^t + \alpha \oplus \text{Lévy}(\lambda) \quad (1)$$

Subsequently, new solutions x_i^{t+1} such as a cuckoo i, can be generated using the Lévy flight with the step size, $a > 0$ that could be changed according to the problem and mostly $a = 1$ [29]. The x_i^t shows the current solution and x_i^{t+1} represents the next solution achieved via a random walk. In Eq. 1, $\oplus$ is the entrywise multiplication product operator. In this case, the Lévy flight provides an efficient random walk for CSA to get the best exploration randomly and globally.

Research Method

An exploratory research method has been opted to provide an exclusive and comprehensive literature review using recent studies, which are based on a nature inspired, swarm intelligence (SI) algorithm called Cuckoo Search Algorithm (CSA).

Modified or Hybridized Variants of CSA

Modification and hybridization of the CSA are becoming popular among new researchers in postulating new directions to utilize the maximum benefits of CSA. Some recent modifications and hybridizations are provided in Table 1.

A modified CSA (MCSA) was proposed for a collision free path planning using the tournament selection function in order to replace the random selection method of conventional cuckoo's algorithm [30]. This paper ensures the higher efficiency and better performance for robotics and the premature convergence were avoided for the global best optima including the path length and time parameters. The proposed MCSA was compared with GA and PSO for performance evaluations. Moreover, the MCSA used less internal parameters than both GA and PSO counterparts. However, this study was not validated using any benchmark.

Chatterjee, S., et al. [31] proposed a modified Cuckoo Search Algorithm (MCSA) trained by Neural Network (NN) generating the NNMCSA to detect chronic kidney disease . Subsequently, global search strategy was used for optimal weights searching. This proposed NNMCSA method was compared with Particle Swarm Optimization-Neural Network (PSONN) and Multilayer Perceptron Feed-Forward Network (MLPFFN) in order to ensure the efficiency of disease detection. The dataset was taken from the University of California Irvine (UCI) Machine Learning Repository. Furthermore, root mean squared error (RMSE) was minimized using the MCS algorithm, as it was involved during the overall NNs training process.

Chen, G., et al. [32] proposed a reliable and efficient hybrid approach using modified CSA along with Differential Evolutionary Algorithm (DEA) producing the MCSDEA in order to solve optimal reactive power dispatch (ORPD) problem. The proposed solution was experimented on three objectives including voltage deviation, voltage stability index and power loss. Additionally, IEEE 30-bus and IEEE 57 bus test power systems were used for examination.

Hybrid multiobjective CSA for many-objective optimization problems (MaOPs) was proposed by Cui, Z., et al. [33]. The reference point strategy and non-dominated sorting was employed to deal MaOPs effectively, which ensured the relative diversity and convergence accordingly. However, the performances for the proposed experiments were verified using the benchmark sets including the test suites, such as ZDT, WFG and DTLZ test suites. As a result, this proposed study provided promising performance as compared to the previous related algorithms.

The authors [34] provided a modified CSA (MCSA), where a hybrid model for the prediction of molten steel temperature in ladle furnace was proposed. Alongside they developed an information interaction-enhanced CSA (IIECSA) to optimize the parameters of empirical part. This significantly improved search performance. Subsequently, the empirical part was trained indirectly with the readily available temperature measurements of molten steel. The drawbacks of this proposed solution were time consuming due to parameter tuning processes, extra parameters used, complexity increased. However, the overall improvement was needed in the selection strategy of the proposed algorithm for information providers in IIECSA.

Modified Factional-Order Cuckoo Search Algorithm (MFOCSA) in [35] used the 18-UCI datasets including two datasets for the COVID-19 X-ray images for testing purposes. The authors provided an enhanced MFOCSA and four different heavy-tailed distributions in place of the Lévy flight to strengthen the algorithm performance during dealing with the COVID-19 multi-class classification optimization task. The strength of the paper shows an improved convergence curve. To get better results, researchers applied the Weibull distribution (heavy-tailed distribution) instead of the Lévy flight, which increased the performance of feature selection process. Furthermore, this also improved the global cuckoo walk using the fractional order. Alongside the switching probability, P_s was generated using the *B* distribution (beta function) and the Mittag-Leffler used in place of the Lévy flight. Though, processing time and complexity level of the proposed algorithm were not provided.

Hybrid clustering method using CSA was proposed in [36] using 4-Twitter datasets. This ensured faster convergence and better optimum solution with Hybrid clustering, K-means and CSA (CSAK). The proposed solution had a better computational efficiency compared to other algorithms. This paper provided K- clusters using the K-means algorithm with K-cluster-heads to initialize the population of CSA.

The authors provided a hybrid Cuckoo Search Algorithm with Rough Sets (CSARS) in [37] using the UCI repository. The proposed solution provided an improved classification method with fast convergence and a reduced number of learning parameters. The Analysis of Variance (ANOVA) test was used then to check the accuracy level. The CSA was modified using rough sets, which computed the degree of dependency used for feature selection (FS). The value of the given parameter, α was modified to decrease with increasing the number of generations via the parallel technique in identifying the abandoned solutions. Subsequently, fourfold cross-validation (CV) was used for labelled training. Two learning algorithms, namely K-Nearest Neighbour (KNN) and Support Vector Machine (SVM) were used to the performance of the proposed CSARS. However, convergence curve was missing, which means it did not show saturated searching operation for optimal solutions.

The authors in [38] presented a MCSA using variation parameter and logistic map (VLMCSA), which dealt high and low dimension problems and provided balance the exploitation and exploration. Furthermore, the overall complexity was reduced. The proposed solution improved computational efficiency. The coefficient function was used to change step size *a*, and detection probability, P_a. Moreover, logistic map was used in each dimension for host nest to initialize and update their locations beyond the boundary. However, the complexity level of the proposed algorithm was not provided.

The hybridization of CSA and Particle Swarm Optimization (PSO) generating the CSPSOA was presented in [39]. This paper provided the solution for the optimization of continuous functions and engineering design problems and delivered better convergence rate and optimal solution, which solved continuous optimization problems. The population of the proposed CSPSOA was initialized by using the principle of Mutually Orthogonal Latin Squares (MOLS). Furthermore, a dynamic step size was employed in CSA instead of the original fixed constant. The proposed solution was only suitable for single objective (SO) optimization problems not for other search space problem.

One popular metaheuristic known as Sine Cosine Algorithm (SCA) was modified using the Latin Hypercube Sampling (LHS) technique, which improved capability of identification of initial solution. Afterwards the modified SCA was hybridized along with the CSA producing the MSCCSA to get the optimal search of host nest in global domain [15]. However, the complexity level of the proposed algorithm was not provided.

The authors in [32] provided a modified CSA (MCSA) using 13 classification datasets. The proposed clustering model worked using clustering-based classification was efficient in colour histopathological image segmentation domain, fitness-based step size incorporated, Furthermore, Levy flight was used with Cauchy mutation, and fitness-based step size and the guidance of global best solution to facilitate the global search using exploration technique. Subsequently, circle topology structure was used for K-neighbourhood. However, the MCSA was found having the local trap problem.

Table 1. State of the Art (SOTA) of CSA for various Optimization Problems

Ref.	Proposed Method/Approach	Applied Techniques/ Sampling method	Strengths/ Contribution	Algorithmic Improvements/ Parameters	Weaknesses/Research Gap
[30]	Modified CSA (MCSA)	Tournament selection function	Provide a collision-free path for the mobile robot/Smoothness.	Path length and time Tournament selection function (6 parameters: G, X_G; Y_G, N, OB_1; OB_2, X_{OB1}; Y_{OB2}, C_1; C_2).	Did not ensure convergence detection in the case of multi-robot system. Did not guarantee exploration.

[31]	Hybrid MCSA trained by Neural Network (NNMCSA)	Weight vector of neural network is optimized.	Efficient chronic kidney disease discovery	MCSA with McCulloch's algorithm.	Proposed NNMCSA did not provide balance between exploration and exploitation.
[32]	Hybrid MCSA with Differential Evolutionary Algorithm (MCSDEA)		.Improve the reactive power distribution.	Fixed values of the parameters α and P_a and enhanced the performance of the algorithm.	The proposed MCSDEA faced local trap problem.
[33]	Hybrid many-objective CSA (MaOCSA)	Non-dominated sorting	Deal with many-objective optimization problems (MaOPs)	To incorporate Lévy flight into MaOPs, the new updating equation was redefined using two new equations.	MOEA/D performs better than the proposed hybrid MaOCSA on the DTLZ benchmark set. Simulation results show that a fixed P_a was not suitable for all test instances.
[34]	Information Interaction-enhanced CSA (IIECSA)		Developed information interaction-enhanced CSA (IIECSA), to optimize the parameters of empirical part.	Empirical part was trained indirectly with the readily available temperature measurements of molten steel	Improvement needed in the selection strategy of information providers in IIECSA.
[35]	Modified Factional-Order Cuckoo Search Algorithm (MFOCSA)	18-UCI datasets, two datasets for COVID-19 X-ray images	Increased the performance of feature selection (FS) process.	Improved the global cuckoo walk using fractional order. The switching probability, P_s has generated using the B distribution (beta function) he Mittag-Leffler used in place of Lévy flight	Imbalance between exploration and exploitation.
[36]	Hybrid clustering, K-means and CSA (CSAK)	4-Twitter dataset	CSAK has a better computational efficiency.	Generated K clusters using the K-means algorithm. Used K cluster-heads to initialize the population of cuckoo search.	Objective function was missing, faced local trap problem.
[40]	Hybrid Cuckoo Search Algorithm with Rough Sets (CSARS)	UCI repository	Improved classification method Fast convergence. .	CSA modified using rough set, which computes the degree of dependency. This is also used for feature selection. The value of a was made to decrease with increasing the number of generations, Used parallel technique to check the abandoned solutions. Fourfold cross-validation (CV) was used for labelled training.	Convergence curve was missing, also did not guarantee smooth search space.
[38]	MCSA using variation parameter and logistic map (VLMCSA)		Reduced complexity. Improved computational efficiency.	Used the coefficient function to change step size a and P_a for detection probability, Used logistic map for each dimension for host nest to initialize and update their locations beyond the boundary. Boundary was constrained by logistic map of each dimension	Did not guarantee exploitation

[39]	Hybrid CSA and Particle Swarm Optimization (CSPSOA)		Provided the solution for the optimization of continuous functions and engineering design problems.	The population of the proposed CSPSOA was initialized. By using the principle of orthogonal Lation squares and a dynamic step size was employed in CS instead of the original fixed constant.	Proposed solution was only suitable for single objective optimization problems, Search space problem.
[31]	Hybrid Modified Sine Cosine Algorithm (MSCA) and CSA (MSCCSA)		Improved capability of identification of initial solution and better capability of finding global optimal solutions	The Latin Hypercube Sampling (LHS) technique in MSCA improved the capability of identifying better fitness of initial solution and the hybridization with CSA avoided the local trap problem.	The complexity level of the proposed algorithm was not provided.
[41]	Modified CSA (MCSA)	13 classification datasets	Proposed clustering model also proves its efficient performance in colour histopathological image segmentation domain.	Fitness based step size incorporated, Lévy flight, Cauchy mutation, fitness-based step size and the guidance of global best solution to facilitate the global search using exploration technique. circle topology structure is used for K-neighbourhood	Convergence curve was missing. Complexity increased. Local trap problem.
[42]	Modified CSA (MCSA)		Efficiently solved economic dispatch problems for large scale systems.	Proposed a self-adaptive step size and some neighbour-study strategies to enhance search performance. An improved lambda iteration strategy is used to generate new solutions.	Local trap problem.
[43]	Hybrid CSA (HCSA) with a largest-order-value method and a multi-neighborhood local search rule		Minimizes the completion time and total carbon emissions via the multi-objective permutation flow shop scheduling problem (MOPFSP).	Largest-order value method was proposed by designing step size to control the search scope. Precisely, the original fixed step size control factor α was replaced with a dynamic step size control factor α. The cosine function was introduced using an improved equation for step size control factor α. In order to further improve local search accuracy of the CSA, a multi-neighborhood local search strategy was proposed to perform fine search based on different neighborhoods.	As the number of iterations increased, it trapped in local convergence. Needs some heuristic algorithms to generate initial population instead of random procedure used.
[44]	K-means CSA (KCSA)		Hybridized with machine learning (ML).	Algorithm uses K-means using random operator using decentralization	Exploration and exploitation of the search space were not discussed to increase or decrease the population

				process harmony search was proposed.	
[45]	Hybrid CSA and Hill Climbing (CSHCA)		Solved the Hydrophobic-Polar (HP) protein folding optimization problem.	The proposed CSHCA optimized HP protein folding problem in a three-dimensional (3D) lattice model better than different benchmark sequences	Poor balance between search space for exploitation and exploration.

A modified CSA or MCSA [33] was proposed to solve economic dispatch problems for large scale systems. The MCSA had a balance between exploitation and exploration as well as better performance in terms of efficiency and robustness. Moreover, the proposed MCSA had a self-adaptive step size and some neighbour-study strategies to enhance search performance. This solution indicated an improved lambda iteration strategy used to generate new solutions, but the results suffered the local trap problem. Table 1 enlists the recent proposed modified and hybridized CSA along with strengths and weaknesses in solving various optimization problems.

Conclusion

This review paper provides an exclusive and comprehensive summary using the recent literatures of the cuckoo search algorithm (CSA). This paper helps researchers to understand the recent trends, methods, and applications of CSA including the analysis for its robust performance. Although, CSA is an interesting and promising algorithm, which is widely used by researchers to provide better solution for different optimization problems from different fields including image processing, medical, data clustering, engineering etc. Subsequently, high-quality results enhanced the popularity of CSA due to its emerging features and methodologies, such as, ease of use, simplicity, hybridization, modification, and parameter tuning. However, a detailed survey of literature was not provided before to compare the performance of improved or hybridized CS algorithm using different parameter settings since these measures govern the performance of CSA.

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