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Crow Search Algorithm: Theory, Recent Advances, and Applications

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ABSTRACT In this article, a comprehensive overview of the Crow Search Algorithm (CSA) is introduced with detailed discussions, which is intended to keep researchers interested in swarm intelligence algorithms and optimization problems. CSA is a new swarm intelligence algorithm recently developed, which simulates crow behavior in storing excess food and retrieving it when needed. In the optimization theory, the crow is the searcher, the surrounding environment is the search space, and randomly storing the location of food is a feasible solution. Among all food locations, the location where the most food is stored is considered to be the global optimal solution, and the objective function is the amount of food. By simulating the intelligent behavior of crows, CSA tries to find optimal solutions to various optimization problems. It has gained a considerable interest worldwide since its advantages like simple implementation, a few numbers of parameters, flexibility, etc. This survey introduces a comprehensive variant of CSA, including hybrid, modified, and multi-objective versions. Furthermore, based on the analyzed papers published in the literature by some publishers such as IEEE, Elsevier, and Springer, the comprehensive application scenarios of CSA such as power, computer science, machine learning, civil engineering have also been reviewed. Finally, the advantages and disadvantages of CSA have been discussed by conducting some comparative experiments with other similar published peers.

INDEX TERMS Crow search algorithm, CSA, swarm intelligence, meta-heuristics, optimization, nature-inspired algorithms.

I. INTRODUCTION

Nowadays, optimization can be considered as one of the most important and hottest research topics [1]–[9]. It is inside the core processes of every aspect and can be found in almost all fields such as engineering, science, energy, computer, etc. [10]–[19]. Since the complexity increasing of the real-world scientific and engineering problem, optimization becomes a big challenge in soft computing. Traditional methods of mathematics sometimes fail to solve and address them [180], [184]. Metaheuristics Algorithm (MA) is very good at solving these NP problems and finding the optimal/near-optimal solution in real-time [185]. These algorithms become very popular since their advantages like easy in implementation, avoiding local optima, and flexible and versatile [188]. They can be considered as a black box, and can solve different problem types: single/multi-objective, constrained or unconstrained, and continuous/discrete.

Generally speaking, MA can be categorized into two major classes: single-based / individual-based algorithms

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TABLE 1. Examples of evolutionary algorithms.

No.	Algorithm	Abb.	Authors	Year
1	Genetic algorithms [20]	GA	Holland	1975
2	Evolutionary programming [61]	EP	Fogel et al.	1966
3	Evolution strategy [62]	ES	Rechenberg	1973
4	Tabu search [22]	TS	Glover	1986
5	Differential evolution [63]	DE	Storn and Price	1997
6	Differential search algorithm [24]	DS	Civicioglu	2011
7	Synergistic fibroblast optimization [70]	SFO	Dhivyaprabha et al.	2019
8	Physarum-inspired computational model [71]	PCM	Chen et al.	2020

and population-based. Examples of single-based algorithms are Tabu Search (TS) [22], Guided Local Search (GLS), and Pattern Search (PS) whereas Particle Swarm Optimization (PSO) [23], Differential Search Algorithm (DSA) [24] and Grey Wolf Optimizer (GWO) [36] are examples of population-based algorithms.

Crow Search Algorithm (CSA) is a recent algorithm developed by Alireza Askarzadeh in 2016, which simulates the crow behavior in storing their food and retrieving it when they need it. Since its appearance, CSA has been widely used and applied to different optimization problem such as chemical engineering [83], medical [84], power energy [85], feature selection [86], and image processing [87].

Reviews/survey papers are critical as they present and discuss recent and up-to-date works. In literature, there are enormous reviews that concern with MA such as Grey Wolf Optimizer [88], Firefly Algorithm [89], Gravitational Search Algorithm [90], Krill Herd Algorithm [90].

To the best of our knowledge, there is no study in literature covers or lists all CSA aspects, variants, and applications. This review article aims to carry a comprehensive study for all CSA aspects, how scientists/researchers are motivated to use this algorithm to solve different real-world optimization problems. Also, This review collects and summarizes all modifications and variants of CSA to overcome its drawbacks.

The main contributions of this article can be listed below:

- A comprehensive review to CSA has been done.
- All modifications to the original CSA has been highlighted.
- All applications and fields that employed CSA have been summarized and presented.
- Advantages and disadvantages of CSA have been discussed.
- Number of challenges/ideas as a future work have been suggested.

This article is organized as follows: Section 2 presents a literature review to MA whereas Section 3 disuses inspiration & mathematical model of CSA. Section 4 presents all variants and modifications of CSA and Section 5 summarizes and highlights all applications that use CSA. An assessment and evaluation to CSA is presented in section 6 whereas Section 7 concludes the paper and adds some suggestions that can be handled in future work.

II. METAHEURISTICS

In literature, enormous types of optimization algorithms has been proposed in the last decades such as Genetic Algorithm (GA) [20], Simulated Annealing (SA) [21], Tabu Search (TS) [22], Particle Swarm Optimization [23], Differential Search Algorithm (DSA) [24], Harmony Search (HS) [25], Cat Swarm Optimization (CSO) [26], Firefly Algorithm (FA) [27], Cuckoo Search (CS) [28], Gravitational Search Algorithm (GSA) [29], Virus Optimization Algorithm (VOA) [30], Bat Algorithm (BA) [31], Ant Colony Optimization (ACO) [32], Flower Pollination Algorithm (FPA) [33], Krill Herd (KH) Algorithm [34], Chicken Swarm Optimization (CSO) [35], Grey Wolf Optimizer (GWO) [36], Social Spider Algorithm (SSA) [37], Ant Lion Optimizer (ALO) [38], Moth-Flame Optimization (MFO) [39], Elephant Herding (EH) Optimization [40], Multi-Verse Optimizer (MVO) [41], Whale Optimization Algorithm (WOA) [42], Dragonfly Algorithm (DA) [43], Sine Cosine Algorithm (SCA) [44], Kidney-Inspired Algorithm [45], Spotted Hyena Optimizer (SHO) [46], Grasshopper Optimization Algorithm (GOA) [47], Salp Swarm Algorithm (SSA) [48], Thermal Exchange Optimization [56], Squirrel Search Algorithm [57], Henry Gas Solubility Optimization (HGSO) [58], Harris Hawks Optimization (HHO) [51], Nuclear Reaction Optimization (NRO) [52].

In literature, there are many metaheuristics algorithms classification. For example, authors in [59] have divided MAs to two categories (evolutionary & Swarm Intelligence) where in [60] authors have divided them to three different classes (Swarm Intelligence, Evolutionary Intelligence, and Physical & Chemical algorithm). In [58], Hashim *et al.* classified them in to four groups (Swarm Intelligence (SI), Bio-Inspired Algorithms (BIAs), Natural Science-based Algorithms (NSAs), and Natural Phenomena-based Algorithm (NPAs)). No unique standard criterion is existed to classify MA. Here, we classify them into the following four categories:

- Evolutionary Algorithms: in this category, algorithms are inspired by natural evolution; examples of this category are shown in Table 1.
- Swarm Intelligence (SIs): these algorithms are inspired by the behavior of insects, birds, animals, bacteria, and fish as algorithms in Table 2.

TABLE 2. Examples of sawarm intelligence algorithms.

No.	Algorithm	Abb.	Authors	Year
1	Ant colony optimization [32]	ACO	Dorigo	1992
2	Particle swarm algorithm [23]	PSO	Kennedy and Eberhart	1995
3	Artificial fish swarm algorithm [64]	AFSA	Li et al.	2002
4	Bacterial foraging optimization algorithm [65]	BFOA	Passino	2002
5	Glowworm swarm optimization [66]		Krishnanand and Ghose	2005
6	Cat swarm optimization [26]	CSA	Chu et al.	2006
7	Artificial bee colony [67], [68]	ABC	Karaboga and Basturk	2007
8	Cuckoo search [28]	CS	Yang and Deb	2009
9	Bat algorithm [31]	BA	Yang	2010
10	Firefly algorithm [27]	FA	Yang	2010
11	Krill herd algorithm [34]	KH	Gandomi and Alavi	2012
12	Dolphin echolocation [69]		Kaveh and Farhoudi	2013
13	Chicken swarm optimization [35]	CSO	Meng et al.	2014
14	Grey wolf optimizer [36]	GWO	Mirjalili et al.	2014
15	Ant lion optimizer [38]	ALO	Mirjalili	2015
16	Dragonfly algorithm [43]	DA	Mirjalili	2015
17	Whale optimization algorithm [42]	WOA	Mirjalili and Lewis	2016
18	Grasshopper optimization algorithm [47]	GOA	Saremi et al.	2017
19	Butterfly-inspired algorithm [72]	BOA	Qi et al.	2017
20	Salp swarm algorithm [48]	SSA	Mirjalili et al.	2017
21	Equilibrium optimizer [49]	EO	Faramarzi et al.	2019
22	Bald eagle search [50]	BES	Alsattar et al.	2019
23	Harris hawks optimization [51]	HHO	Heidari et al.	2019
24	Nuclear reaction optimization [52]	NRO	Wei et al.	2019
25	Slime mould algorithm [53]	SMA	Li et al.	2020
26	Border collie optimization [54]	BCO	Dutta et al.	2020

TABLE 3. Examples of physics-based algorithms.

No.	Algorithm	Abb.	Authors	Year
1	Simulated annealing [21]	SA	Kirkpatrick et al.	1983
2	Harmony search [25]	HS	Geem et al.	2001
3	Gravitational search algorithm [29]	GSA	Rashedi et al.	2009
4	Big bang–big crunch optimization [73]	BBCB	Erol and Eksin	2005
5	River formation dynamics [74]	RFD	Rabanal et al.	2007
6	Ray optimization [75]	RO	Kaveh and Khayatazad	2012
7	Mine blast algorithm [76]	MBA	Sadollaha et al.	2013
8	Lightning search algorithm [77]	LSA	Shareef et al.	2015
9	Sine cosine algorithm [44]	SCA	Mirjalilia	2016
10	Multi-verse optimizer [41]	MVO	Mirjalili et al.	2016
11	Thermal exchange optimization [56]	TEO	Kaveh and Dadras	2017
12	Henry gas solubility optimization [57]	HGSO	Hashim et al.	2019

TABLE 4. Examples of human related algorithms.

No.	Algorithm	Abb.	Authors	Year
1	Human-inspired algorithm [78]	HIA	Zhang et al.	2009
2	Social emotional optimization [79]	SEOA	Xu et al.	2010
3	Brain storm optimization [80]	BSO	Shi	2011
4	Teaching–learning-based optimization [81]	TLBO	Rao et al.	2011
5	Volleyball premier league algorithm [82]	VPL	Moghdani and Salimifard	2018
6	Gaining-sharing knowledge [55]	GSK	Mohammed et al.	2019

- Physics-based algorithm: in this category, algorithms inspired by physical laws or chemical phenomena. Examples of these are given in Table 3.
- Human-Inspired algorithm: the last category contains algorithms inspired by human being behavior as in Table 4.

III. CROW SEARCH ALGORITHM

In this section, we discuss the mathematical model of CSA and its research status/trend.

A. STANDARD CROW SEARCH ALGORITHM

A new population-based algorithm called Crow Search Algorithm (CSA) was proposed by Askarzadeh, which simulates the hiding of food behavior of crow [92]. Crow is an intelligent bird that can remember faces and warn its species in danger. One of the most evidence of their cleverness is hiding food and remember its location. Moreover, the exploration and exploitation of CSA can be learned from Figure 1. Overall, the pseudocode of CSA can be modeled as shown in **Algorithm** 1, Figure 2 is the flowchart of CSA, and its main phases can be shown as follows:

1) Initializing crows swarm in d-dimensional randomly.
2) A fitness function is used to evaluate each crow, and its value is put as an initial memory value. Each crow stores its hiding place in its memory variable m_i.
3) Crow updates its position by selecting a random another crow, i.e x_j and generating a random value. if this value is greater than Awareness Probability 'AP', then crow x_i will follow x_j to know m_j

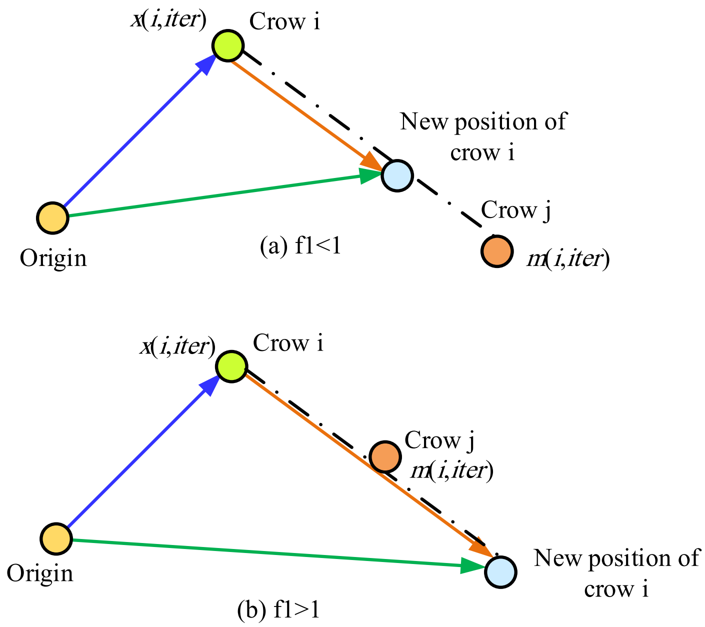

FIGURE 1. Exploration and exploitation of CSA.

Algorithm 1 CSA: Crow Search Algorithm

Input: n Number of crows in the population.
$iter_{max}$ Maximum number of iteration.
Output: Optimal crow position
Initialize position of crows.
Initialize crows' memory
while $iter < iter_{max}$ **do**
  for $crow_i$ belong to crows **do**
    choose a random crow.
    determine a value of awareness probability AP
    Update $x_{i,iter+1}$ using **Eq.**(1)
  end for
  Check solution boundaries.
  Calculate the fitness of each crow
  Update crows' memory using **Eq.**(2)
end while

4) Crow updates its position by selecting a random other crow i.e x_j and following it to know m_j. Then new x_j is calculated as follows:

$$x_{i,iter+1} = \begin{cases} x_{i,iter} + r_i \times & \\ fl_{i,iter} \times & \\ (m_{j,iter} - x_{i,iter}) & r_j \geq AP_{j,iter} \\ & \\ \text{a random position} & otherwise \end{cases} \quad (1)$$

where $AP_{j,iter}$ refers to crow j awareness probability, iter refers to iteration number, r_i, r_j refers to random numbers, $fl_{i,iter}$ is the crow i flight length to denote crow j memory.

5) Updating memory

$$m_{i,iter+1} = \begin{cases} x_{i,iter+1} & f(x_{i,iter+1}) \leq f(m_{i,iter}) \\ & \\ m_{i,iter} & otherwise \end{cases} \quad (2)$$

B. CROW SEARCH ALGORITHM RESEARCH TRENDS

CSA has gained huge attention from all researchers and scientists all over the world. According to Google Scholar[1] 558 times (accessed in 23rd May 2020): 375 in journals, 138 in conferences, 38 in book chapters, and 4 in review papers.Table 5 shows the top 10 journals with the highest paper numbers dealing with CSA. Also, Figure 3 shows the number of publications per different publisher such as Elsevier, Springer, IEEE, and others, whereas Figure 4 shows the number of publications per year.

IV. DIFFERENT METHODS OF CROW SEARCH ALGORITHM

In the section, CSA variants have been divided to 3 classes: modified CSA, hybrid CSA, and multi-objective CSA.

A. MODIFIED CSA

I this section, we discuss all modified versions of CSA such as binary version, Opposition-based learning-based, Levy flight-based, etc.

1) BINARY CSA

De Souza *et al.* [93] proposed a binary version of CSA called BCSA in which a V-shape transfer function was

[1](https://scholar.google.co.uk/scholar?hl=en&as_sdt=0%2C5&q=A+novel+metaheuristic+method+for+solving+constrained+engineering+optimization+problems%3A+Crow+search+algorithm&btnG=)

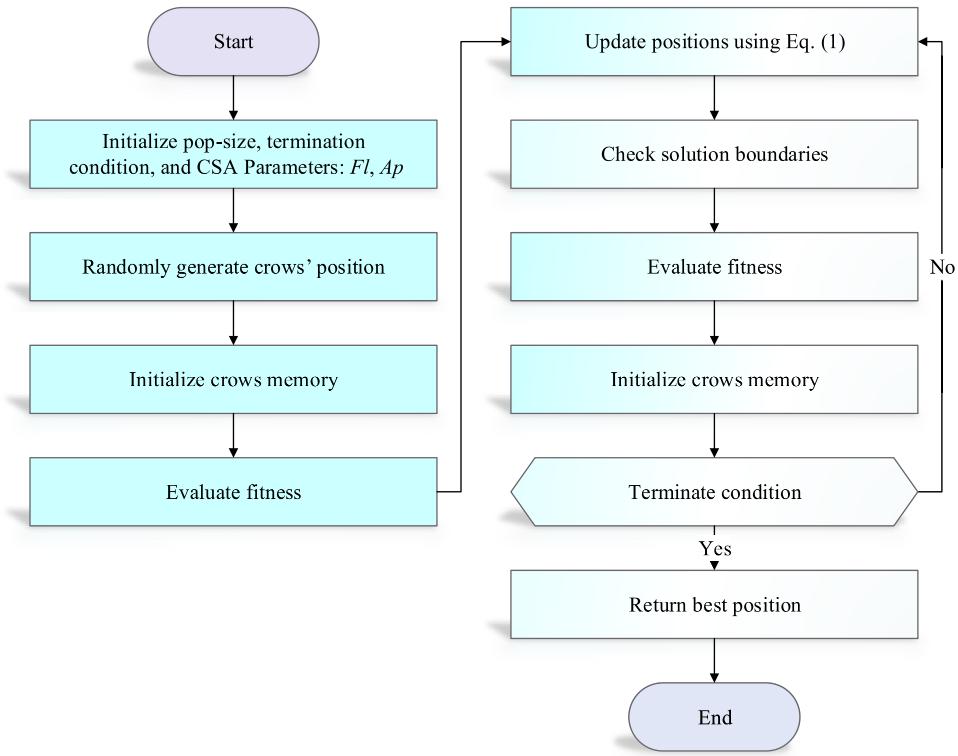

FIGURE 2. Flowchart of CSA.

TABLE 5. The top 10 journals with the largest number of the papers on CSA.

Rank	Journals	Number of papers
1	Applied Soft Computing Journal	24
2	Neural Computing And Applications	15
3	IEEE Access	14
4	Advances In Intelligent Systems And Computing	13
5	Expert Systems With Applications	12
6	Soft Computing	11
6	Studies In Computational Intelligence	11
8	Applied Intelligence	7
8	Swarm And Evolutionary Computation	7
9	Applied Mathematical Modelling	6
9	Engineering Applications Of Artificial Intelligence	6

used to convert the continuous values to discrete ones. Laabadi *et al.* [161] did another work. They developed a binary version of CSA to solve the 2D bin packing problem.

2) MODIFIED CSA

In [94], Coelho *et al.* [95] tried to propose a modified CSA by using Gaussian distribution and diversity information of the population. Also, Gupta *et al.* tried to extract usability features by proposing a novel approach of CSA called modified CSA (MCSA) in which a particular selected feature number is generated and applied to the life cycle of software development by using usability factors hierarchical model. Mohammadi and Abdi in [96] enhanced the classical version of CSA by performing two modifications 1) Introducing a priority-based technique which shows how each crow will choose another crow to move towards its position. 2) Introducing a method to determine the sufficient flight length amount. The authors applied it to economic load dispatch. Likewise, another enhancement to CSA has done by Cuevas *et al.* [97] by modifying two CSA parameters, namely: awareness probability and random perturbation. They argued that these modifications would affect the diversity of the population and also improve the convergence speed. In [98], authors added local search and niching methods to enhance the searching capabilities of CSA.

3) LÉVY FLIGHT AND OPPOSITION-BASED CSA

Wu *et al.* [99] introduced a novel approach of CSA named CCSA, in which an Lévy flight was used. The novel algorithm was tested on two different models: a simple structure (beam) and a complex structure. In [100], Majhi *et al.* tried to prevent SCA from getting trapped into local optima by

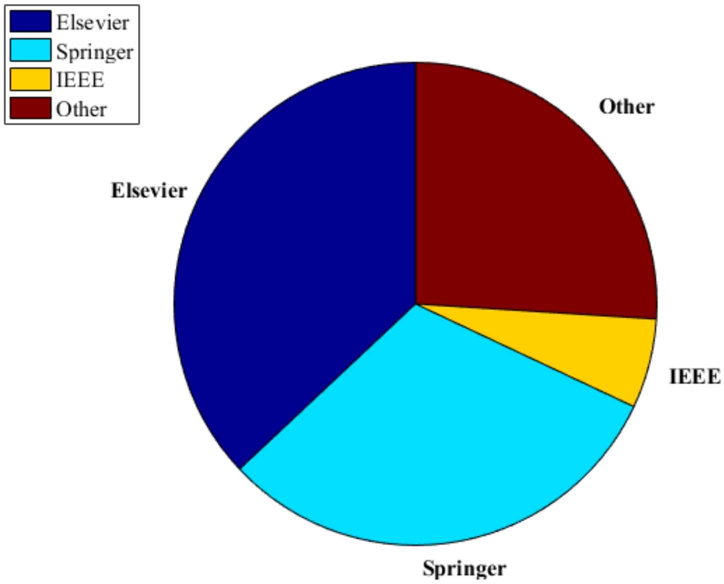

FIGURE 3. Number of publications of CSA per publisher.

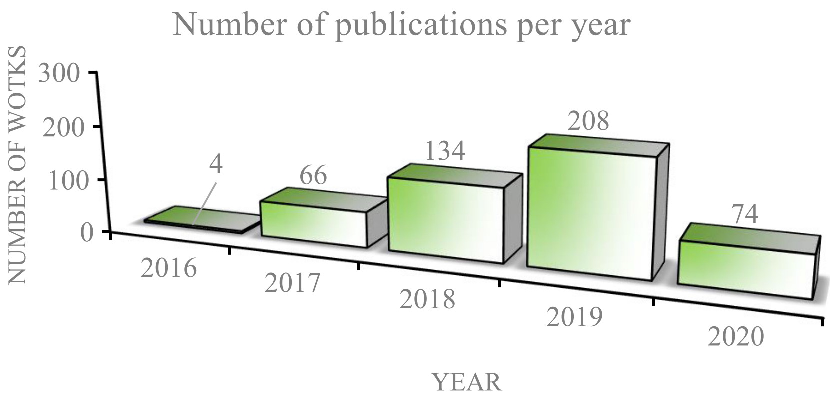

FIGURE 4. Number of publications of CSA per Year.

developing another enhanced version of CSA with the use of opposition learning strategy and mutation operator. They tested their algorithm which named OBL-SCA-MO by using CEC2017 and used it to design fractional order PID (FOPID). Another enhancement called CCSA was proposed in [101] by Zamani *et al.* by using three strategies, namely:neighborhood-based local search, non-neighborhood based search, and wandering around search.

4) ENHANCED CSA

A new version called ECSA was developed by Javidi *et al.* [102]. In this version, the authors tried to improve the performance of the original CSA in handling problems of structural optimization by adding three enhancements: 1) replacing each variable of violated decision with its corresponding variable. 2) suggesting a free-fly mechanism. 3) introducing the upper bound strategy. Likewise, Bhullar *et al.* [103] proposed another version of CSA by 1) adding an archive component to use crow experience. 2) formulating a non-hideout position. 3) exploiting the 1/5th of exploitation by using awareness probability. In [104], the authors proposed a version called ICSA by restructuring two properties of CSA: awareness probability and a random perturbation and adding a dynamic probability.

5) IMPROVED CSA

Another effort to enhance the original CSA to be able to solve high dimensional optimization tasks is shown in [105] where three operators have been added to a balance between exploration and exploitation. These factors are Lévy flight, experience factor, and adaptive adjustment factor. In [106], Zhang and Huang added an inertia weight factor and used the Roulette wheel as a selection scheme. Likewise, Díaz *et al.* [107] developed another improvement

TABLE 6. Summary of literature review on variants and modified CSA algorithms.

No.	Modification Name	Ref.	Parameters.	Test Benchmark fun.	Authors	Journal /Conf.	Remarks
1	Standard Crow search algorithm	[92]	N=50, $iter_{max}$ = 500 , fl=2, AP=0.1	13 unconstrained benchmark function & 6 constrained engineering design problems	Alireza Askarzadeh	Computers and Structures	This algorithm has designed to solve unconstrained problems such as Three-bar truss, Pressure vessel, etc
2	modified CSA	[95]	N=23, $iter_{max}$ = 10 , fl=2, AP=0.1	A private dataset [2]	Gupta et al.	Neural Computing and Applications	Authors proved that MCSA algorithm can find the most important feature that can be obtained using various models.
3	Oppositional CSA with mutation operator	[100]	N=30, $iter_{max}$=1000, AP = 0.1, and fl = 2	IEE CEC 2017	Majhi et al.	Evolving Systems	2 operators are added to improve CSA performance of: oppositional learning & mutation operator.
4	modified crow search algorithm (MCSA)	[96]	N=100, $iter_{max}$=100, AP = 0.1, and fl = 2, 1.9	4 unconstrained func. & five different well-known ELD	Mohammadi and Abdi	Applied Soft Computing	improves CSA by using an innovative crows selection & adaptive flight length adjustment
5	Conscious neighborhood-based CSA	[101]	N=200, $iter_{max}$=1500	CEC 2017 & 4 engineering design problems	Zamani et al.	Applied Soft Computing	CCSA uses 3 strategies NLS, NGS, and WAS
6	Enhanced crow search algorithm	[102]	N = 70, fl = 3 and AP =0.1	4 popular benchmark structures	Javidi et al.	Applied Soft Computing	Three modifications were made 1) each decision variable was replaced by corresponding one. 2) a free-fly mechanism 3) the personal upper bound strategy.
7	Improved crow search algorithm	[105]	15 unconstrained function	fl = 2, AP =0.1, $iter_{max}$=40000	Jain et al.	Journal of Intelligent & Fuzzy Systems	CSA is improved by adding experience factor, adaptive adjustment operator and Lévy flight
8	Enhanced crow search algorithm	[103]	N=10,AP= [0.05, 2], fl= [0.5, 2.5]	23 unconstrained functions	Bhullar et al.	Soft Computing	(1) archive component addition (2) of non-hideout formulation (3) Rechenberg's 1/5th rule is exploited (4) awareness probability is regulated.

to CSA and applied the new version to solve energy optimization problems. Also, in [108], Gupta *et al.* introduced an improved CSA version called optimized CSA (OCSA). They tested their novel algorithm using 20 datasets and compared OCSA with the original CSA and chaotic CSA. Moghaddam *et al.* [109] used GA operators: crossover and mutation and employed it in CSA to increase its performance and prevent it from getting stuck into sub-optimal regions. Fallah *et al.* [110] introduced an improved CSA (ICSA) in which each crow must choose a random crow as a leader. In [111], Sahoo and Padhy replaced random movement and 'AP' with Lévy flight and Dynamic AP (DAP). Likewise, Anter *et al.* [86] used CSA with a fast fuzzy c-mean to identify crops. CSA also has been improved by Han *et al.* [160] by using a spiral search mechanism. Their new algorithm, which called ISCSA, is enhanced using weight coefficient, optimal guidance position, spiral search, Gaussian variation, and random perturbation. They tested their algorithm using 23 benchmark functions and four different engineering problems. Rizk-Allah *et al.* [173] has designed another chaotic CSA for the fractional optimization problem. Likewise, the Space Transform Search (STS) method has been combined with CSA to improve the performance of the original algorithm [174]. The authors used the CEC 2017 benchmark to test their method. To solve truss sizing optimization, Ozbasaran and Yildirim developed modified CSA called CSA_M [175]. Overall, literature reviews on variants and modified CSA algorithms can be summarized in Table 6.

B. HYBRID CSA

In literature, CSA has been hybridized with many other MA and machine learning to combine and benefit from the strength of both. In [112], a novel hybrid algorithm called GWOCSA, which combined GWO with CSA. To test the hybrid algorithm, the authors used 23 benchmark functions, and the results were compared with GWO, augmented GWO (AGWO), and Enhanced GWO (EGWO). GWOCSA was also applied to solve the feature selection problem. Davoodkhani *et al.* also hybridized GWO and CSA [113] in which the hybrid algorithm (hGWO-CSA) was used to maximize photovoltaic power point tracking. Another hybrid algorithm was proposed by Pratiwi [114], which combined cat swarm optimization with CSA. The novel algorithm was applied to the vehicle routing problem. The same hybrid algorithm was done by Kumar [115] and was applied to the economic emission dispatch problem. Javaid *et al.* [116] has combined the BA and CSA. The proposed algorithm, which is called BCSA, was employed in smart grid applications. Likewise, Wu *et al.* [117] tried to solve the flow shop scheduling problem using a novel algorithm named CPO,

TABLE 7. Summary of literature review on hybrid CSA algorithms.

No.	Modification Name	Ref.	Parameters.	Test Benchmark fun.	Authors	Journal /Conf.	Remarks
1	Hybrid algorithm based on grey wolf optimization and crow search algorithm	[112]	N=50, $iter_{max}$=300 , fl=2, AP=0.1	23 unconstrained benchmark function & 21 datasets	ARORA et al.	IEEE Access	hybrid GWO with CSA called GWOCSA is introduced to find global optima efficiently.
2	Hybrid crow particle optimization	[117]	N=20, fl=2, AP=0.05	12 dataset PFSP	Wu et al.	ICESS2018	CPO combines CSA and PSO to solve permutation flow shop scheduling problems
3	DECSA	[119]	fl=2, AP=0.1		Mahesh et al.	Neural Computing and Applications	a hybrid dolphin echolocation and crow search optimization
4	Sine–cosine crow search algorithm	[121]	$iter_{max}$=1000 , fl=2, AP=0.1	28 unconstrained benchmark function	Khalilpourazari	Neural Computing and Applications	SCCSA is hybrid algorithm combines CSA and SCA.
5	hybrid rough crow search algorithm	[125]	N=50, $iter_{max}$=500 , fl changes dynamically, AP=0.1	IEEE CEC 2005, IEEE CEC 2010 and 4 engineering design problems	Aboul Ella Hassanien et al.	Journal of Ambient Intelligence and Humanized Computing	RCSA combines CSA with rough searching scheme (RSS) in solving engineering optimization problems
6	CFCSA	[123]	N=10, $iter_{max}$=10 , fl=2, AP=0.1	10 dataset	Anter and Ali	Soft Computing	hybrid crow search optimization algorithm integrated with chaos theory and fuzzy c-means

which is a hybridization between CSA and PSO. Another CSA version was employed in the vehicle routing problem in which CSA has been hybridized with ACO [118]. Also, Mahesh and Vijayachitra in [119] proposed a new version of CSA called DECSA in which dolphin echolocation and CSA were hybridized together to classify energy-aware routing. Pasandideh and Khalilpourazari in [120], [121] developed a hybrid algorithm SCCSA in which SCA was combined with CSA. Their novel algorithm was compared with original SCA, DA, GSA, CS, and PSOGSO. Allaoui *et al.* [122], combined CSA with a local search method to accelerate the searching process to solve the fragment assembly of DNA problems that follow the OLC model. Likewise, Anter and Ali integrated the CSA with the Fuzzy C-means algorithm and chaos theory and applied it to medical problems [123]. Also, Nawaz–Enscore–Ham (NEH) strategy was used to generate CSA population [124]. Also, in [169] the authors developed a hybrid algorithm that combined WOA with CSA called CrowWhale to solve energy trust routing (ETR). In [170], Farh *et al.* introduced (CSA-PSO), which hybridized CSA with PSO. The authors tried to find the optimal size and allocation of distributed generation. Another version called Crow Search Mating - based Lion Algorithm (CSM-LA) was developed by Gaddala and Raju [171] to solve unified power quality conditions (UPQC). Another hybrid version between the CSA, lion algorithm, and AFL called crow-FAL was developed by Ganeshan and Rodrigues [172] and was applied to intrusion detection. In [176], Huang *et al.* developed a hybrid version of CSA called HCSA in which CSA was integrated with Nawaz-Enscore-Ham (NEH). The novel algorithm has been applied to the flow shop scheduling problem. And, literature reviews on hybrid CSA algorithms can be shown in Table 7.

C. MULTI-OBJECTIVE CSA

In many areas, the process starts with the modeling and design of objective functions for searching for feasible solutions, which cannot necessarily be an optimal value [179], [181]–[183]. One of the most challenging characteristics in solving the real-world problem is the multi-objective fitness function. Many variants of multi-objective CSA have been developed in the literature. Nobahari and Bighashdel in [126] developed a multi-objective version called MOCSA. They also added a chasing operator to improve the convergence speed. They compared their results with ten multi-objective algorithms using 13 unconstrained functions. Also, in [127], Hinojosa *et al.* proposed another multi-objective CSA version hybridized with chaos theory. The authors tested MOCCSA using different datasets, and they argued that the proposed algorithm achieved better results than the Multi-Objective Dragonfly Algorithm (MODA) and Multi-Objective Particle Swarm Optimization (MOPSO). Likewise, a multi-objective crow and fruit fly optimization algorithm has been developed by Ramgouda and Chandraprakash [128]. Rizk-Allah *et al.* [129] developed an orthogonal opposition-based version of CSA known as M2O-CSA. In their algorithm, two crows selected randomly to undergo crossover. Then, the orthogonal

TABLE 8. Summary of literature review on variants and modified Multi-Objective CSA algorithms.

No.	Modification Name	Ref.	Parameters.	Test Benchmark fun.	Authors	Journal /Conf.	Remarks
1	Multi-objective CSA	[126]	N=600 900 4290, fl=2, AP=0.3, 0.22, 0.2	13 multi-objective functions	Nobahari & Bighashdel	CSIEC2017	Multi-Objective CSA (MOCSA).
2	Multi-objective chaotic crow search algorithm	[127]	N=100, fl=2, AP=0.1	CEC 2009	Hinojosa et al.	Neural Computing and Applications	2 versions Multi-Objective Crow Search Algorithm (MOCSA) & Multi-Objective Chaotic Crow Search Algorithm (MOCCSA) have been proposed.
3	Multi-objective orthogonal opposition-based CSA	[129]	N=100, max_{iter}=200, fl=2, AP=0.1	ZDT test suits	Rizk-Allah et al.	Neural Computing and Applications	multi-objective orthogonal opposition-based crow search algorithm (M2O-CSA) is proposed for solving large-scale multi-objective optimization problems.
4	Multi-objective taylor crow optimization	[130]	fl=2, AP=0.1	The simulation is carried out by considering 50 nodes and 100 nodes	John & Rodrigues	Mobile Networks and Applications	Multi-Objective Taylor Crow Optimization (MOTCO) algorithm is proposed which is a combination of the Taylor series and the CSA

array was founded to have nine solutions (individuals). John and Rodrigues [130] developed a version called MOTCO, which refers to the Multi-objective Taylor Crow Optimization algorithm. They used it in clustering aware wireless sensor network. Totally, some summary of literature review on variants and modified Multi-objective CSA algorithms are displayed in Table 8.

V. APPLICATION(OPTIMIZATION AND ENGINEERING)

CSA has been successfully applied to different application domains, as shown in Figure 5.

A. POWER ENGINEERING

In this subsection, all CSA applications related to power engineering have been discussed.

1) OPTIMAL POWER FLOW

In [85], Saha *et al.* used CSA to solve the optimal power flow problem. Authors used IEEE 30 bus to validate the effectiveness of CSA and compared it with DSA [131],MOHS [132], TLBO [133], QoTLBO [133]. Also, Fathy and Abdelaziz [134] tried to solve single-objective OPF for electric power. They argued that the results obtained from CSA are significant when applied to the IEEE 30-bus system and IEEE 118 bus system. Similar work was done in [135] by Naresh, Reddy, and Reddy.

2) LOAD DISPATCH AND UNIT COMMITMENT

Economic Load Dispatch Problem (ELDP) is the problem of finding the minimum scheduling outputs of the generating units' outputs. In [96], Mohammadi and Abdi used a modified version of CSA to solve ELDP. To proof the applicability of their novel algorithm, they used five different test systems. Also, Kumar *et al.* [136] used CSA to solve constrained nonconvex ELDP with prohibited operation zones. Sheta has done similar works in [137] and Spea in [138]. In [139], Habachi *et al.* tried to solve unit commitment problems and economic dispatch using CSA based on the eagle strategy.

B. COMPUTER SCIENCE

In this subsection, all CSA applications related to computer science have been discussed.

1) FEATURE SELECTION

Feature selection (FS) can be defined as the process of selecting the most critical dataset and removing irrelevant ones [140], [141]. If it is a wrapper method, it is often related to the neural networks in its application part [186], [187]. In [93], Souza *et al.* used a binary version of CSA called BCSA, which has the V-shape to solve the FS problem. The authors used six different datasets and compared their results with BBA, BPSO, SFS, and SBS. Also, Allahverdipoor and Gharehchopogh in [142] combined K-nearest neighbor with CSA to solve the FS problem in classifying text documents. Likewise, Anter and Ali [123] hybridized CSA with chaos theory and c-means to solve medical diagnosis problems. Sayed *et al.* [143] used CSA with chaos theory to solve the FS problem.

2) IMAGE PROCESSING

In [87], the authors used CSA to estimate multilevel threshold optimal values of image based on Kapur's entropy. They tested their model on different values of thresholds (2, 4, 8, 16, and 32). They argued that CSA achieved better results than PSO, DE, GWO, MFO, and CS in terms of PSNR, SSIM, and FSIM metrics. Oliva *et al.* [144] used CSA to find the optimal cost of cross-entropy in image segmentation. They tested their model in multi-dimensional spaces. Thomas and Rangachar [145] used CSA to recognize faces in low-resolution images by combining Gabor filter + wavelet + texture (GWTM). Fred *et al.* [84] proposed the fuzzy-CSA algorithm and applied it to the segmentation of medical images. They compared it with ABC, FA, and SA.

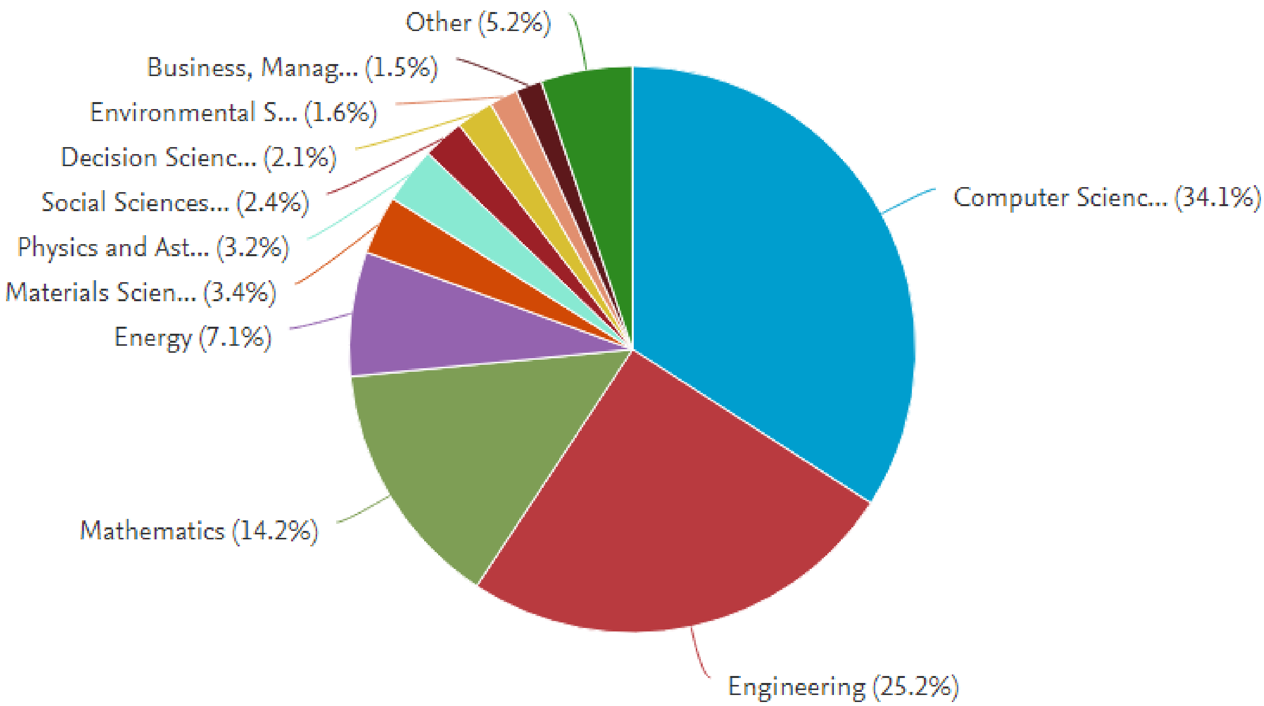

FIGURE 5. Distribution of CSA related papers in many application, as reported by Scopus.

3) NEURAL NETWORK AND SUPPORT VECTOR MACHINE

Chithra and Jagatheeswari [146] Combined CSA with Support Vector Machine (SVM), neural network, and fraction theory to classify tuberculosis patients. They mentioned that their combination increased the speed of computation and decreased time and cost spent on test samples. Also, in [147], Chakravarthy and Rajaguru integrated their modified version of CSA with a neural network to detect lung cancer. Likewise, More and Ingle [148] introduced a dragonfly-crow algorithm called D-Crow hybridized with Support Vector Regression (SVR). They applied it to Virtual Machine Migration (VMM).

4) CLOUD

Satpathy *et al.* [149] used CSA in order to propose a resource-aware to consolidate a substantial Virtual Machine (VM) numbers on minimal in the cloud data center. They proposed two different technique CSA-based travel salesman problem (TSPCS) and Greedy Crow Search (GCS). The same problem has been handled by Satpathy *et al.* [150] where a 2-tier VM placement algorithm has been proposed. First, a queuing structure to schedule VMs, whereas the second (CSAVMP) CSA-based VM problem was developed to reduce the consumption of power at data centers. Likewise, In [151], authors enhanced cloud task scheduling by using CSA. They proved that the CSA-based system has better results than Min-Min and an ant algorithm. In [152], George and Sumathi proposed the Crow Lion Algorithm (C-lion) and applied it in privacy protection on the cloud using the dyadic product. Also, Firefly Crow Search Algorithm (FF-CSA) is developed in [153] by Malleswaran and Kasireddi to produce efficient task scheduling in the cloud environment. Another attempt has been made by Kumar and Vimala [154], which combined an integrated Fractional Dragonfly Algorithm (C-FDLA) to achieve load balance in cloud environments. The latter approach was performed by Makhdoomi and Askarzadeh [155], which tried to optimize the photovoltaic / diesel generator operation with pumped hydro storage by a modified version of CSA.

C. CIVIL ENGINEERING

Recently, many works have been proposed to solve structural optimization problems using different MAs. In [102], authors employed their new version of CSA in finding the design of the optimum structure. Also, Lin *et al.* [156] used modified CSA with a fuzzy concept to control adjacent connected building by magnetorheological dampers concerning soil–structure interaction.

D. CHEMICAL ENGINEERING AND QSAR

Abdallh and Algmal [83] used an improved binary version of CSA in order to classify skin sensitization potential based on quantitative structure-activity relationship (QSAR) model.

TABLE 9. The average results for solving benchmark functions.

No.	CSA	GWO	PSO	SCA	BA	FA	MFO	WOA	IWO	EM
F1	1.99E+06	5.85E+07	8.33E+06	2.57E+08	8.57E+05	2.77E+08	1.06E+08	2.95E+07	1.10E+06	2.50E+07
F2	8.58E+03	2.01E+09	1.43E+08	1.49E+10	5.66E+05	1.55E+10	1.28E+10	3.57E+06	3.86E+06	5.29E+08
F3	8.22E+02	2.99E+04	9.48E+02	3.79E+04	4.93E+02	6.48E+04	1.02E+05	4.21E+04	1.19E+04	1.63E+04
F4	5.44E+02	6.78E+02	4.81E+02	1.43E+03	4.43E+02	1.46E+03	1.04E+03	5.78E+02	4.59E+02	6.60E+02
F5	5.20E+02	5.21E+02	5.21E+02	5.21E+02	5.21E+02	5.21E+02	5.20E+02	5.20E+02	5.21E+02	5.21E+02
F6	6.30E+02	6.14E+02	6.23E+02	6.35E+02	6.35E+02	6.34E+02	6.22E+02	6.36E+02	6.37E+02	6.25E+02
F7	7.00E+02	7.20E+02	7.02E+02	8.32E+02	7.01E+02	8.33E+02	8.30E+02	7.01E+02	7.01E+02	7.08E+02
F8	9.35E+02	8.82E+02	9.69E+02	1.05E+03	1.04E+03	1.02E+03	9.44E+02	9.77E+02	1.08E+03	8.92E+02
F9	1.05E+03	1.01E+03	1.11E+03	1.17E+03	1.18E+03	1.16E+03	1.12E+03	1.13E+03	1.30E+03	1.06E+03
F10	4.32E+03	3.21E+03	5.19E+03	6.72E+03	5.39E+03	7.54E+03	4.63E+03	4.90E+03	5.57E+03	2.74E+03
F11	4.82E+03	4.04E+03	5.73E+03	7.96E+03	5.62E+03	7.96E+03	5.45E+03	6.03E+03	5.53E+03	4.91E+03
F12	1.20E+03	1.20E+03	1.20E+03	1.20E+03	1.20E+03	1.20E+03	1.20E+03	1.20E+03	1.20E+03	1.20E+03
F13	1.30E+03	1.30E+03	1.30E+03	1.30E+03	1.30E+03	1.30E+03	1.30E+03	1.30E+03	1.30E+03	1.30E+03
F14	1.40E+03	1.40E+03	1.40E+03	1.44E+03	1.43E+03	1.40E+03	1.40E+03	1.40E+03	1.40E+03	1.40E+03
F15	1.52E+03	1.59E+03	1.52E+03	4.15E+03	1.53E+03	1.64E+04	2.21E+05	1.58E+03	1.52E+03	1.53E+03
F16	1.61E+03	1.61E+03	1.61E+03	1.61E+03	1.61E+03	1.61E+03	1.61E+03	1.61E+03	1.61E+03	1.61E+03
F17	1.54E+04	1.77E+06	2.47E+05	7.37E+06	1.12E+05	7.01E+06	2.33E+06	4.07E+06	5.56E+04	8.11E+05
F18	2.13E+03	6.78E+06	2.20E+06	1.94E+08	1.08E+05	2.79E+08	2.06E+05	7.77E+03	5.22E+04	6.08E+07
F19	1.93E+03	1.95E+03	1.92E+03	1.99E+03	1.93E+03	2.00E+03	1.96E+03	1.95E+03	1.92E+03	1.94E+03
F20	2.40E+03	1.77E+04	2.32E+03	1.51E+04	2.40E+03	2.14E+04	7.13E+04	2.42E+04	4.05E+03	2.70E+03
F21	1.23E+04	9.02E+05	1.11E+05	1.31E+06	5.87E+04	1.71E+06	3.87E+05	1.18E+06	3.45E+04	1.72E+05
F22	2.82E+03	2.57E+03	2.86E+03	2.95E+03	3.30E+03	2.99E+03	3.04E+03	2.96E+03	3.40E+03	2.85E+03
F23	2.62E+03	2.63E+03	2.62E+03	2.66E+03	2.62E+03	2.73E+03	2.67E+03	2.63E+03	2.62E+03	2.57E+03
F24	2.61E+03	2.60E+03	2.63E+03	2.60E+03	2.66E+03	2.71E+03	2.69E+03	2.61E+03	2.70E+03	2.60E+03
F25	2.71E+03	2.71E+03	2.71E+03	2.73E+03	2.73E+03	2.73E+03	2.72E+03	2.71E+03	2.73E+03	2.70E+03
F26	2.70E+03	2.74E+03	2.77E+03	2.70E+03	2.70E+03	.70E+03	2.70E+03	2.70E+03	2.79E+03	2.79E+03
F27	3.17E+03	3.34E+03	3.50E+03	3.55E+03	3.89E+03	3.80E+03	3.59E+03	3.87E+03	3.85E+03	3.63E+03
F28	6.55E+03	3.89E+03	7.07E+03	4.74E+03	5.39E+03	.24E+03	3.90E+03	5.07E+03	7.87E+03	5.67E+03
F29	1.93E+06	2.48E+06	3.39E+04	1.06E+07	3.41E+07	2.66E+06	3.66E+06	6.04E+06	6.39E+05	8.28E+06
F30	1.09E+04	5.19E+04	1.30E+04	2.62E+05	1.47E+04	1.77E+05	5.64E+04	8.67E+04	9.56E+03	1.13E+04

FIGURE 6. The average ranking results of the CSA and other peers.

E. CONTROL ENGINEERING

Kumar *et al.* [157] used CSA to find the static VAR compensator (SVC) optimal dynamic control assisted Single Machine Infinite Bus (SMIB). Also, in [158], authors applied the island-based CSA in solving optimal control problems: parallel reaction, continuous stirred tank reactor, batch

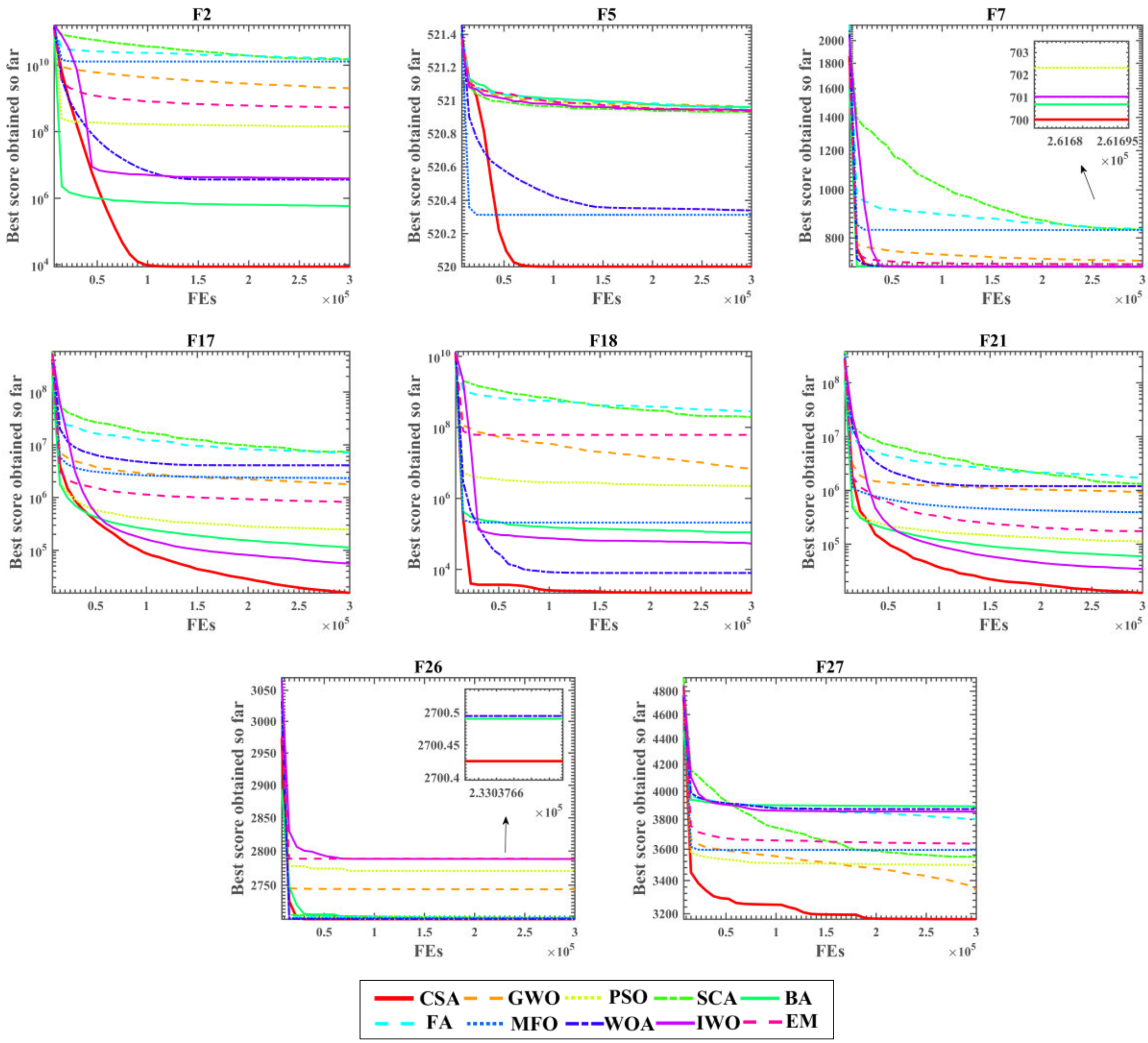

FIGURE 7. Convergence curves of the CSA and other peers.

reactor consecutive reaction, nonlinear constrained mathematical system, nonlinear continuous stirred tank reactor, and nonlinear crane container problems. In [159], the hybrid CSA with a pattern search algorithm has been applied in studies of a multi-area LFC system using the FOPID-PDN controller. Likewise, Majhi *et al.* [100] applied their improved version of CSA, which called OBL-CSA-MO in the FOPID controller design.

F. OTHER APPLICATIONS

1) WATER MANAGEMENT

Optimal management in water and energy is needed as many countries suffering from a lack of water & energy resources. Banadkooki *et al.* [162] employed CSA to optimize the operation of the reservoir and minimize water in irrigation. They compared their results with PSO, Shark Algorithm (SA), GA, and Weed Algorithm (WA).

2) AIRCRAFT MAINTENANCE CHECK

Siswanto *et al.* [163] used CSA in order to check aircraft maintenance and airworthiness program. To validate their model, they compared CSA with PSO and hybrid PSO with a greedy randomized adaptive search (PSO-GRASP).

3) WIRELESS SENSOR NETWORK

Gupta *et al.* [164] used CSA to detect fault that may accrue in the wireless sensor network, which may lead to system failure.

4) PRIVACY PRESERVATION IN HEALTH CARE

Health care information privacy and security is one of the most critical requirements for pharmacological or health practitioners [165]. Mandala and Rao [166] used CSA with the probability of adaptive awareness to improve the preservation of medical data in the health care sector. Their improved CSA (AAP-CSA) was compared with PSO, GA, DE, and original CSA.

5) TRAVELLING SALESMAN PROBLEM

Azezan *et al.* [167] tried to solve the common Traveling Salesman Problem (TSP) using the CSA. They used ten datasets from TSPLIB and compared them with ACO and SA. They argued that CSA's performance is the best.

6) STOCK INDEX PRICE MOVEMENT PREDICTION

Future prediction of stock index price is critical for investors who plan to increase profit and researchers who wish to extract complex stock market data over time series data. Dash *et al.* [168] used TOPSIS and CSA to predict stock index price movement.

VI. ASSESSMENT AND EVALUATION OF CSA

In this section, CSA analysis and evaluation has been discussed first, then a comparison between CSA and other metaheurstics algorithm have been performed and discussed.

A. CSA EVALUATION AND ANALYSIS

CSA has many advantages: easy in implementation and simple inspiration. Moreover, CSA has a fewer number of parameters. However, CSA has many drawbacks like all other MA, as according to No Free Lunch (NFL), CSA has not the ability to solve all optimization problems. Furthermore, CSA does not perform well in high dimensional & complex problems. Furthermore, the ability to control the parameters of CSA is deficient.

B. RESULTS AND COMPARISONS

To show the effectiveness and the power of CSA. A comparison among many MA has been made including Grey Wolf Optimization, Particle Swarm Optimization, Sine Cosine Algorithm, Bat Algorithm, Firefly Algorithm, Moth-Flame Optimization, Whale Optimization Algorithm, Invasive Weed Optimization (IWO) [177], and Electromagnetism like Mechanism Algorithm (EM) [178]. As seen in Table 9, CSA has achieved promising and better results in approximately all functions. As shown in Figure 6, a statistical test called the Friedman test is used to assess and evaluate CSA results. As shown, we can observe that CSA has ranked first. Figure 7 shows the convergence curves for some representative functions in which we can observe the dominant speed of CSA convergence.

VII. CONCLUSION AND FUTURE WORK

Crow Search Algorithm (CSA) is a recently developed algorithm that simulates the behavior of crows in storing and retrieving food. Researchers have given great interest and attention to CSA due to its excellent characteristics. This article introduces a comprehensive review of the CSA. About 135 papers have been collected and summarized. All CSA modifications have been highlighted and categorized into three classes: variants, hybrid, and multi-objective. The limitations and strengths of CSA have been discussed in details. A comprehensive set of applications has been studied. Although, the success and popularity of CSA, many areas and challenges need to be addressed in the future. Several areas that may be handled in the future is list below:

- No work in the literature studied the tuning parameters of CSA.
- No work in the literature has been introduced to adapt CSA to work in dynamic & Multi-objective dynamic problems.
- CSA can be hybridized with many other algorithms.
- No work in the literature has been introduced to adapt CSA to work in a noisy optimization problem.
- CSA needs more theoretical studies.

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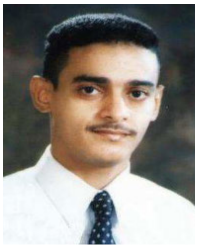

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