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Artificial Intelligence Review

Recent Studies on Chicken Swarm Optimization Algorithm: A review (2014-2018)

--Manuscript Draft--

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We would like to thank the reviewers and the Editor for their valuable time spent on reviewing our manuscript and for the constructive comments that have been given. The responses to the reviewer's comments are provided in the following sections in the order of the comments received. The reviewers' comments are cited in italics, while the answers are in regular font.

Reviewer 1

Comment 1

Please rephrase: Table 5 Strength Weakness and Future works related to CSO to be Table 5. Strength, weakness, and future works of CSO.

Author's Response

The authors would like to thank the reviewer for this comment. The title of Table 5 is changed to 'Strength, weakness, and future works of CSO' as suggested by the reviewer.

Comment 2

Please use one pattern in all figures caption Fig.X. space then its name : Fig.7- Trend in research works related to CSO, Fig.6 Area wise applications of CSO

Author's Response

The authors would like to thank the reviewer for this comment. In the revised paper, one pattern (Fig.X. space then its name) is followed in all the figures.

Comment 3

Please divide or table 5 again as it contains many inner tables in only one table which is not clear use a paragraph with points or subsections

Author's Response

The authors would like to thank the reviewer for this constructive comment. Table 5 is redrawn as suggested by the reviewer.

Comment 4

Figure 2 not professionally presented please redraw or represent using a better way

Author's Response

Figure 2 is redrawn in a better way as suggested by the reviewer.

Comment 5

Figure 1, the keyword of Rooster is out of its shape please resize the word to be in the shape

Author's Response

The keyword 'Rooster' is resized in orderto bring it to proper shape.

Comment 6

Spelling mistakes such as " Hierarchal " please revise spelling mistakes again in the whole paper

Author's Response

The revised paper has been thoroughly proof-read to eliminate all the spelling mistakes.

Author Biographies
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BIOGRAPHY

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Recent Studies on Chicken Swarm Optimization Algorithm: A review (2014-2018)

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Abstract- Solving a complex optimization problem in a limited timeframe is a tedious task. Conventional gradient-based optimization algorithms have their limitations in solving complex problems such as unit commitment, microgrid planning, vehicle routing, feature selection, and community detection in social networks. In recent years population-based bio-inspired algorithms have demonstrated competitive performance on a wide range of optimization problems. Chicken Swarm Optimization Algorithm (CSO) is one of such bio-inspired meta-heuristic algorithms mimicking the behaviour of chicken swarm. It is reported in many literature that CSO outperforms a number of well-known meta-heuristics in a wide range of benchmark problems. This paper presents a review of various issues related to CSO like general biology, fundamentals, variants of CSO, performance of CSO, and applications of CSO.

Keywords—Chicken Swarm Optimization algorithm, nature inspired intelligence, Optimization algorithm, Applications, Review

1. Introduction

The complexity of engineering optimization problem is increasing day by day. Many real-world optimization problems are difficult to solve by gradient-based classical optimization algorithms. The limitation of classical optimization algorithms in solving complex optimization problems has motivated researchers to develop nature-inspired algorithms. Also, increasing computational complexity has made new nature-inspired algorithms necessary to be executed. The emergence of Artificial Intelligence (AI) has re-introduced soft computing methods not only to the scientific community but also to the general public.

In recent years, the field of evolutionary computation has witnessed the development of a number of novel algorithms based on the metaphor of some natural process. Further, depending on the natural phenomenon mimicked, these algorithms can be divided into Evolutionary Algorithms (EA), swarm intelligence based algorithms, and bio-inspired non swarm intelligence based algorithms. An EA utilizes effectively the process of biological evolution such as reproduction, mutation, recombination, and selection (Hertz and Kober 2000). Genetic Algorithm (GA) (Goldberg and Holland 1988), Genetic Programming (GP) (Poli and Langdon 1998), Differential Evolution (DE) (Das and Suganthan 2011), Self Organizing Multi-objective Evolutionary Algorithm (MOEA) (Zhang et al. 2016) fall under the category of EA. Bio-inspired algorithms effectively utilize~~s~~ the behaviour of social animals such as ants, bees, fireflies, bat, elephant ~~and others~~ for solving complex problems. Bio-inspired swarm intelligence based algorithms directly follow the swarming behaviour of animals. Particle Swarm Optimization (PSO) utilizes the phenomenon of bird flocking (Poli et al. 2007), Ant Colony Optimization (ACO) utilizes the movement of ants in a group for searching food (Dorigo and Blum 2005), Krill Herd Optimization (KH) mimics the herding behaviour of krill (Gandomi & Alavi 2012), Grey Wolf Optimization (GWO) utilizes the hunting mechanism of grey wolf (Mirjalili et al. 2014), Bird Swarm Algorithm (BSA) utilizes the social interaction in a bird swarm (Meng et al. 2015), Elephant Herding Optimization (EHO) utilizes herding behavior of a group of elephant (Wang et al.2016) , Artificial Bee Colony (ABC) mimics the foraging behavior of honeybee (Karaboga and Basturk 2008), Cuckoo Search Optimization (CS) mimics the brood parasitism behaviour of the bird cuckoo (Yang and Deb 2009), Firefly Algorithm (FA) utilizes flashing phenomenon of the fireflies (Yang 2010), Novel Bat Algorithm (NBA) utilizes the behaviour of bat along with bat's selection of habitat and self-adjustable compensation for Doppler effect (Meng et al. 2015; Cai et al. 2016). On the other hand Bio-inspired non-swarm intelligence based algorithms are inspired by biological processes but do not directly follow swarming behavior. Flower Pollination Algorithm (FPA) follows the role of flowers proliferation (Yang 2012), Symbiotic Organisms Search (SOS) mimics the symbiotic interaction of organisms in the ecosystem for survival (Cheng and Prayogo 2014), and Spotted Hyena Optimizer (SHO) mimics the social behaviour of spotted hyenas (Dhiman & Kaur 2017).

The aforementioned Evolutionary and Bio-inspired algorithms have many real-life applications in various domains such as energy, industry, medical, clustering, and feature selection. Ahmed et al. (2016) used hybrid KH and Adaptive Neuro-Fuzzy Inference System (ANFIS) for forecasting of wind speed. Heng et al. (2016) used FPA for wind speed prediction. Sultana et al. (2016) utilized GWO for power distribution network planning. Zareiegovar et al. (2012) used swam intelligence for optimal Distributed Generation (DG) placement. Basha et al. (2018) used GA and a Neotrosophic Rule-Based Classification System (NRCS) for sperm quality assessment. Marinakis & Dounias (2008) used ACO for classifying Pap smear cells. Logesh et al. (2018) used quantum inspired swarm intelligence for recommending trips in the context of a smart city. Mohsenzadeh et al. (2018) used GA for solving the charging station placement problem. Ahmed et al. (2017) used hybrid FPA and ANFIS for prediction of forest fire. Ahmed et al. (2017) used EHO for community detection in complex social networks. Ahmed et al. (2018) used a number of swarm intelligence based methods such as NBA, CS for community detection in complex social networks. Gao et al. (2015) used modified Harmony Search algorithm for wind generator design.

Chicken Swarm Optimization (CSO) is one such swarm intelligence based methods developed by Meng et al. in the year 2014. CSO effectively utilizes the hierarchal order in the chicken swarm and the food-searching phenomenon of chicken swarm. In the aforesaid algorithm, the positions of the members of the chicken swarm are regarded as the candidate solutions of the optimization problem. The chicken swarm is divided into rooster, hens, and chicks depending upon the food searching capability. The competition between different chickens under a specific hierarchal order and mother-child relationship is also taken into account in this algorithm. In recent years, CSO has gained popularity and recent literature demonstrate that CSO exhibits competitive performance on a number of benchmark functions (Meng et al. 2014) as well as real-world problems like performance prediction of posted data over Facebook (Ahmed et al. 2018), community detection in social networks (Ahmed et al. 2016), feature selection (Ahmed et al. 2017) and charging station placement (Deb et al. 2017). Engineering involves various problems where CSO could bring benefit. Moreover, CSO can also be used in conjunction with other AI-related tools. The success of CSO in solving a wide range of optimization problems has inspired the authors to discuss comprehensively the latest findings related to CSO. Thus, this review work will endow the research community with the latest developments and research findings related to CSO.

The organization of the paper is as follows. Section 2 elaborates the general biology of chicken swarm. Section 3 elaborates the basic CSO algorithm. Section 4 elaborates the different variant or improved version of the basic CSO. Section 5 elaborates the tuning of parameters in CSO. Section 6 elaborates the different applications of CSO. Section 7 presents the discussion and future work. Section 8 concludes the work.

2. General Biology

Chickens are social animal living and searching for food together in a group. However, the food searching capability and behaviour of different individuals of the chicken swarm varies. Roosters have the highest food searching ability followed by hens. The chicks have the lowest food searching ability and they follow their mother hens. The chickens communicate among themselves by using over 30 distinct sounds (Meng et al. 2014). The sounds made by chickens for expressing pleasure, distress, panic, and danger are different. Chicks often use an irregular soft chirp for expressing that they are fine to the mother hens (Marino 2017). Roosters also emit distinctive alarm calls when a predator invades their territory (Marino 2017). When the roosters see an aerial predator they give one alarm call, and when they see a terrestrial predator they give another distinct alarm call (Marino 2017). The strongest alarm calls are made by the roosters when a large, fast-moving hawk appears overhead (Marino 2017). Hens sometimes make a hiss like sound to show her anger (Marino 2017). Moreover, chickens are socially intelligent animal, and they utilize their previous experience while making decisions in the food searching process (McGrath et al. 2016).

The hierarchical order that plays an important role in the chicken swarm is illustrated in Fig. 1. Rooster occupies the topmost position in the hierarchy, as they possess the best food searching capability. The roosters will also fight with other chickens who invade their territory. Hens occupy the second position and they follow their group mate roosters in the food searching process. There is also competition among the chickens in the food searching process. Chicks occupy the lowest position and they follow their mother while searching for food. Thus, the chickens coordinate among themselves in the food searching process. This biological behaviour of chickens is associated with the objective function to be optimized and is utilized to develop a new meta-heuristics.

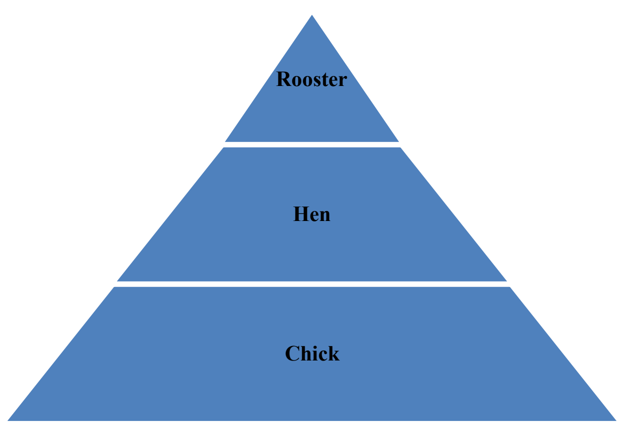

Fig.1 Hierarchical order in the chicken swarm

3. Basic CSO

3.1. Algorithm

CSO is one of the novel bio-inspired algorithms developed by Meng et al. (2014). This algorithm imitates the natal behavior of chicken swarm mentioned in section 2. The astuteness and social interaction of chicken swarm are exploited effectively to obtain the optimal solution. The chain of command in the chicken swarm and the collective food searching mechanism of the swarm is mimicked by the algorithm. The populace of chicken in the group is segregated into dominant rooster, hens, and chicks depending upon the fitness values of the chickens as mentioned in section 2. The chickens with highest strength are designated as roosters, chickens with least strength are designated as chicks, and the chickens with intermediate strength are assigned as hens. The mother-child relationship is also established randomly. The hierarchical order and mother-child relationship are updated after every *G* time steps. The natal behavior of hens to go behind their group mate rooster and chicks to go behind their mother in the quest for food is utilized effectively in the algorithm. It is also presumed that the chickens would try to scratch the food found by others thereby giving rise to a competition for food in the group. The algorithm is divided into two steps- Initialization and Update.

In Initialization, the population size and other related parameters of CSO like number of roosters, number of hens, number of chicks, number of mother hens, *G* are first defined. The fitness values of the randomly generated initial population of chickens are evaluated and a hierarchical order is established based on this fitness values as illustrated in Fig.2. The algorithm is based on the following assumptions-

- The number of hens is highest in the group
- All the hens are not mother hens
- The mother hens are selected randomly from the set of hens
- The number of chicks is less than the number of hens

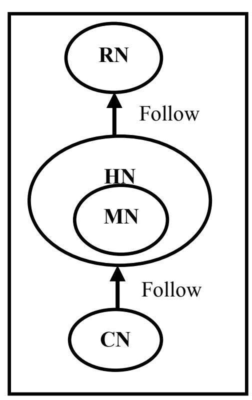

Fig.2 Hierarchical relationship in the chicken swarm

The concept of set theory gives:

$$MN \subset HN \quad (1)$$

$$PN = RN \cup HN \cup CN \quad (2)$$

where MN represents the set of mother hens, RN represents the set of roosters, HN represents the set of hens and CN represents the set of chicks.

There is variation in the food searching capacity of different members of the group. In the update step, the fitness values of the initial population are updated depending on the food searching capacity of the different members of the group. Food searching capacity of rooster depends on their fitness values and their update formula is as follows:

$$x_{i,j}^{t+1} = x_{i,j}^{t} \times (1 + \mathrm{randn}(0, \sigma^2)) \tag{3}$$

If $f_i \le f_k$

$$\sigma^2 = 1 \tag{4}$$

Else

$$\sigma^2 = \exp\left(\frac{(f_k - f_i)}{|f_i| + \varepsilon}\right) \tag{5}$$

where randn$(0,\sigma^2)$ is a Gaussian distribution function with mean 0 and standard deviation σ^2. f is the fitness value of corresponding x, k is randomly selected rooster's index.ϵ is a small constant value which is used to avoid zero division error.

Hens follow their group mate roosters in their quest for food. Moreover, there is also a tendency among the chickens to steal the food found by other chickens. The mathematical representation of their update formula is as follows-

$$x_{i,j}^{t+1} = x_{i,j}^{t} + S1 \times \mathrm{rand} \times (x_{r1,j}^{t} - x_{i,j}^{t}) + S2 \times \mathrm{rand} \times (x_{r2,j}^{t} - x_{i,j}^{t}) \tag{6}$$

$$S1 = \exp\left(\frac{f_i - f_{r1}}{abs(f_i) + \varepsilon}\right) \tag{7}$$

$$S2 = \exp(f_{r2} - f_i) \tag{8}$$

where rand is a randomly generated number between 0 and 1. $r1 \in [1, N]$ is an index of rooster which is i^{th} hen's group mate. And $r2 \in [1, N]$ is an index of rooster or hen which is randomly chosen such that $r1$ is not equal to $r2$.

The natural tendency of chicks to follow their mother is mathematically formulated as follows-

$$x_{i,j}^{t+1} = x_{i,j}^{t} + FL \times (x_{m,j}^{t} - x_{i,j}^{t}) \tag{9}$$

where $x_{m,j}^{t}$ represents the position of i^{th} chick's mother. FL is a parameter which signifies that the chick would follow its mother. FL is generally chosen in between 0 and 2.

The pseudo code and flowchart of CSO is as shown in Algorithm 1 and Fig.3 respectively.

Algorithm 1-Pseudo code of CSO
Initialize the population of chicken having size N and define other algorithm specific parameters like G, size of RN, HN,CN, and MN;
Evaluate the fitness value of all chickens, t=0 , establish the hierarchical order in the swarm as well as mother child relationship;
While (t<gen)
t=t+1;
If(t%G==0)
Establish the hierarchical order in the swarm as well as mother child relationship;
Else
For i=1: N
If i==rooster
Update its solution by Eq.(3);
End if
If i==hen
Update its solution by Eq.(6);
End if
If i==chick
Update its solution by Eq.(9);
End if
Evaluate the new solutions;
Update the new solutions if they are better than the previous one;
End for
End if else
End while

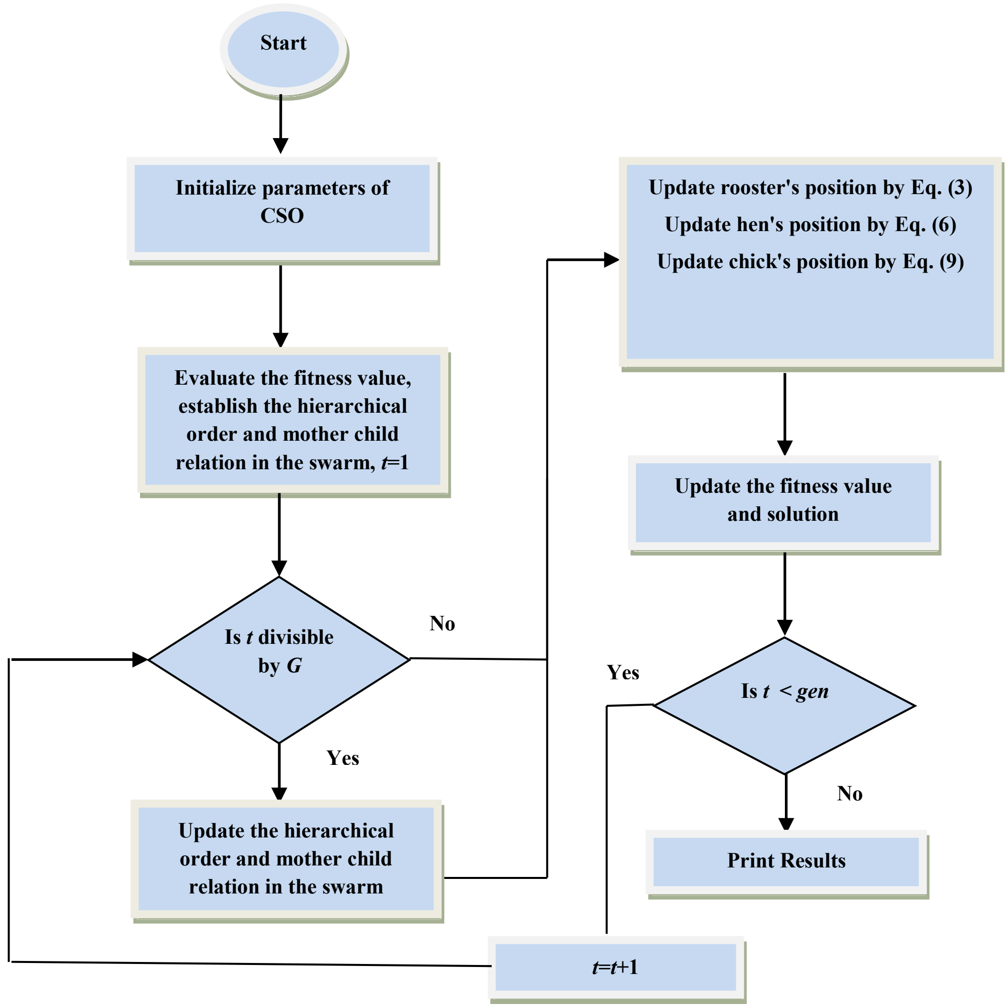

Fig.3 Flowchart of CSO

3.2. User Defined Parameters

CSO like any other EA is a probabilistic algorithm characterized by some common control parameters like population size (*N*) and number of generations (*gen*). Besides these common control parameters, CSO is characterized by a number of algorithm-specific control parameters like sizes of *RN*, *HN*, *MN*, *CN*, and values of *G*, *FL*. Chickens are domestic animal and are predominantly kept as a source of food. Hens (*HN*) can lay eggs and thus, they are considered as a source of food. Hence, keeping more number of hens (*HN*) compared to number of roosters (*RN*) and chicks (*CN*) is more beneficial. In any group of chickens, the number of hens (*HN*) is always more than the number of roosters (*RN*). All the hens (*HN*) do not hatch eggs at the same time. Hence the number of hens (*HN*) is more than the number of mother hens (*MN*). Each hen can raise multiple numbers of chicks. However, the algorithm assumes that the population of adult chickens exceeds that of the chicks (*CN*). *G* is another algorithm specific control parameter of CSO regulating the establishment of hierarchal order and the mother-child relation in the chicken swarm. A very large value of *G* may affect convergence of the algorithm. On the other hand, a small value of *G* may trap the algorithm into local optima. Though the value of *G* is highly problem-specific it is concluded that

G must be in the range of 2 and 20 (Meng et al. 2014). It is observed that $FL \in [0.4, 1]$ is capable of achieving good results for most of the problems (Meng et al. 2014).

3.3. Similarity and difference of CSO with other Nature-Inspired Algorithms

CSO resembles other nature-inspired algorithms like PSO and DE in many ways. When the size of *RN* and *CN* are set to 0 and it is assumed that *S1* and *S2* resemble learning coefficients (*c1* and *c2*), CSO becomes same as standard PSO (Meng et al. 2014). Also, the formula of the chick's movement can be associated with the mutation scheme of DE. If the size of *RN* and *MN* are set to 0, the chick's update formula resembles the mutation scheme of DE (Meng et al. 2014).

The unique feature or difference of CSO with other algorithms is the division of the population into three groups named rooster, hen, and chick. The division of the population into three groups increases the utilization rate of the population. Moreover, CSO maintains a good balance between exploration and exploitation as compared to other algorithms. Maintaining a balance between exploration and exploitation of search space greatly influences the performance of EAs. Exploration refers to visiting entirely new regions within the search space (Črepinšek et al. 2013). On the other hand, exploitation refers to visiting those regions of a search space within the neighborhood of previously visited points (Črepinšek et al. 2013). In CSO, the food searching mechanism of roosters, hens and chicks are different. The algorithm works as a multi-swarm optimization where each group has different search ability. The food searching mechanism of roosters symbolizes the exploration of the search space where entirely new regions are explored within the search space. The update mechanism of hens and chicks symbolizes exploitation of the search space where the regions of search space within the neighborhood of the previously visited points are visited. The solutions obtained after the update of roosters are further fine-tuned by the update mechanism of hen and chick. Thus, a balance between exploration and exploitation is maintained in the algorithm.

Table 1 presents a comparison of CSO with some selected nature-inspired optimization algorithms such as GA, TLBO, GWO, ACO, ABC, DE, FPA, and, SHO highlighting the similarities and differences of CSO with those algorithms.

Table 1- Comparison of CSO with other nature-inspired algorithms

Algorithms	Categories				Parameter less	Division of population
	Evolutionary algorithms	Swarm-based algorithms	Non Swarm-based algorithms	Others		
GA	✓					
TLBO				✓	✓	✓
PSO		✓				
CSO		✓				✓
GWO		✓				
ACO		✓				
ABC		✓				
DE	✓					
FPA			✓			
SHO			✓			

3.4. Weaknesses of CSO

CSO possesses some unique features like the division of search space into roosters, hen, and chicks, different food searching capacity of roosters, hens, and chicks, chicks following their mother resulting in good utilization of population and a good balance between exploration and exploitation. However, CSO also has some minor drawbacks that cannot be overlooked. CSO has a number of algorithm-specific control parameters like *RN*, *HN*, *MN*, *CN*, *G,* and *FL*. The algorithm may sometimes get stuck in local optima due to poor tuning of these parameters. In the basic CSO algorithm, the chicks follow the mother hens and the hens follow their group mate roosters. Thus, if the roosters fall into local optima then both hens and chicks will also fall into local optima resulting in premature convergence of the algorithm. In the conventional CSO, the chicks learn only from their mother and not from the roosters. Thus, the chicks obtain the position information of their mother and not the roosters. The chicks may get trapped in local optima when their mother gets trapped in local optima.

4. Variants of CSO

Several variants of CSO are available in the existing literature as shown in Fig.4. An overview of these variants of CSO is presented in this section. Further, Fig. 5 presents a timeline of development of CSO over the years.

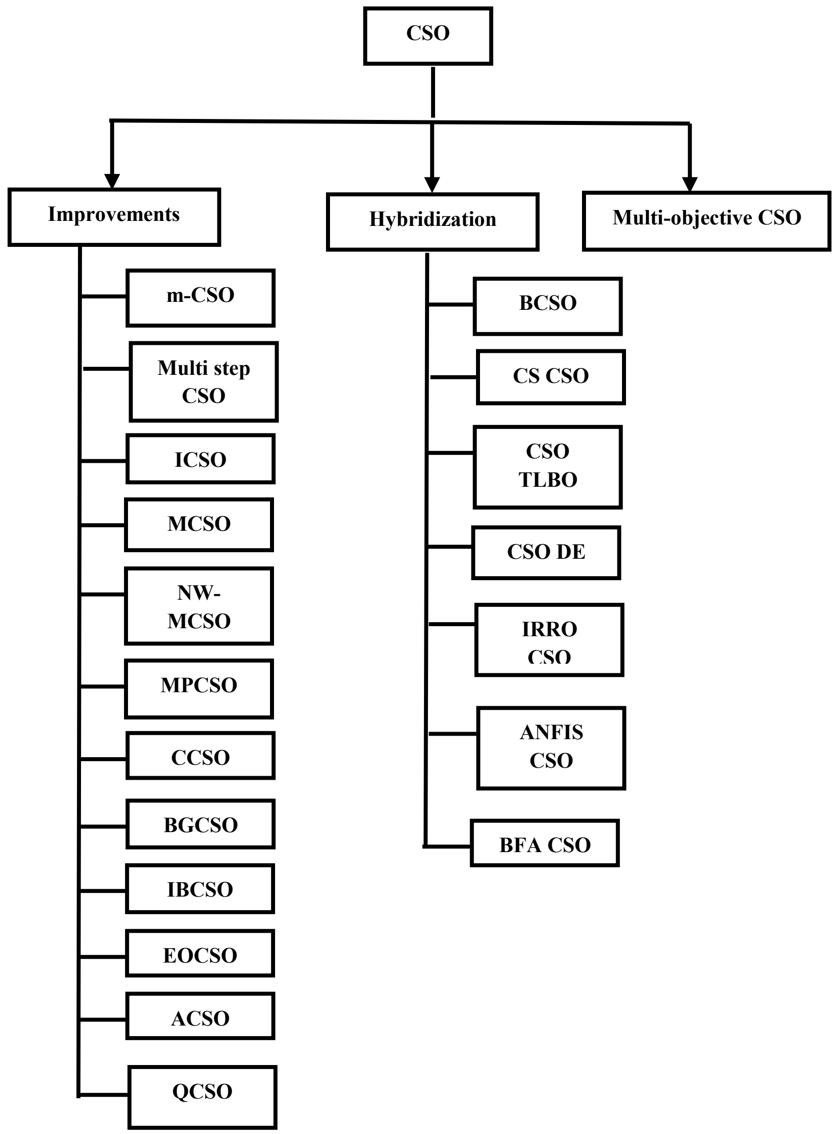

Fig.4 CSO and its variants

Fig.5 Timeline of development of CSO

4.1. Improvements

Although CSO has exhibited its efficiency in solving a number of standard benchmark problems as well as real-world problems, it has some inherent shortcomings like getting stuck in local optima. Hence, many improved versions of the algorithm are available. Some of the improved versions of CSO are presented in this sub-section.

4.1.1. Modified Chicken Swarm Optimization (m-CSO)

Chen et al. (2015) proposed an improved version of CSO with modified update equation of hen. The number of hens is highest in the group and their food searching process is the most complex. Hence, it is believed that the update mechanism of hens would directly affect the performance of the algorithm. The update equation of hens is modified as:

$$x_{i,j}(t+1) = x_{i,j}(t) + S1 \times U_1(0,1) \times (x_{r1,j}(t) - x_{i,j}(t)) + S2 \times U_2(0,1) \times (x_{r2,j}(t) - x_{i,j}(t)) \tag{10}$$

where $S1 = \exp(\frac{f_i - f_{r1}}{abs(f_i) + \varepsilon}) \qquad S2 = \exp(f_{r2} - f_i)$

$U_1(0,1)$ and $U_2(0,1)$ are uniform distributions in the range of 0 and 1, 1. $r1 \in [1, N]$ is an index of head rooster which is i^{th} hen's group mate. And $r2 \in [1, N]$ is an index of chicken different from $r1$.

Experimental results established the supremacy of m-CSO over CSO, BA in solving benchmark functions such as Schaffer, Griewank, and Rosenbrock.

4.1.2. Multi- step CSO

Irsalinda et al. (2017) proposed a new multi-step CSO. The original CSO is modified to multi-step CSO by performing the update of rooster, hen, and chick for the entire population. The algorithm is subdivided into two steps. The first step is diversification (exploration) where the update mechanism of hen is applied to the whole population in order to explore the global optima. The second step is intensification (exploitation) where the update mechanisms of rooster and chick are applied to the whole population for local search or exploiting the current position. The proposed algorithm yields better quality of solutions and favors fast convergence as compared to CSO, PSO, DE, and GA in case of some selected standard benchmark functions.

4.1.3. Improved CSO (ICSO)

Wu et al. (2015) proposed an improved version of CSO with modified update equation of chicks. In the conventional CSO, proposed by Meng et al. (2014) the chicks learn only from their mother and not from the roosters. Thus, the chicks obtain the position information of their mother and not the roosters. The chicks may get trapped in local optima when their mother gets trapped in local optima. Hence, to avoid this shortcoming of conventional CSO the update equation of chick is modified as

$$x_{i,j}(t+1) = w \times x_{i,j}(t) + FL \times (x_{m,j}(t) - x_{i,j}(t)) + C \times (x_{r,j}(t) - x_{i,j}(t)) \tag{11}$$

where m is the index of mother hen of chick i, r is the index of the rooster in the subgroup, C is the learning factor indicating that the chicks learn from the rooster, w is the self-learning coefficient.

It is observed from Eq. (11) that in ICSO the chicks inherit the position information of their mother and the rooster in the sub-group. Experimental results showed that ICSO outperforms other algorithms like CSO, BA and PSO in solving high dimensional problems.

4.1.4. Mutation CSO (MCSO)

Wang et al. (2017) introduced the mutation strategy in the update mechanism of chicks to enhance the search ability of chicks. Chicks follow their mother blindly and hence they can easily fall into local optima if the mother hen falls into local optima. Thus, the introduction of mutation strategy in the update mechanism of chicks will enhance the population diversity and will help the chicks to escape from getting trapped in local optima. The mutation strategy is added to the position update of chicks as:

$$x_{i,j}(t+1) = x_{i,j}(t+1) \times (1 + 0.5\eta) \tag{12}$$

where η is a random variable obeying Gaussian distribution.

Experimental results showed that the proposed algorithm outperforms CSO and DE in solving 6 benchmark problems of dimension 100.

4.1.5. Mutation CSO Based on Non Linear Inertia Weight (NW-MCSO)

In the conventional CSO algorithm, the chicks follow the mother hens and the hens follow their group mate roosters. Thus, if the roosters fall into local optima then both hens and chicks will also fall into local optima. Thus, Wang et al. (2017) proposed NW-MCSO where a non-linear decreasing weight is added to the update mechanism of the rooster as:

$$x_{i,j}(t+1) = x_{i,j}(t) \times (1 + \phi(0, \sigma^2))w(t) \tag{13}$$

In Eq. (13) *w(t)* is a non-linear decreasing weight given by Eq. (14)

$$w(t) = (w_{strat} - w_{end})(t/t_{\max})^2 + (w_{end} - w_{strat})(2t/t_{\max}) + w_{strat} \tag{14}$$

where w_{strat} and w_{end} are the initial inertia weights and maximum iteration count respectively, t_{max} is the maximum iteration that can be allowed, t is the current iteration count.

Experimental results established that NW-MCSO outperforms CSO, MCSO and DE in solving six benchmark functions and prediction of anti saccharification activity.

4.1.6. Monomer Turbulence and Particle Renovation Based CSO (MPCSO)

Shi et al. (2018) proposed an improved version of CSO by adding monomer turbulence and particle renovation in the update mechanism of roosters and hens respectively. The number of hens is highest in the group and thus it is expected that the impact of the update mechanism of hens will be highest on the performance of the algorithm. The particle renovation strategy drawn from PSO is introduced in the update mechanism of hens to avoid unnecessary movements. The modified update equation of hen is as follows:

$$v_{i,w}(t+1) = w \times v_{i,w}(t) + c_1 \times \text{rand} \times (p_{r_i,w}(t) - p_{i,w}(t)) + c_2 \times \text{rand} \times (Hbest_{i,w}(t) - p_{i,w}(t)) \tag{15}$$

$$p_{i,w}(t+1) = p_{i,w}(t) + v_{i,w}(t+1) \tag{16}$$

where $v_{i,w}(t)$ represents the velocity of the i^{th} hen, $p_{i,w}(t)$ represents the position of the group mate rooster of i^{th} hen, $Hbest_{i,w}(t)$ represents the best or optimal position of the hen from the previous iteration, c_1 and c_2 are acceleration coefficients , w is the inertia coefficient.

MPCSO is applied to solve optimization of directional reader antennas in ultra-high frequency radio-frequency identification problem. Experimental results established the supremacy of MPCSO over CSO, DE and PSO.

4.1.7. Chaotic CSO (CCSO)

Ahmed et al. (2017) combined chaos theory with CSO and proposed CCSO. The authors combined tent map and logistic map with swarm intelligence and used the algorithm to solve feature selection problem. Experimental results showed that CCSO performs better than CSO, BA, PSO and dragonfly optimization algorithm on five datasets.

4.1.8. Binary Improved CSO (BGCSO)

Han et al. (2017) proposed BGCSO where the mutation operator is applied to the population with the worst fitness value. The authors used the proposed algorithm to solve ten varieties of 0-1 knapsack problem. Simulation results validated the supremacy of BGCSO over PSO and wolf pack algorithm in finding better solution as well as convergence speed.

4.1.9. Improved Boundary CSO (IBCSO)

Chen et al. (2016) proposed an improved version of CSO with better constraint handling capacity. In conventional CSO when a decision variable crosses the upper or lower limit, then it is replaced by the upper or lower limit. In order to improve the convergence speed, the authors modified the constraint handling mechanism. In IBCSO when a variable crosses the threshold value, it is replaced by a random variable between the individual's best fitness and the global best fitness. The proposed algorithm is found efficient in solving standard benchmark functions as well as parameter optimization of non-linear systems.

4.1.10. CSO based on Elite Opposition Based Learning (EOCSO)

Basic CSO sometimes gets trapped into a local optimum. Moreover, the convergence rate of the algorithm is sometimes affected by the poor tuning of parameters. Hence, to overcome these drawbacks Qu et al. (2017) proposed a new version of CSO based on elite opposition based learning. In the update mechanism of rooster random search based on Gaussian distribution is replaced by adaptive t distribution. It is expected that this modification will balance the global exploitation and local development of the algorithm. Moreover, in the update mechanism of hen, elite opposition-based learning is introduced to enhance the diversity of the population. The algorithm is validated on 18 standard benchmark problems and 2 engineering problems. Experimental results validated that the algorithm performs better than CSO, BA, ACO, CS, FPA, and PSO.

4.1.11. Adaptive CSO (ACSO)

Ahmed et al. (2016) presented an adaptive approach based on CSO for solving community detection in social network problem. The community detection problem is discrete in nature. The basic CSO being a continuous algorithm cannot be directly applied for solving the community detection problem. Hence, Ahmed et al. converted the basic CSO to a discrete form by encoding and decoding. In ACSO algorithm, the best and worst index of the chicken swarm is searched in the same iteration. The worst index of the chicken swarm is replaced with the best index. Replacement of the worst index with the best index enhances the exploration of search space and increases the accuracy of the algorithm. The proposed algorithm was validated on four benchmarks datasets named Zachary karate club, Bottlenose dolphin, American college football, and Facebook. Experimental results showed that ACSO performs better than BA, KH, and Artificial fish swarm algorithm.

4.1.12. Quantum CSO (QCSO)

Meng and Li (2017) proposed an improved version of CSO based on quantum theory. The basic CSO sometimes gets trapped into local optima due to poor search capacity of the chicks. Hence, the update equation of chick is modified as follows:

$$x_{i,j}^{t+1} = x_{i,j}^{t} + FL \times (x_{m,j}^{t} - x_{i,j}^{t}) \times \log\left(\frac{1}{\mathrm{rand}}\right) \tag{17}$$

$$FL = \max - (\max - \min) \times \frac{t}{t_{\max}} \tag{18}$$

where *max* is the maximum value of *FL*, *min* is the minimum value of *FL* and t_{max} is the maximum iteration count. The proposed algorithm was used to optimize the parameters of an improved probabilistic fuzzy logic system with Dempster–Shafer structure (DS PFLS) for prediction of wind speed.

4.2. Hybridization

CSO is also hybridized with other algorithms to enhance its performance. The hybridized forms of CSO present in the existing literature are listed in this sub-section.

4.2.1. Bat CSO (BCSO)

Liang et al. (2016) amalgamated BA with CSO to improve the performance of conventional CSO. In conventional CSO the update method of roosters follows Gaussian distribution. As a consequence, the algorithm sometimes gets stuck in local optima. Hence, the authors replaced the update mechanism of roosters with the update mechanism of BA. The modified update equation of roosters is as:

$$x_{i,j}(t+1) = \begin{cases} x_{best} + 0.01 \times \mathrm{randn}(1,N) & rand \geq r_i^t \\ x_{i,j}(t) \times \mathrm{randn}(0,\sigma^2) + \varepsilon \times A^t & rand < r_i^t \end{cases} \tag{19}$$

where x_{best} is the global best solution found after comparing all the solutions among all the *N* chickens, A_i and r_i are the two parameters of BA and is given by Eq. (20) and Eq. (21). ε is a random number in the range of 0 and 1.

$$A_i^{t+1} = \alpha A_i^t \tag{20}$$

$$r_i^{t+1} = r_i^0 (1 - \exp(-\lambda t)) \tag{21}$$

where α and λ are constants.

In BCSO, the authors also modified the update equation of chicks as in Eq. (11). The proposed algorithm is used for solving sidelobe reduction problem by transmission power optimization in distributed beam forming. Experimental results showed that the proposed algorithm performed better than BA, PSO, and CSO in solving the aforementioned problem.

4.2.2. Cuckoo Search CSO (CS CSO)

Liang et al. (2017) proposed a new hybrid meta-heuristic algorithm by combining CS with CSO. In CS CSO, CS is performed in all the generations and CSO is periodically invoked in some generations to enhance the utilization rate of population. Simulation results show that the performance of CS CSO is better than CS and CSO in solving radar pattern optimization of linear antenna array and circular antenna array.

4.2.3. CSO TLBO

Deb et al. (2017) hybridized CSO with TLBO. The method of combining CSO with TLBO is somewhat similar to CS CSO. In CSO TLBO, TLBO is performed in all the generations and CSO is periodically invoked in some generations to enhance the utilization rate of population. The proposed algorithm is used for solving charging station placement problem. Simulation results show that CSO TLBO performs better than CSO as well as TLBO in solving the charging station placement problem.

4.2.4. CSO DE

Kumar and Veni (2018) hybridized CSO with DE. The solution obtained by CSO is fine-tuned by DE to avoid premature convergence. The proposed algorithm is applied for solving the routing problem.

4.2.5 IRRO CSO

Torabi and Esfahani (2018) hybridized Improved Raven Rooster Optimization (IRRO) with CSO. The method of combining CSO with IRRO is somewhat similar to CSO DE. The solutions obtained by IRRO are fine-tuned by applying IRRO. The proposed algorithm is applied for solving task scheduling problem. The authors claimed that the synergy of CSO and IRRO will maintain a balance between local and global search as well as prevent premature convergence. The proposed algorithm outperforms CSO, BA, and IRRO in solving task scheduling problem.

4.2.5. ANFIS CSO

Ahmed et al. (2018) proposed a hybrid ANFIS CSO based method for performance prediction of posted data over Facebook. CSO was used for optimization of the parameters of the ANFIS for enhancing accuracy of the model. Experimental results showed that ANFIS CSO performs better than ANFIS, Krill-ANFIS, PSO-ANFIS, and GA-ANFIS in prediction of posted data over facebook.

4.2.6. BFA CSO

Abbas et al. (2018) hybridized Bacterial Foraging Algorithm (BFA) with CSO for solving the demand side management problem. Experimental results confirmed that the proposed BFA CSO algorithm effectively scheduled the household appliances and reduced the overall peak load as well as the cost of electricity. The proposed BFA CSO performed better than CSO and BFA in solving the demand side management problem.

4.3. Multi-objective CSO

Deb et al. (2018) proposed Pareto dominance based multi-objective CSO. In the multi-objective CSO, the selection is done based on ranking and crowding distance (Mishra & Harit 2010; Pei & Hao 2017). The algorithm is applied to solve the charging station placement problem. Simulation results showed that the proposed multi-objective CSO performed better than NSGA II in solving the charging station placement problem.

4.4. Comparative Analysis of different variants of CSO

From the previous sub-sections it is clear that different variants of CSO are available in the existing literature. A comparative analysis of different variants of CSO is presented in Table 2

Table 2 Comparative Analysis of different variants of CSO

Author	Algorithm	Key Feature	Problems solved	Performance
Chen et al. (2015)	m CSO	Modification in the update mechanism of hen	Schaffer, Griewank and Rosenbrock	Performs better than DE, BA, DEBA and CSO
Irsalinda et al. (2017)	Multi-step CSO	Update equation of rooster, hen and chicks are applied to the entire population	De jong, Rastrigin, Griewank, Rosenbrock, Ackley, Shuberts, Michaelwiz d modal and speed reducer design problem	Performs better than CSO, CS, PSO, GA
Wu et al. (2015)	ICSO	Modification in the update mechanism of chicks	Sphere, Rosenbrock, Grienwank, Ackley	Performs better than PSO, BA, CSO
Wang et al. (2017)	MCSO	Introduction of mutation strategy in the update mechanism of chicks	Sphere, Alpine, Bent Cigar, Axis Parallel Hyper Ellipsoid, Discus, Schewehel	Performs better than PSO, CSO
Wang et al. (2017)	NW-MCSO	Introduction of non-linear decreasing in the update mechanism of rooster	Sphere, Alpine, Bent Cigar, Axis Parallel Hyper Ellipsoid, Discus, Schewehel	Performs better than PSO, CSO and MCSO
Shi et al. (2018)	MPCSO	Introduction of monomer turbulence and particle renovation in the update mechanism of roosters and hens respectively	Optimization of Directional Reader Antennas in ultra-high frequency radio-frequency identification (UHF RFID) system	Performs better than PSO, APSO, CSO, SAPSO, GPSO, DE
Qu et al. (2016)	EOCSO	Replacement of Gaussian distribution in the update mechanism of rooster by *t* distribution and introduction of opposition based learning in the update mechanism of hen	Sphere, Schwefel, Modified Schwefel, Rosenbrock, Quartic, Step, Rastgrin, Ackley, Griewank, Penalized function, Hartman etc and Speed reducer design, Pressure vessel design	Performs better than CSO, PSO, BA, ACO, FPA,

Author	Algorithm	Key Feature	Problems solved	Performance
Ahmed et al. (2017)	CCSO	Combination tent map and logistic map with swarm intelligence	Feature Selection	Performs better than CSO, PSO, BA and dragonfly algorithm
Han et al. (2017)	BGCSO	Application of mutation operator is applied to population with worst fitness value	0-1 Knapsack problem	Performs better than CSO, PSO
Chen et al. (2016)	IBCSO	Modification of the constraint handling mechanism	Parameter optimization of non-linear systems	Performs better than CSO, PSO, TLBO, GA
Ahmed et al. (2016)	ACSO	Conversion of basic CSO to discrete swarm algorithm by encoding and decoding	Community detection in social networks	Performs better than BA, KH and Artificial fish swarm algorithm
Meng and Li (2017)	QCSO	Introduction of a quantum operation to the update mechanism of chicks	Optimization of the parameters of an improved probabilistic fuzzy logic system with Dempster–Shafer structure (DS PFLS) for prediction of wind speed	Performs better than Fuzzy logic system
Liang et al. (2016)	BCSO	Hybridization of BA with CSO	Sidelobe reduction by transmission power optimization in distributed beam forming	Performs better than CSO, PSO and BA
Liang et al. (2017)	CS CSO	Hybridization of CS with CSO	Sidelobe level suppression in linear and circular antennas	Performs better than CS and CSO
Deb et al. (2017)	CSO TLBO	Hybridization of CSO with TLBO	Charging station placement problem	Performs better than CSO and TLBO
Kumar and Veni (2018)	CSO DE	Hybridization of CSO with DE	Mobile Ad Hoc Network (MANET) path optimization	----------------------------
Deb et al. (2018)	Multi-objective CSO	Pareto dominance based CSO where selection is performed based on rank and crowding distance	Charging station placement problem	Performs better than NSGA II

Author	Algorithm	Key Feature	Problems solved	Performance
Torabi & Esfahani (2018)	IRRO CSO	Hybridization of IRRO with CSO	Task Scheduling	Performs better than CSO, BA, IRRO
Ahmed et al. (2018)	ANFIS CSO	Hybridization of ANFIS with CSO	Performance prediction of posted data over Facebook	Performs better than ANFIS, Krill-ANFIS, PSO-ANFIS and GA-ANFIS
Abbas et al. (2018)	BFA CSO	Hybridization of BFA with CSO	Demand side management	Performs better than BFA and CSO

5. Tuning of parameters in CSO

CSO involves a number of algorithm-specific parameters as mentioned in section 3.2. Poor tuning of these algorithm-specific parameters affects the convergence of the algorithm. After preliminary analysis, Meng et al. (2014) found that *RN*=0.2**N*, *HN*=0.6**N*, *MN*=0.1**N*, *G*=10 and *FL* belonging to [0.4, 1] is capable of achieving good results for most of the standard benchmark problems.

Wu et al. (2016) performed sensitivity analysis and found the optimal values of some of the algorithm-specific control parameters of ICSO as reported in Table 3. The authors tried to find out the optimal value of *G* by varying it from 2 to 20. The other algorithm-specific parameters are fixed as: *PN*=50, *C*=0.4, *RN*=0.2**PN*, *HN*=0.6**PN*, *MN*=0.1**PN*, *CN*=*PN*-*MN*-*HN*, *FL*=0.8, *w*=0.5.Wu et al. (2016) also tried to find the optimal value of *C* by varying it from 0.2 to 1. The other algorithm-specific parameters are fixed as: *PN*=50, *G*=10, *RN*=0.2**PN*, *HN*=0.6**PN*, *MN*=0.1**PN*, *CN*=*PN*-*MN*-*HN*, *FL*=0.8, *w*=0.5. After preliminary analysis, the authors concluded that *C*=0.4 gives best results for Sphere, Griewank, Rastrigin and Ackley functions.

Shyokh & Shin (2017) used CSO for Wireless Sensor Network (WSN) localization problem and tried to find the size of *RN* for which least localization error is achieved. After sensitivity analysis, they concluded that *RN*=5 gives best results.

Table 3 Optimal value of G

Benchmark Function	*G*
Sphere	10
Griewank	10
Rastgrin	13
Ackley	10

6. Applications of CSO

CSO is applied for solving many real-world optimization problems because of its efficiency and flexibility as shown in Table 4. The area wise applications of CSO and its variants are elaborated in this section.

6.1. Scheduling

Scheduling is the process of allocating work to resources and involves a lot of computational effort if performed manually. Mohamed (2018) applied CSO for solving exam time tabling problem. Exam time tabling is one of the challenging tasks of credit hour system where a large number of subjects and students need to be allotted against some degree of resources. Results showed that the proposed approach is capable of designing a feasible and efficient time table with minimum number of time slots. Torabi and Esfahani (2018) also applied IRRO CSO for scheduling of tasks in cloud computing. The authors performed simulation with different number of tasks. Simulation results demonstrate that the proposed algorithm yields a better quality of solutions in less execution time as compared to CSO, IRRO, and BA for all the test cases with different number of tasks.

6.2. Routing

Mu et al. (2016) employed CSO to optimize trajectory of robotic manipulators that is used for surface polishing of metals. The optimization aims at minimization of travel time subject to kinematical constraints like velocity, acceleration, and jerk. Li et al. (2017) applied CSO to optimize trajectory of hypersonic vehicles. Trajectory optimization of hypersonic vehicles is tedious because of the involvement of non-linear couplings in the aerodynamic propulsion system. The authors formulated the trajectory optimization problem as an optimal control problem with cost as the objective function. Various constraints like dynamic pressure, aerodynamic heating, and load factor are taken into account by imposing penalties for violation of these constraints. The authors performed a number of experiments to validate the efficacy of the proposed method. Later, Kumar and Veni (2018) applied CSO DE to solve optimization of Mobile Ad-hoc Networks (MANET) problem. MANET path selection is a complex problem involving the traversal of minimum number of intermediate nodes to reach the target node. The authors proposed an Enhanced Energy Steady Clustering (EESC) scheme for steady clustering communication. Simulation results showed the efficacy of the proposed approach in solving MANET routing problem.

6.3. Power and Energy

Sivashakti & Muralikrishnan (2016) and Hu et al. (2016) applied CSO to solve economic load dispatch problem. Sivashakti & Muralikrishnan (2016) considered prohibited operation zones and network losses as well as cost in their problem formulation. Experimental outcomes showed that CSO performs better than other evolutionary algorithms like PSO, GA, BA in solving economic load dispatch problem of a six-unit test system. Hu et al. (2016) solved the economic load dispatch problem of microgrid consisting of solar, wind, micro gas turbines, diesel generators, and fuel cells by applying CSO. The authors formulated the economic load dispatch problem in a multi-objective framework considering both economic and environmental factors. Voltage limit and power balance equation are considered as constraints in the formulation. Simulation results confirmed the accuracy of the proposed approach.

Deb et al. (2017) proposed a new hybrid meta-heuristic named CSO TLBO and applied the novel algorithm to solve charging station placement problem. Charging station placement problem mimics a typical planning problem concerned with finding the optimal locations of charging stations in the test network. The authors considered cost as the objective function. The operating parameters of the distribution network like voltage deviation, Average Energy Not Served (AENS) are taken into account by imposing penalties for violation of the safe limits of these constraints. The proposed approach is validated on a superimposed network of IEEE 33 bus distribution network and 25 node road network. Simulation results show that CSO TLBO outperforms CSO and TLBO in solving charging station placement problem. Later, Deb et al. (2018) formulated the charging station placement problem in a multi-objective framework with cost, accessibility, Voltage stability, Reliability , Power loss (VRP) index (Deb et al. 2018) as objective functions. The authors solved the multi-objective charging station placement problem by employing a Pareto dominance based CSO, TLBO and CSO TLBO. Simulation results verified that the proposed algorithms performed better than NSGA II in solving many objective charging station placement problem.

Meng & Li (2017) introduced a quantum based CSO to optimize the parameters of an improved probabilistic fuzzy logic system with Dempster–Shafer structure (DS PFLS) for prediction of wind speed.

Further, Abbas et al. (2018) solved the demand side management problem by applying BFA CSO.

6.4. Communication

Banerjee & Chattopadhay (2015) proposed an enhanced Serially Concatenated Convolution Turbo Code (SCCTC) to improve Bit Error Rate (BER) functioning at higher values of Signal Noise Ratio (SNR) applying CSO. Simulation results showed that the impact of applying CSO based search technique on the performance of SCCTC is praiseworthy. Yi et al. (2016) applied CSO for Peak to Average Power Ratio (PAPR) reduction in Orthogonal Frequency Division Multiplexing (OFDM) system. OFDM is a highly efficient tool in high-speed optical fiber transmission as it possesses high spectral efficiency and clemency against chromatic dispersion. However, high PAPR is the major hitch in OFDM system. The authors proposed a novel methodology to minimize PAPR ratio in OFDM system by applying CSO. Application of CSO optimized the initial phase of the subcarriers. Simulation results showed that PAPR of CSO optimized signal is lessened by 5.5dB and 1.5dB compared with that of the original signal and the signal optimized by PSO respectively. Liang et al. (2016) proposed a new hybrid meta-heuristic named BCSO and applied the algorithm for sidelobe reduction in distributed beam forming. Collaborative beamforming enhances the transmission band of sensor nodes in wireless sensor networks. The high level of sidelobe is a major shortcoming in collaborative beamforming. The authors applied BCSO to optimize peak sidelobe level in the array of antenna. Simulation results showed that BA CSO performs better than CSO, PSO, and BA. Later, Liang et al. (2017) proposed another hybrid meta-heuristic named CSCSO and applied the algorithm for sidelobe level suppression in linear antenna array (LAA) and circular antenna array (CAA). Simulation results showed that CSCSO performs better than CS, PSO, and CSO in solving the sidelobe reduction problem. Wang & Zhu (2017) applied CSO for reduction of energy consumption of Wireless Sensor Network (WSN). The authors used CSO to reduce the energy consumption of WSN and enhance the survival time of the network. The simulation outcomes proved that the proposed approach is better than Low Energy Adaptive Clustering Hierarchy (LEACH) protocol clustering routing protocol based on PSO. Awal et al. (2017) used CSO for Peak to Average Power Ratio

(PAPR) reduction in Orthogonal Frequency Division Multiplexing (OFDM) system. It is observed from simulation results that CSO reduces the computational complexity and improves the reduction of PAPR up to 2.25 dB at 0.0011 complementary cumulative distribution function (CCDF) for an unmodified OFDM signal. Shi et al. (2017) proposed an improved version of CSO named MPCSO and applied the algorithm for optimization of Directional Reader Antennas in ultra-high frequency radio-frequency identification (UHF RFID) system. Firstly, the authors established a propagation model by examining the gain characteristics of patch and dipole antenna. Then, they build a new planning model for identifying the position of a fixed number of reader antennas maximizing coverage and minimizing location error and interference. Finally, the problem was solved by MPCSO. Shayokh & Shin (2017) applied CSO for localization of WSN. Results demonstrate that CSO performs more 55% more accurately than PSO and BPSO. Sun et al. (2017) used CS CSO for collaborative beamforming in WSN. Simulation results show that the node position selection and current excitation optimization based on CS CSO can successfully reduce the maximum sidelobe level. Shi et al. (2018) proposed a modified version of CSO named MPCSO and applied the algorithm for optimization of Directional Reader Antennas in ultra-high frequency radio-frequency identification (UHF RFID) system.

6.5. Environment

Liu et al. (2016) applied CSO for quality assessment of river water. Firstly, the authors modelled a projection pursuit evaluation system for river water and employed CSO for its solution. The study is carried out in the Jiansanjiang Administration, Heilongjiang Province, China. On comparison of the performance of CSO with GA, the authors found that CSO performs much better in terms of quality of solution and convergence speed. Later, Sutoyo et al. (2017) again employed CSO for river water quality assessment. For practical implementation, the dataset from Jangkok river of Indonesia was collected and used. The experimental results verified the efficacy of CSO in solving river water quality assessment problem.

6.6. Control System

Chen et al. (2016) proposed a new version of CSO called IBCSO and employed the algorithm for parameter optimization of non- linear systems. Experimental results are validated on a coupled motor system that showed that the proposed algorithm performs better than CSO, TLBO, and PSO. Later, Ren et al. (2017) used CSO for controller design of fast steering mirror. Results confirm that the proposed method reduces the execution time and the time of the entire control system design.

6.7. Others

CSO is also applied for solving problems of other areas like diagnosis of brain tumor, feature selection, and 0-1 knapsack problem. Taie & Ghonaim (2017) applied CSO for diagnosis of brain tumor. The detection of brain tumor from MRI presently has many challenges because of different size and shape of the tumor. The authors proposed a framework for automatic detection of brain tumor consisting of four steps: segmentation, feature extraction and feature reduction, classification, and optimization of the parameters of the classifier. CSO is effectively used in the aforesaid work for dynamically optimizing the parameters of the classifier. Han et al. (2017) proposed a new version of CSO called BGCSO for solving knapsack problems. Knapsack problem mimics a resource allocation problem concerned with maximization of profit and minimization of weight of the items present in the set. The authors solved ten varieties of 0-1 knapsack problem by BGCSO. Simulation outcomes showed that the proposed method is superior to PSO and wolf algorithm. Further, Hafez et al. (2015) and Ahmed et al. (2017) used CSO for solving the feature selection problem. Ahmed et al. (2016) used an adaptive approach based on CSO for solving community detection in social network problem. Ahmed et al. (2018) used a hybrid ANFIS CSO based method for performance prediction of posted data over Facebook. Meng et al. (2018) used CSO for temperature monitoring of Lithium-ion batteries. Moldovan et al. (2018) used CSO for fault detection in manufacturing system.

Table 4 Applications of CSO

Author	Algorithm applied	Area	Application
Mohamed (2018)	CSO	Scheduling	Exam time tabling
Kumar and Veni (2018)	CSO DE	Routing	Mobile Ad Hoc Network (MANET) path optimization
Sivashakti & Muralikrishnan (2016)	CSO	Power and Energy	Economic load dispatch
Wang & Zhu (2017)	CSO	Communication	Reduction of energy consumption of Wireless Sensor Network
Sutoyo et al. (2017)	CSO	Environment	Classification of river water quality
Banerjee & Chattopadhay(2015)	CSO	Communication	Improvement of Concatenated Convolution Turbo Code
Mu et al. (2016)	CSO	Routing	Planning of trajectory for robotic manipulators
Taie & Ghonaim (2017)	CSO	Other	Diagnosis of brain tumor
Liang et al. (2016)	BCSO	Communication	Sidelobe reduction by transmission power optimization in distributed beamforming
Awal et al. (2017)	CSO	Communication	Peak to Average Power Ratio (PAPR) reduction in Orthogonal Frequency Division Multiplexing (OFDM) system
Yi et al. (2016)	CSO	Communication	Peak to Average Power Ratio (PAPR) reduction in Orthogonal Frequency Division Multiplexing (OFDM) system

Author	Algorithm applied	Area	Application
Shi et al. (2018)	MPCSO	Communication	Optimization of Directional Reader Antennas in ultra-high frequency radio-frequency identification (UHF RFID) system
Liang et al. (2017)	CSCSO	Communication	Sidelobe level suppression in linear and circular antennas
Li et al. (2017)	CSO	Routing	Trajectory optimization of hypersonic vehicles
Shayokh & Shin (2017)	CSO	Communication	Localization of Wireless Sensor Network
Sun et al. (2017)	CSCSO	Communication	Collaborative beanforming in Wireless Sensor Network
Torabi & Esfahani (2018)	IRRO CSO	Scheduling	Task scheduling
Hu et al. (2017)	CSO	Power and Energy	Economic operation of microgrid
Deb et al. (2017)	CSO TLBO	Power and Energy	Charging station planning for Electric Vehicles
Ren et al. (2017)	CSO	Control System	Control of fast steering mirror
Chen et al. (2016)	IBCSO	Control System	Parameter optimization of non-linear systems
Liu et al. (2016)	CSO	Environment	Assessment of water quality
Han et al. (2017)	BGCSO	Other	0-1 Knapsack problem
Hafez et al. (2015)	CSO	Other	Feature selection
Ahmed et al. (2017)	CCSO	Other	Feature selection
Ahmed et al. (2016)	ACSO	Other	Community detection in social network
Ahmed et al. (2018)	ANFIS CSO	Other	Performance prediction of posted data over Facebook
Deb et al. (2018)	Multi-objective CSO	Power and Energy	Charging station planning for Electric Vehicles
Meng & Li (2017)	QCSO	Power and Energy	Optimization of the parameters of an improved probabilistic fuzzy logic system with Dempster–Shafer structure (DS PFLS) for prediction of wind speed

Author	Algorithm applied	Area	Application
Meng et al. (2018)	CSO	Others	Temperature monitoring of Lithium-ion batteries
Abbas et al. 92018)	BFA CSO	Power and Energy	Demand side management
Moldovan et al. (2018)	CSO	Others	Fault detection in manufacturing system

7. Discussion and Future Work

This work reviews the existing literature related to CSO. Fig. 6 presents the area wise applications of CSO. Fig. 7 presents the trend in research work related to CSO from its origin in 2014 to 2018. From Fig.7, it is clear that the popularity of CSO is increasing day by day and reached its zenith in 2017. Fig. 7 shows that the number of research works on CSO in 2014 and 2015 are relatively less. This clearly indicates that the use of CSO in the field of optimization has yielded interest after 2 years. Fig.6 reveals that CSO and its variants are mostly applied for solving problems related to communications. It is found that despite the competitive performance of CSO in solving many standard benchmark problems and real-world problems, the algorithm is not much popular among power system engineers. The performance of CSO in solving complex power system optimization problems like hydro-thermal scheduling, optimal operation of microgrids, combined economic and emission dispatch are not yet explored.

CSO has good utilization rate of population and it maintains a good balance between exploration and exploitation. However, the algorithm sometimes gets stuck in local optima. As a consequence researchers have developed a number of improved versions of CSO.

Optimization problem differs in every area and No Free Lunch theorem confirms that a single algorithm cannot perform satisfactorily on all the problems. This leads to the refinement of basic CSO to solve a wide range of optimization problems. The previous sections report that the update mechanisms of hen, roosters, and chicks are modified accordingly to fix the desired problem. Moreover, CSO is also hybridized with other evolutionary algorithms like TLBO, IRRO, BA to enhance the performance of the algorithm. However, it is found that hybridization of CSO with traditional techniques like Taguchi method, dynamic programming, or other theories like Adaptive Reinforcement Learning (Meng et al.2018) is rare. Table 5 presents a summary of CSO thereby highlighting its strengths, weaknesses, and future research works. Further, the benchmark problems to be solved by CSO, performance of evolutionary algorithms on solving these benchmark problems to be compared with CSO and real-world problems to be solved by CSO are also suggested in Table 5.

Many improvements are made by previous researchers and every objective of study need a different approach to achieve the desired outcomes. The outcomes of every problem cannot be limited to just one method and hence the development of the algorithms will continuously expand. Some of the future works related to CSO are:

- **Theoretical Analysis**- CSO has demonstrated competitive performance in solving a large number of standard benchmark functions. However, the performance of CSO on computationally expensive benchmark functions proposed by IEEE Congress on Evolutionary Computation is not evaluated. There is necessity of solving the aforesaid computationally expensive benchmark functions by CSO and comparison of its performance with the other evolutionary algorithms that have demonstrated competitive performance on CEC benchmark problems

- **Self Adaptivity**- Adaptive or Self Adaptive evolutionary algorithms are those that have the capacity of self-tuning of its algorithm-specific and common control parameters. CSO has a number of algorithm specific parameters like *RN, HN, CN, MN, G*, and *FL*. In most of the existing research works the tuning of these parameters were performed by trial and error that is time-consuming. Hence, there is necessity of developing an adaptive version of CSO having the capability of self-tuning its algorithm specific control parameters.
- **Hybridization**-Generally, hybrid algorithms perform better than the stand-alone algorithms. Hence, hybridization of CSO with other evolutionary algorithms like GA, DE, conventional methods like Taguchi method, dynamic programming, or other theories like Adaptive Reinforcement Learning is a promising area of research
- **Applications**-There is no dearth of complex optimization problems in real world. CSO is used for solving only some of the complex real-world optimization problem. CSO may yield competitive results in solving complex power system problems like unit commitment, hydro-thermal scheduling, and Distributed Generation (DG) placement, scheduling problems like microgrid scheduling, control system problems like Proportional Integral Derivative (PID) controller design, microgrid control.

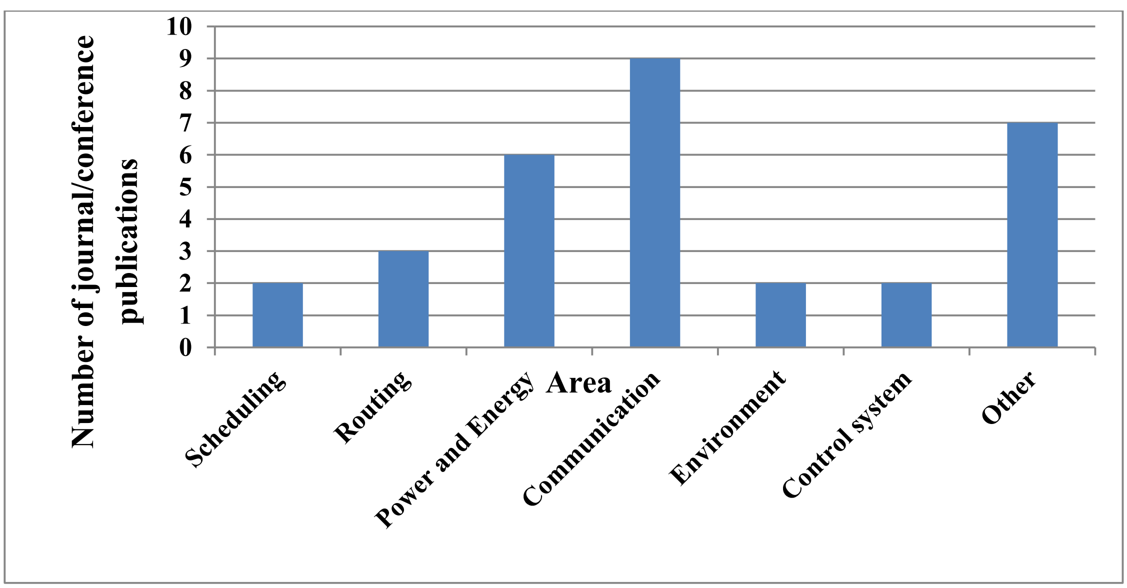

Fig.6 Area wise applications of CSO

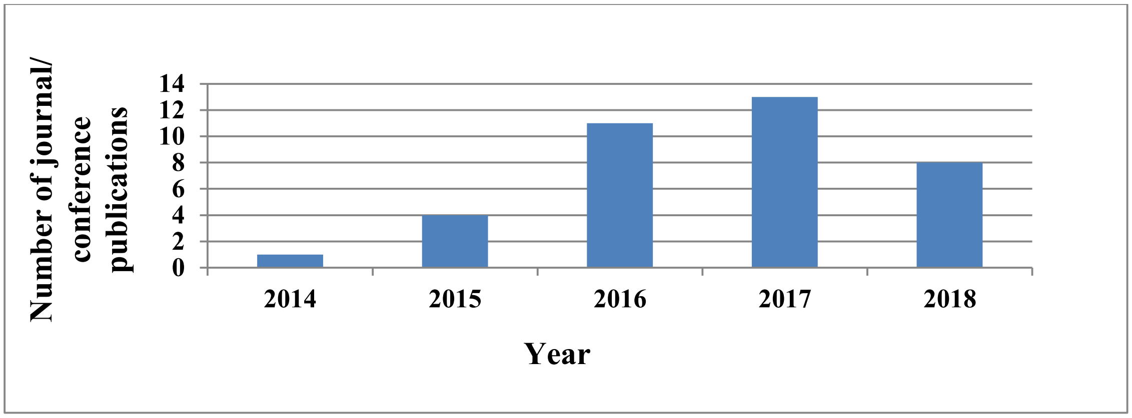

Fig.7 Trend in research works related to CSO

Table 5 Strength Weakness and Future works of CSO

Strengths	Weakness	Future Works
Good Utilization rate of population	Tuning of algorithm-specific control parameters	Development of adaptive CSO
Balance between exploration and exploitation	Premature convergence in some problems	Performance of CSO on computationally expensive benchmark problems such as CEC 2015, CEC 2016, CEC 2017, CEC 2018
		Comparison of the performance of CSO with other nature-inspired algorithms such as Multiple Parent Crossover GA, variants of DE, Jaya algorithm, Sine Cosine algorithm
		Hybridization with other evolutionary algorithms such as Jaya algorithm, Sine Cosine algorithm
		Hybridization with other conventional algorithms/ methods such as Dynamic programming, Adaptive Reinforcement Learning
		Solution of real-world problems such as Hydro thermal scheduling, Microgrid control and scheduling, PID controller design

8. Conclusions

This review reports the existing research works related to CSO. The general biology, key features, advantages, drawbacks, variants, and applications of CSO are discussed comprehensively in the paper. From the statistical results reported in the paper, it can be concluded that CSO is widely used in many domains like power system, control system, communications, scheduling, feature selection, and community detection of social networks. Experimental results reported in the existing research works confirm that CSO outperforms many nature-inspired algorithms like CS, PSO, and GA in solving a wide range of standard benchmark and real-life problems. Optimization problem differs in every area and No Free Lunch theorem confirms that a single algorithm cannot perform satisfactorily on all the problems. To conclude, since there is still scope of improvement, CSO could be extended into various hybridizations and modifications based on the necessity of the problems. Therefore, the results of this review could be used by other prospective researchers for improvement purpose by taking into consideration on the applications, advantages, and drawbacks of CSO reported by the previous researchers.

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