SSRG International Journal of Computer Science and Engineering
ISSN: 2348–8387 / https://doi.org/10.14445/23488387/IJCSE-V13I4P104

Volume 13 Issue 4, 51-55, April 2026

Review Article

Sand Cat Swarm Optimization: Implementation, Issues, and Existing Approaches

Ab Wahid Bhat[1], Abhiruchi Passi[2]

[1,2]*Department of ECE, FET MRIIRS, Faridabad, Haryana, India.*

[1]*Corresponding Author : abwahid1994@gmail.com*

Received: 22 February 2026 Revised: 30 March 2026 Accepted: 15 April 2026 Published: 29 April 2026

Abstract - *Population-based swarm-intelligence algorithms are metaheuristic algorithms inspired by the behaviour of animals, birds, and insects found in nature. These algorithms are based on a balanced strategy of exploration and exploitation and can be used to optimize multiple NP-hard problems. The Sand Cat Swarm Optimization (SCSO) algorithm is a novel and recently proposed algorithm based on the hunting behaviour of sand cats. These sand cats have extraordinarily low-frequency hearing that helps them locate and catch their prey. The sand cat swarm optimization algorithm has been successfully tested for solving various optimization problems, and it performed efficiently in comparison to other existing algorithms. However, the SCSO has certain limitations when it comes to convergence and optimality of the global solution. The main aim of the paper is to present a detailed description of the implementation of SCSO and highlight its limitations. In addition to this, various approaches proposed to enhance the performance of SCSO are mentioned, and the adopted methodology is analysed. The changes incorporated in the modified versions of SCSO have been tabulated at the end of the paper.*

Keywords - *Metaheuristic Algorithms, Sand Cat Swarm Optimization, Limitations, Approaches, Genetic Algorithm.*

1. Introduction

In the present scenario, there are numerous optimization problems with varying natures, some being polynomial time (P) while others are non-deterministic polynomial time (NP-hard) problems. Although the P-type optimization problems can be solved by a deterministic algorithm in a definite time, obtaining a solution to an NP-hard problem is both hard and complex. These NP-hard optimization problems can be solved either by deterministic or approximate approaches. The Deterministic approaches are difficult to apply due to the time complexity and dynamic nature of these problems. The famous methods used to obtain the solution to such problems are the heuristic and metaheuristic algorithms. Both of these algorithms are based on the approximate-solution strategy that does not guarantee the optimal solution; a near-optimal solution can be obtained. While the heuristic methods are more problem-specific and have the issue of local optima and complexity in the case of larger and more complex problems, the metaheuristic algorithms can be applied to a wide range of optimization problems with reduced complexity and better performance. The metaheuristic algorithms, owing to their random and balanced nature, do not have slow convergence and local optima issues. These algorithms are based on a balanced mechanism between the exploration and exploitation phases, with a proper selection of coefficients to ensure a global optimum solution. During the exploration phase, these algorithms focus on the random global search and try to explore more and more unvisited areas of the search space. An extended and random search helps to avoid the local optima and achieve a better success rate. In the exploitation phase, more focus is laid on finding the best global solution in the already explored search space. In simpler words, exploration promotes "diversity" while exploitation focuses on "intensification"[1].

The metaheuristic algorithms are divided into multiple categories based on different classifications. Depending upon the variables considered, these are classified as single solution-based[2] and population-based algorithms[3]. The single solution algorithms focus more on exploitation, while population-based algorithms prefer exploration. The prominent examples of single search metaheuristic algorithms include the Tabu search, Simulated annealing, iterated local search, and Hill climbing. The population-based metaheuristic algorithms are further classified into evolutionary algorithms, physics-based, and Swarm intelligence-based algorithms. The Evolutionary Algorithms(EAs) are influenced by the process of natural evolution and include the Genetic Algorithm(GA), Differential Evolution(DE) algorithm, Evolutionary Strategies (ES), and Genetic Programming (GP). The physics-based metaheuristics algorithms are based on different laws of physics acting in nature, such as Newton's laws and Faraday's laws. The prominent examples include the Gravitational Search Algorithm (GSA), the Black-Hole Algorithm (BHA), and the Galaxy-based Search Algorithm(GbSA).

The last category of the metaheuristic algorithms is the Swarm-Intelligence (SI) based algorithms[4]. These algorithms are based on the social abilities of animals, birds, and insects interacting with each other and their surroundings. These individuals live in herds, flocks, and swarms, acting, reacting, and interacting with each other to obtain an optimal solution or position.

The most important and popular SI-based algorithms are Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Artificial Bee Colony (ABC) optimization, Whale Optimization Algorithm (WOA), Grey Wolf Optimization (GWO) algorithm, and Sand Cat Optimization (SCO) algorithm.

The metaheuristic algorithms, though, can be applied to general optimization problems, but as the No Free Lunch (NFL) theorem [5] argues, no single optimization algorithm can be helpful to provide an optimal solution to all the practical problems; therefore, it is necessary to propose new or modify the existing algorithms to overcome the limitations and enhance their efficiency.

The SCSO is a recent swarm-based metaheuristic algorithm imitating the behavior of the sand cats while searching and hunting prey. The SCSO algorithm is simple and easy to implement with only a few control parameters and a balanced and adaptive mechanism for transition from exploration to exploitation phases[6].

2. Sand Cat Swarm Optimization

Sand Cat Swarm Optimization is a swarm intelligence, population-based meta-heuristic algorithm proposed by Amir Seyyedabbasi et al. in 2022, inspired by the behavior of the sand cat. The Sand cats have two unique features: the ability to detect frequencies below 02 KHz that assist them to locate the prey above as well as under the ground, and enhanced digging capability. These cats can detect insects and rodents moving under the ground by detecting differences in the time of arrival of different sounds. They are about 8dB more sensitive to frequencies below 02KHz than domestic cats due to a longer middle ear canal. The hunting behavior of the sand cats can be categorized into two phases: the exploration of the search area in all dimensions and catching the prey. In the SCSO algorithm, these two stages have been balanced properly by means of convergence and control parameters. The following are the important stages present in the SCSO algorithm.

2.1. Defining the Population

In SCSO, each of the sand cats represents problem variables, and the collective value of all the variables forms the fitness function. In the SCSO algorithm, the population is defined in vector form as per the dimension of the optimization problem. In an m-dimensional problem, with n variables (sand cats), the population matrix is shown below.

$$Popoulation\ Matrix_{n\times m} = \begin{bmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,m} \\ x_{2,1} & x_{2,2} & \cdots & x_{2,m} \\ \vdots & \vdots & \cdots & \vdots \\ x_{n,1} & x_{n,2} & \cdots & x_{n,m} \end{bmatrix}$$

The fitness function for obtaining the optimal solution is formed by comparing all the individual cost functions of the sand cats, as shown below.

$$Fitness\ Value = \begin{bmatrix} f(x_{1,1}; x_{1,2}; \cdots x_{1,m}) & \xrightarrow{yields} & cost_{s1} \\ f(x_{2,1}; x_{2,2}; \cdots x_{2,m}) & \xrightarrow{yields} & cost_{s2} \\ \vdots & \vdots & \vdots \\ f(x_{n,1}; x_{n,2}; \cdots x_{n,m}) & \xrightarrow{yields} & cost_{sn} \end{bmatrix}$$

The optimal solution is chosen based on the maximization or minimization of the total fitness value.

2.2. Searching the Prey (Exploration Phase)

After defining the population, the algorithm shifts to exploration of the search space with each sand cat trying to reach out to the prey in a minimum number of iterations. The extraordinary ability of the sand cat to locate the prey is due to its sharp hearing sensitivity for frequencies below 02 kHz. Therefore, based on it, the general sensitivity range of the sand cats is supposed to be in the range of 0 to 2, mathematically expressed as

$$S_G = S_M - \left(\frac{S_M \times t}{T}\right) \quad (1)$$

The value decreases linearly from 2 to 0 with each iteration as t (current iteration) reaches T (total count).

The sensitivity range of each sand cat is chosen to be different to avoid local optima, and is a function of the general sensitivity obtained as

$$S_p = S_G \times rand(0,1) \quad (2)$$

Another important parameter in the SCSO algorithm is the control parameter, which is adjusted to establish a balance between the exploration and exploitation phases of the algorithm.

$$C_p = 2 \times S_G \times rand(0,1) - S_G \quad (3)$$

In the exploration phase, the sand cats update their position with respect to the best position in the entire population by a random mechanism to explore the search space more diversely through the expression.

$$X(t+1) = S_p \times (X_{bc}(t) - rand(0,1) \times X_{cp}(t)) \quad (04)$$

Where $X(t+1)$ is the new position. X_{bc} is the candidate's best position, and X_{cp} is the current position of each sand cat.

2.3. Catching the Prey (Exploitation Phase)

When the sand cat reaches close to the prey, it switches from exploration to exploitation to catch the prey. In SCSO, each sand cat first determines the distance to the best solution (location of prey) and then moves in a random direction based on the Roulette Wheel selection algorithm in a circular region. The direction factor is introduced as a function of the cosine of the angle and can have values in the range of -1 to 1, corresponding to 0 to 360.

The position update mechanism in the exploitation phase is done as per the expression given below.

$$Dist = \left|rand(0,1) \times (X_{bp}(t) - X_{cp}(t)\right| X(t+1) = X_{bp}(t) - S_p \times Dist \times \cos(\alpha) \quad (5)$$

Where X_{bp}(t) is the global best position (location of prey).

2.4. Balanced Transition between Exploration and Exploitation

The most important feature of the SCSO algorithm is the appropriate transition from the searching stage to the hunting stage. The control factor C_p plays a crucial role in maintaining this balance.

The search mechanism depends upon the value of the C_p. If$C_p > 1$, the algorithm uses equation 4 to update the position and keep searching for an optimal solution.

For $C_p \leq 1$, the algorithm shifts to the exploitation phase and starts catching the prey. In the exploitation phase, the position is updated as per expression (06).

$$\vec{X}(t+1) = \begin{cases} S_p \times \left(X_{bc}(t) - rand(0,1) \times X_{cp}(t)\right) & |R| > 1; Exploration \\ X_{bp}(t) - S_p \times Dist \times \cos\theta & |R| \leq 1; Exploitation \end{cases} \quad (6)$$

3. SCSO Limitations

3.1. Random Search Mechanism

The randomness in the search mechanism results in some areas being continuously or discontinuously explored or exploited.

3.2. Slow Convergence and Delayed Transition

The delayed transition of the algorithm from the exploration to the exploitation phase results in slow convergence of the algorithm.

3.3. Low Population Diversity

The performance of any metaheuristic algorithm is highly affected by the initial conditions. Defining the population more efficiently, rather than randomly in SCSO, which can explore the search space effectively and quickly, is needed. In SCSO, low population diversity sometimes can lead to premature convergence of the algorithm.

3.4. Local Optimum Trap

During exploration, the sand cats search for the prey and try to capture it in the exploitation phase. The imbalance between the two phases restricts the movement of the sand cats, resulting in their falling into the local optimal trap. A weighted search mechanism that focuses more on the exploration of the global optimum should be adopted.

3.5. Dependence on Global Best Position

The performance of the SCSO is dependent on the position of the global optimum solution.

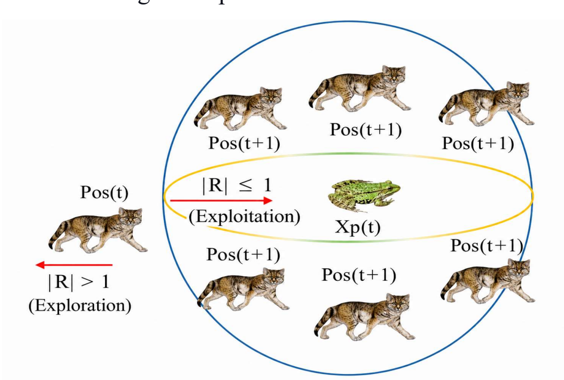

Fig. 1 Searching for prey (exploration; $C_p > 1$) & attacking prey (exploitation; $C_p \leq 1$) [6]

4. Recently Proposed Approaches to SCSO

To overcome the above-mentioned limitations, various methods have been proposed, some of which are discussed below:

In CSCSO [7], the limitations of the earlier SCSO are addressed by adopting several chaotic maps. The main objective of the proposed algorithm is to improve the search mechanism for a better global optimum and to expedite the convergence rate.

In PSCSO [8], the author has tried to address the local optimum trap issue in SCSO by adopting a new position update mechanism inspired by the parliamentary political system that incorporates both the intra and inter-party competition to find the best candidate. In addition to it, a new mathematical model is adopted for achieving a wide range of the parameter 'C', for flexible and better switching and balance between exploration and exploitation phases.

In HSCSO [9], a multi-strategy methodology is adopted to enhance the efficiency of the SCSO. For better initialization and a diverse population, the Logistic-Tent Chaotic mapping is employed to explore the search space more efficiently in the initial stages, followed by the Momentum-Bellicose strategy for an efficient transition between the exploration and exploitation phases. The limitations of local optimum and poor population diversity are addressed by adopting the elite-crossover pool and an adaptive lens-opposition-based learning strategy, thus enhancing the global search ability of the algorithm.

In COSCO [10], the author has adopted three different techniques to address the limitations of the SCSO algorithm. Firstly, in order to overcome the local optimal trap and for an intensified search mechanism, a non-linear parameter is used for the sensitivity range (Se) of the sand cats instead of a linear one used in SCSO. Secondly, for improving the convergence rate, a Cauchy mutation operator is used for selecting a variable step size during local and global optimum search. Lastly, for a more diverse population, an optimum neighbourhood disturbance strategy is used.

In IMSCSO [11], the issues of slow convergence and population diversity issues of the SCSO are addressed. The author has proposed a Roulette rule and Fitness Distance Balancing Strategy (FDB) for the selection of the best possible candidate to guide the population and achieve a rapid convergence rate. However, to avoid falling into a local optimum trap, a population-perturbation strategy is used to enhance the population diversity.

In ISCSO [12], twin functions of frequency factor and position –offset coefficient are used in the exploration phase to optimize the search mechanism and expedite the convergence rate. To resolve the issue of local optimum during the exploitation phase, the algorithm proposed spiral contraction and a bounding walk strategy instead of circular search, as in the case of SCSO, to decrease the search area and control the search direction. Along with the above, Stochastic Opposition-based Learning and restart strategy are also used to avoid falling into a local optimum.

In LSSCSO [13], during exploration, the sand cats adopt the lens opposition-based learning strategy, and the dynamic spiral search strategy is introduced in the exploitation phase. These techniques help the sand cats to search the best possible candidate, that too in a defined and bounded search area, thus accelerating the convergence rate and also preventing the local optimum trap.

Table 1. Summary of the Pertinent Work on SCSO

ALGORITHM	YEAR	METHODOLOGY	OBJECTIVES
SCSO [6]	2022	**Original algorithm with random initialization, unbalanced transition, and local optimum solution**	
CSCSO [7]	2023	Chaotic Map-based Search	To achieve a global optimum solution and a better convergence rate
PSCSO [8]	2023	Political system-based search	To address the local optimum trap and achieve a balanced transition between exploration and exploitation phases
HSCSO [9]	2023	Logistic-Tent chaotic and adaptive lens –opposition strategy. Momentum-Bellicose and elite-cross pool strategy	Better initialization, balanced transition, faster convergence, and a diverse population for improving overall performance.
COSCSO [10]	2023	Adaptive parameter with Cauchy mutation and neighbourhood disturbance strategy	An intensive search with rapid convergence and a diverse population for a better Global solution
IMSCSO [11]	2024	Fitness–distance and balancing strategy	To achieve Population diversity and address the slow convergence.
ISCSO [12]	2024	Frequency factor and position –offset coefficient, spiral contraction, and bounding walk strategy.	Better search during exploration and balanced transition to the exploitation phase. Diverse and controlled search for the global optimum.
LSSCSO [13]	2024	LOBS and dynamic spiral search strategy	Expedite the convergence rate and better search strategy for avoiding the local optimum trap.

5. Conclusion

The Sand Cat Swarm optimization is a metaheuristic algorithm influenced by the hunting behaviour of the sand cats. Although the algorithm performed very well when compared to other single-solution or population-based metaheuristic algorithms, it suffered from the issue of slow convergence rate, lack of population diversity, and falling into a local optimum trap. To address these issues, various modified approaches have been proposed for proper initialization, efficient and intense search mechanisms, a balanced transition between the exploration and exploitation phases, and strategies to diversify the population for obtaining an optimum global solution. The paper presented a detailed discussion on the implementation of the original SCSO and highlighted the limitations. A thorough description of all the approaches proposed for improving its performance is presented and summarized as well. From all this discussion, it is concluded that a proper initialization strategy and intensified search mechanism can efficiently address the issues of a poor population pool and a global solution. For expediting the convergence rate, a balance between the exploration and exploitation phases must be established. Another approach that can be adopted for faster convergence of the SCSO is based on Baker's Map function for defining the sensitivity range while searching for the prey during the exploration phase.

References

[1] Alexandre Bettinger, Armelle Brun, and Anne Boyer, "Independent Influence of Exploration and Exploitation for Metaheuristic-based Recommendations," *The Genetic and Evolutionary Computation Conference*, pp. 475-478, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[2] Vittorio Maniezzo, Marco Antonio Boschetti, and Thomas Stützle, "Single Solution Metaheuristics," *Matheuristics*, pp. 61-94, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[3] Zahra Beheshti, and Siti Mariyam Hj. Shamsuddin, "A Review of Population-based Meta-Heuristic Algorithm," *International Journal of Advances in Soft Computing and its Application*, vol. 5, no. 1, 2013. [Google Scholar] [Publisher Link]

[4] Kumeshan Reddy, and Akshay K. Saha, "A Review of Swarm-Based Metaheuristic Optimization Techniques and their Application to a Doubly Fed Induction Generator," *Heliyon*, vol. 8, no. 10, pp. 1-33, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[5] Thomas Joyce, and J. Michael Herrman, "A Review of No Free Lunch Theorems, and Their Implications for Metaheuristic Optimisation," *Nature-Inspired Algorithms and Applied Optimization*, vol. 744, pp. 27-51, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[6] Amir Seyyedabbasi, and Farzad Kiani, "Sand Cat Swarm Optimization: A Nature-Inspired Algorithm to Solve Global Optimization Problems," *Engineering with Computers*, vol. 39, pp. 2627-2651, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[7] Xing Wang, Qian Liu, and Li Zhang, "An Adaptive Sand Cat Swarm Algorithm Based on Cauchy Mutation and Optimal Neighborhood Disturbance Strategy," *Biomimetics*, vol. 8, no. 2, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[8] Farzad Kiani, Fateme Aysin Anka, and Fahri Erenel, "PSCSO: Enhanced Sand Cat Swarm Optimization Inspired by the Political System to Solve Complex Problems," *Advances in Engineering Software*, vol. 178, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[9] Zhe Sun et al., "A Path Planning Method Based on a Hybrid Sand Cat Swarm Optimization Algorithm of Green Multimodal Transportation," *Applied Sciences (Switzerland)*, vol. 14, no. 17, pp. 1-22, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[10] Xing Wang, Qian Liu, and Li Zhang, "An Adaptive Sand Cat Swarm Algorithm Based on Cauchy Mutation and Optimal Neighborhood Disturbance Strategy," *Biomimetics*, vol. 8, no. 2, pp. 1-38, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[11] Kuan Zhang et al., "Improved Multi-Strategy Sand Cat Swarm Optimization for Solving Global Optimization," *Biomimetics*, vol. 9, no. 5, pp. 1-39, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[12] Heming Jia et al., "Improved Sandcat Swarm Optimization Algorithm for Solving Global Optimum Problems," *Artificial Intelligence Review*, vol. 58, no. 1, pp. 1-68, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[13] Yanguang Cai, Changle Guo, and Xiang Chen, "An Improved Sand Cat Swarm Optimization with Lens Opposition-Based Learning and Sparrow Search Algorithm," *Scientific Reports*, vol. 14, no. 1, pp. 1-24, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[14] Ab Wahid Bhat, and Abhiruchi Passi, "A Novel SCH-VSCH Selection-Enabled Energy Efficient Optimal Path Selection in WSN using LA-FLS and BM-SCSO," *SSRG International Journal of Electrical and Electronics Engineering*, vol. 13, no. 3, pp. 125-139. [CrossRef] [Publisher Link]