A Systematic Literature Review on the Sand Cat Swarm Algorithm: Enhancements, Applications, and Future Directions

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***Abstract*—The Sand Cat Swarm Algorithm (SCSA) has emerged as a promising metaheuristic optimization technique inspired by the behavior of sand cats in their natural habitat. This paper presents a systematic literature review synthesizes the enhancement, performance comparing algorithms, applications of SCSA across various domains and future direction on SCSA enhancement. The study aims to contribute to the evolution, enhancements, applications, and performance of the Sand Cat Swarm Algorithm (SCSA), providing a comprehensive analysis of its development, performances evaluation, application, limitations, and future research opportunities in SCSA in solving optimization problems. The SLR methodology was applied, and a total of 77 scientific articles were analyzed. The analysis reveals that SCSA demonstrates competitive performance across a wide range of benchmark problems and real-world applications in engineering, computer science, and other fields such as engineering design optimization, feature selection, energy systems optimization, flexible job shop scheduling and medical diagnosis problems. This review also identifies several key strengths of SCSA, including its ability to balance exploration and exploitation effectively, its adaptability to various problem domains, and its potential for hybridization with other algorithms. Lastly, this paper outlines potential improvements and future research directions, such as the development of multi-objective SCSA variants, integration with machine learning techniques, and exploration of parallel and distributed implementations. Overall, this paper provides researchers and practitioners with valuable insights into the current state of SCSA, its practical applications, and promising avenues for future research in the field of metaheuristic optimization.**

Keywords—Sand cat swamp algorithm; sand cat optimization; optimization; metaheuristic

I. Introduction

The field of optimization has seen remarkable growth in recent years, driven by the increasing complexity of real-world problems across various domains. Among the numerous optimization techniques, nature-inspired metaheuristic algorithms have gained significant attention due to their ability to efficiently solve complex, non-linear, and multi-dimensional problems[1], [2], [3], [4]. These algorithms draw inspiration from natural phenomena, biological systems, and animal behaviors to develop robust and adaptable optimization strategies.

The Sand Cat Swamp Algorithm (SCSA) is an emerging heuristic algorithm that has recently joined the pantheon of nature-inspired optimization techniques. Inspired by the unique foraging behavior of the sand cat (Felis margarita), this algorithm simulates the exceptional auditory capabilities of these desert-dwelling felines. Sand cats possess the remarkable ability to detect low frequencies below 2 kHz, allowing them to locate prey buried beneath the sand. The SCSA leverages this natural behavior to create an innovative approach to optimization problems, potentially offering new solutions in various fields of study.

While the SCSA is a relatively new addition to the field of metaheuristic algorithms, several systematic literature reviews have been conducted on related nature-inspired optimization techniques. For instance, the study in [5] provides a comprehensive review of the Grey Wolf Optimizer, another algorithm inspired by animal behavior. Their study examined the algorithm's principles, variants, and applications across different domains, offering valuable insights into the development and potential of such nature-inspired techniques. Similarly, [6], [7], [8] conducted a broad survey of bio-inspired optimization algorithms, including ant colony optimization, particle swarm optimization, and genetic algorithms. Their review highlighted the strengths and limitations of these approaches, as well as their applicability to various problem domains. While these reviews offer a solid foundation for understanding nature-inspired algorithms, there is a notable gap in the literature regarding a comprehensive analysis of the SCSA, its developments, and applications.

The Sand Cat Swarm Algorithm (SCSA) algorithm, inspired by the hunting behavior of sand cats, has emerged as a promising metaheuristic for solving various optimization problems. Since its introduction, SCSA has garnered attention for its simplicity and effectiveness in global optimization. The algorithm mimics the sand cats' use of their acute hearing to locate prey, with each sand cat in the swarm gradually approaching better positions to catch prey [9].

Several studies have proposed enhancements to the original SCSA to address its limitations and improve its performance. For instance, researchers have developed modified versions incorporating strategies such as wandering behavior, lens opposition-based learning, elite decentralization, and crossbar approaches to enhance the algorithm's exploration and exploitation capabilities [10], [11], [12]. These improvements aim to mitigate issues like premature convergence, local optima entrapment, and slow convergence speed that are common in many metaheuristic algorithms.

The versatility of SCSA has been demonstrated through its application to a wide range of optimization problems. In engineering design, SCSA and its variants have been employed to solve constrained optimization problems, including structural design and parameter identification tasks [13], [14], [15]. The algorithm has also shown promise in addressing complex real-world challenges such as feature selection in medical diagnosis [16], [17] and power system optimization [18].

The rapid emergence of the SCSA and its potential applications in solving complex optimization problems necessitates a thorough and systematic review of the existing literature. As the algorithm continues to evolve and find new applications, it becomes crucial to consolidate the current knowledge, identify research trends, and highlight areas for future investigation. This review aims to provide researchers, practitioners, and decision-makers with a comprehensive understanding of the SCSA, its capabilities, and its potential impact on various fields, including global optimization problems in supply chain networks. The main contribution of this paper is to examine the new variants of SCSA, application SCSA in various domains and research gaps toward future works direction. The objectives behind this analysis are as follows:

- To explore the evolution of this research area, it evolved in terms of the number of publications.
- To identify the new variations and enhancements of the SCSA proposed in the literature.
- To compare the performance of the SCSA with other state-of-the-art metaheuristic algorithms across various benchmark problems.
- To compare the evaluation methods of the SCSA with other state-of-the-art metaheuristic algorithms across various benchmark problems.
- To investigate the applications of the SCSA in different domains such as engineering, computer science, and others.
- To identify the key challenges and future research directions for the SCSA in global optimization problems.

This work is mainly based on a systematic literature review (SLR) on 77 papers to synthesize existing methods and areas of study, highlighting current focuses and future research directions in enhancement of SCSA and application of SCSA in various domains. Specifically, to answer the following research question:

RQ1. How has this research area evolved in terms of the number of publications?

RQ2. What have the new variations and enhancements made to SCSA since its inception?

RQ3. How does the performance of the SCSA compare with other swamp intelligent metaheuristic algorithms in terms of convergence rate, accuracy, robustness, and computational cost?

RQ4. What are the evaluation methods of the SCSA compared with other swamp intelligent metaheuristic and the performance metrics used?

RQ5. In which domains have the SCSA been applied, and what are the outcomes and benefits of these applications?

RQ6. What are the current limitations of the SCSA, and what potential improvements and future research directions can be identified?

This work aims to present critical aspects of SCSA, from its enhancement to practical applications, offering valuable insights for researchers and practitioners. The key contributions of this research are:

- Examination of the evolution of SCSA-related research, offering insights into the algorithm's growing adoption and adaptation in the scientific community.
- Identification and analysis of new variations and enhancements to the SCSA since its inception, highlighting the algorithm's development and refinement over time.
- Comparative performance evaluation of SCSA against other swarm intelligence metaheuristic algorithms, assessing its effectiveness in terms of convergence rate, accuracy, robustness, and computational cost.
- Identification of the evaluation methods of the SCSA compared with other swamp intelligent metaheuristic algorithm.
- Exploration of various domains where SCSA has been applied, showcasing its versatility and the benefits it brings to different fields of study.
- Critical assessment of SCSA's current limitations, coupled with recommendations for potential improvements and future research directions, paving the way for further advancements in this area.

These contributions collectively enhance our understanding of the SCSA, its capabilities, and its potential for future development and application in diverse fields of study.

The remainder of this work is organized as follows: Section II describes the literature review; Section III describes the methodology adopted for the literature review; Section IV explains the results and analysis; and Section V draws the conclusions.

II. Literature Review

A. *Swarm Intelligence (SI)*

Single-solution based metaheuristics, also known as trajectory methods, emphasize exploitation, while key population-based metaheuristics prioritize exploration [19]. A single-solution approach begins with a single solution and iteratively operates to discover the best optimal single solution. Whereas population-based solutions begin with a collection of solutions rather than just one answer. Swarm intelligence (SI) is an intelligent approach to addressing optimization issues under this class. SI draws inspiration from the collective behavior of social insect colonies and other animal groups. Some examples are Ant colony Algorithm, Particle Swarm Algorithm, Bacterial foraging Algorithm, Bee Colony Algorithm, Artificial Immune Systems, and Biogeography-Based Algorithm are all examples of population-based algorithm techniques.

Sand Cat Swamp Algorithm (SCSA) was introduced by [9] as a nature-inspired metaheuristic for the solution of hard combinatorial optimization problems also categorized as SI algorithm. SCSA operates as population-based metaheuristic algorithm which can be divided into three main stages namely initialization stage, exploration stage, and exploitation stage. The balance between exploration and exploitation phase is crucial in any SI algorithm to ensure the operation of this algorithm is well performed in various NP-Hard problems.

B. SCSA Initilization

The Sand Cat Swamp Algorithm (SCSA) begins with the initialization phase, which is crucial to produce high quality of initial population. Since SCSA is categorized under population-based method, in this stage, a population of sand cats is generated, each representing a potential solution to the optimization problem. As SI group algorithm, the algorithm initializes the following key parameters to perform the optimization processes:

- Population size: The number of sand cats in the swamp denotes as N size.
- Maximum number of iterations: The number of algorithm running as termination criterion for the algorithm.
- Problem dimension: The number of variables in the optimization problem represents how big the problem is.
- Search space boundaries: The upper and lower limits for each variable represent the boundaries of searching area.

Each sand cat is randomly positioned within the search space, with its location vector representing a candidate solution. The related structure is defined as a vector as shown in [9]. In a dimensional optimization problem, a sand cat is a 1 × d array representing the solution to the problem. Each of the variable values (x1, x2, …, xd) is a floating-point number. Here every x must be located between the lower and upper boundaries (∀xi ∈ [lower, upper]). To start the SCSA algorithm, first, a candidate matrix is created with the sand cat population according to the size of the problem (Npop × Nd), (pop = 1,,, n).

In addition, the fitness cost of each sand cat is obtained by evaluation of defined fitness function. This function defines the relevant parameters of the problem, and the best values of the parameters (variables) will be obtained by the SCSA. A value for the corresponding function will be output from each sand cat. When an iteration is finished, the sand cat with the best cost in that iteration is chosen so far, the best solution (if there was no answer as good as this in the previous iterations) and the other sand cats try to move towards this best-chosen cat in the next iteration. Because the best solution in each iteration can represent the cat closest to the prey. If a better solution is not found in the next iterations, the solution for that iteration is not unnecessarily stored in memory and this ensures efficient use of memory.

C. SCSA Exploration

The exploration phase of the SCSA mimics the sand cat's behavior of searching for prey in a wide area. This stage aims to diversify the search and explore the solution space broadly. Sand cats use their exceptional hearing to detect low-frequency sounds. In the algorithm, this is simulated by generating random movements in the search space, allowing sand cats to "listen" for better solutions. To search for prey, it is assumed that the sand cat sensitivity range starts from 2 kHz to 0 and guided by the parameter rG (2). The search space is randomly initialized between the defined boundaries. In the searching step, position updating of each current search agent is based on a random position. In this way, the search agents able to explore new spaces in the search space. The sensitivity range for each sand cat is different, to avoid the local optimum trap is defined as r.

In addition, the variable controlling the phase transition is defined as R. The position of the search phase is updated randomly by (1), while a new search space is opened. Here, SM is the constant used to characterize the sand cat hearing and is set to 2, iterc and itermax denote the current and maximum number of iterations, respectively. Posbc and Posc are defined as the best candidate position and the current position. As sand cats explore the swamp, the algorithm keeps track of the global best solution found so far. This information is used to guide the search process in subsequent iterations as shown in Eq. (3) and Eq. (4).

$$R = 2 \times r_G \times \text{rand}(0,1) - \text{r}_\text{G} \tag{1}$$

$$r_G = S_M - \left(\frac{2 \times S_M \times iter_c}{iter_{max}}\right) \tag{2}$$

$$r = r_G \times rand(0,1) \tag{3}$$

$$Pos_{(t+1)} = r.(Pos_{bc}(t) - rand(0,1).Pos_c(t)) \tag{4}$$

D. SCSA Exploitation

The exploitation phase represents the sand cat's behavior when it has located a promising area and begins to focus its search more intently. This phase aims to refine the current best solutions and converge towards the optimal solution. An angle is randomly selected between [0,360] using the roulette wheel selection algorithm to simulate the movement direction of the sand cat. This allows the sand cat to explore the search area and approach its prey from various directions which can produce diverse solution options and reduce the risk of missing potential options.

Next, the positions of sand cats are updated based on a combination of their current position, the global best position, and a random component. This update rule balances the exploitation of known good solutions with the exploration of new areas. In the attack phase, the position of each sand cat is updated according to Eq. (5) and Eq. (6) where Pos_{rnd} denotes the position of the candidate sand cat randomly generated according to any two sand cats, Pos_b is the position of the current optimal solution. Finally, the transition between the above two modes is controlled by R in Eq. (1). When the value of $|R| > 1$, the sand cat performs the search phase shown in Eq. (4) to find prey by moving over a longer distance (searching for new solutions at a global range). When $|R| \leqslant 1$, the sand cat enters the exploitation phase shown in Eq. (6) to search in a small range to attack the prey.

$$\overrightarrow{Pos_{(rnd)}} = \left| rand\ (0,1) \cdot \overrightarrow{Pos_b}(t) - \overrightarrow{Pos_c}(t) \right|,$$

$$\overrightarrow{pos(t+1)} = \overrightarrow{Pos_b}(t) - \vec{r} \cdot \overrightarrow{Pos_{rnd}} \cdot cos(\theta) \tag{5}$$

$$\overrightarrow{X(t+1)} = \begin{cases} \overrightarrow{Pos_b(t)} - \overrightarrow{Pos_{rnd}} \cdot cos(\theta) \cdot \vec{r} & |R| \leq 1; exploitation \\ \vec{r} \cdot \left(\overrightarrow{Pos_{bc(t)}} - rand(0,1) \cdot \overrightarrow{Pos_{c}(t)} \right) & |R| > 1; exploration \end{cases} \tag{6}$$

Throughout both the exploration and exploitation phases, the algorithm continuously evaluates the fitness of new solutions, updating the global best solution when improvements are found. The process iterates until a termination criterion is met, such as reaching the maximum number of iterations or achieving a satisfactory solution quality.

III. Methodology

This section explains the literature review process using the Systematic Literature Review (SLR) method. This methodology, inspired by prominent machine learning literature surveys [19] comprises three main stages: Planning, Conducting, and Reporting. This structure ensures a comprehensive and methodical approach to reviewing literature, helping researchers to systematically gather, evaluate, and synthesize existing research on a specific topic.

A. *Planning the SLR*

In this stage, three activities are involved. First, identify the main objective of the review by formulating research questions (RQs), which focus to determine the gaps in current knowledge and justifying why this SLR is necessary. Second, developing criteria and procedures where guidelines for conducting the review are established, including search terms, databases to be used, and initial inclusion/exclusion criteria. Lastly, evaluating the criteria and procedures, where at this step the testing and refine, the established criteria is done to ensure they are effective and appropriate in fulfilling the research objectives. Having the research question established, the search terms based on the research question are:

- Sand Cat Swarm Algorithm keywords: “Sand Cat Swamp Algorithm”,” Sand Cat Optimization”, “SCSA Optimization”.
- Review keywords: “survey”, “review”, “overview”, “literature”, “bibliometric”, “challenge”,“trend”, research direction.

B. *Conducting the SLR*

In the second phase of the Systematic Literature Review (SLR), the focus is on conducting an extensive search and selecting relevant literature. This involves identifying pertinent studies, extracting relevant information, and synthesizing the findings to obtain a comprehensive understanding of the research topic. As shown in Fig. 1, the flow diagram illustrating the selection process conducted from the initial data collection in chosen databases using the inclusion and exclusion criteria specified in Table I, PRiSMA flow diagram is used to represent the activities taken to conduct the analysis.

TABLE I. Criteria for Study Selection

Inclusion Criteria	Exclusion Criteria
Publications written in English	Research not written in English
Publications starting from 2022 until 2024 (Dicember)	Research published before 2022
Publications that truly focus on the keywords: Sand Cat Swarm Algorithm / optimization	Research that discusses topics other than SCSA Algorithm/optimization
Publications that increasingly focus on the SCSA, specifically discussing the new variants, challenges and future work of SCSA	Publications that not focus on the SCSA, specifically not discussing the new variants or challenges or future work of SCSA
Open access documents	Not an open access documents

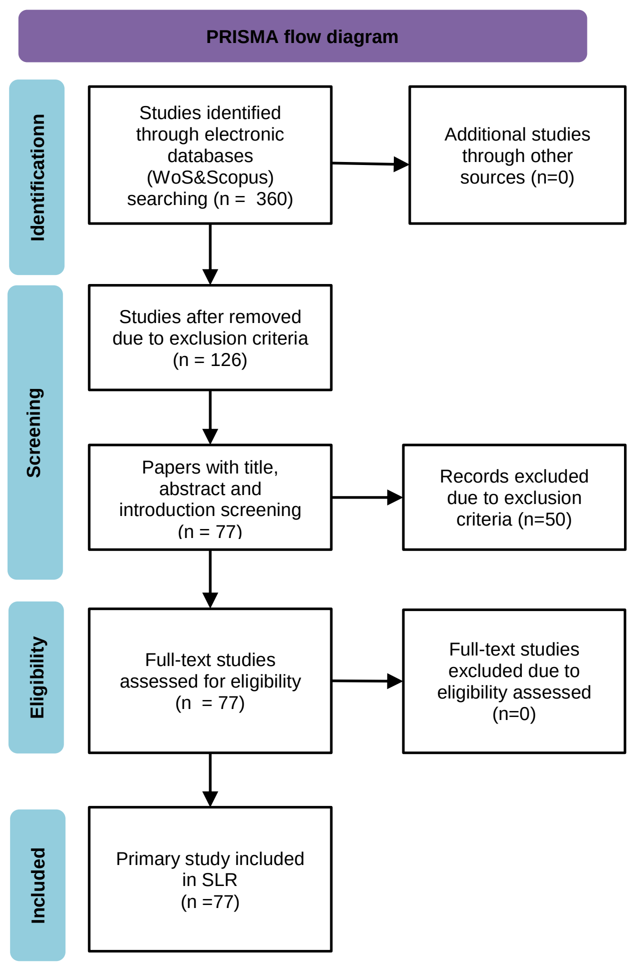

Fig. 1. Selection process of primary studies using PRISMA flow diagram.

C. *Reporting*

The final stage of the Systematic Literature Review (SLR) involves reporting and presenting the findings in a structured and transparent manner. The results are systematically documented and analyzed based on the research questions established during the initial phase of the study, ensuring clarity, relevance, and alignment with the review's overall objectives.

In this study, the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework was systematically applied to ensure a transparent, reproducible, and rigorous methodology. The structured approach included identification, screening, eligibility assessment, and inclusion of relevant studies, guided by predefined criteria to maintain accuracy and reliability. By following PRISMA guidelines, the selection process minimized bias and ensured a comprehensive and well-documented synthesis of existing literature. This methodological approach strengthens the validity of the findings and provides a robust foundation for future research and practical applications.

IV. Results and Analysis

Based on the outlined SLR objectives, this section will present the findings for the specified research questions to address each SLR objective.

A. *RQ1. How has this Research Area Evolved in Terms of Number of Publications?*

The analysis provides an insightful overview of research output spanning the period 2022 to 2024 to describe the evolvement of SCSA studies since 2022. The result encompasses 126 documents sourced from 98 journals, books, and related publications, reflecting a diverse range of scholarly contributions but only 77 articles was selected to be analyzed. Notably, the annual growth rate of research activity stands at an impressive 28.92%, signifying a substantial increase in the adoption and exploration of the subject during this timeframe. The documents exhibit an average age of 1.21 years, indicating the recency and relevance of the included works. However, the relatively low average citation rate of 0.6056 citations per document suggests either a nascent field or limited citation impact thus far. Interestingly, no references are explicitly listed within the dataset.

Overall, the bibliometric results portray a dynamic and evolving research landscape characterized by rapid growth, strong collaborative efforts, and a focus on high-quality journal publications. However, the lack of international co-authorship and limited citation impact suggest opportunities for fostering global partnerships and enhancing scholarly influence in future research endeavors.

TABLE II. Number of Publications over the Years

Year of Publication	2022	2023	2024
No. of Publication	7	30	89

Table II presents the distribution of publications on the Sand Cat Swamp Algorithm across a three-year period from 2022 to 2024. In 2022, the field experienced a modest output, with only seven articles published, suggesting a nascent stage of exploration. This number significantly increased to 30 articles in 2023, marking a noteworthy growth in scholarly contributions and interest. The trend reached its peak in 2024, with an impressive 89 articles published, signifying a period of heightened research activity and substantial engagement within the scientific community. This temporal analysis illustrates a rapid rise in research output between 2022 and 2024, possibly driven by growing interest and developments in the field. Overall, the data provides a clear depiction of the dynamic nature of annual scientific production, reflecting both growth opportunities and challenges in sustaining research momentum.

TABLE III. Top 10 Most Relevant Sources

Sources	No. of Articles
IEEE Access	7
Biomimetics	5
Scientific Reports	5
Mathematics	4
Alexandria Engineering Journal	3
Applied Sciences-Basel	3
Electronics	3
Energies	3
Expert Systems with Applications	3
International Journal of Electrical Power & Energy Systems	3

The analysis of the most relevant sources in Sand Cat Swarm Algorithm (SCSA) research reveals an interesting citation pattern among the top 10 most influential sources. As shown in Table III, IEEE Access emerges as the leading publication platform, contributing 7 articles, indicating its role as a primary venue for disseminating high-impact studies on SCSA. This is followed closely by Biomimetics and Scientific Reports, each with 5 articles, highlighting their relevance in publishing research that bridges bio-inspired optimization and computational intelligence. Additionally, Mathematics contributes 4 articles, reinforcing the importance of mathematical modeling in metaheuristic algorithm analysis and development. The remaining six sources, each contributing 3 articles, represent a diverse range of journals, covering applications in engineering, computation, and optimization methodologies.

This distribution of publications offers valuable insights into the preferred journals and conferences for SCSA-related research, guiding future researchers in selecting relevant references and identifying potential publication avenues. The observed concentration in specific journals suggests that certain academic communities are more actively engaged in advancing and refining SCSA, further emphasizing the growing impact and recognition of this algorithm in the field.

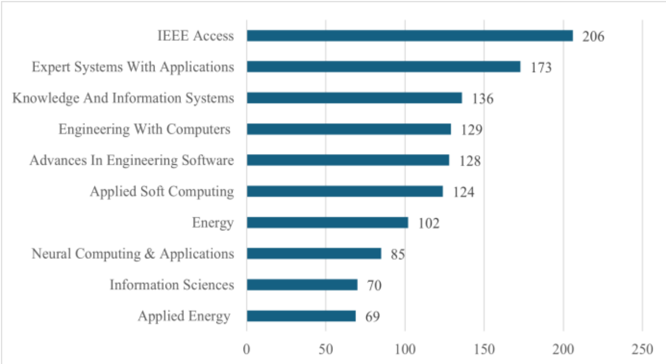

Fig. 2. The top 10 highest total citation of publications.

Fig. 2 shown the top 10 highest total citations of research publications across top ten academic journals. IEEE Access exhibits the highest publication count (206), followed by Expert Systems with Applications (173). Other journals with substantial contributions include Knowledge and Information Systems (136), Engineering with Computers (129), Advances in Engineering Software (128), and Applied Soft Computing (124). The remaining journals, Energy (102), Neural Computing & Applications (85), Information Sciences (70), and Applied Energy (69), report comparatively lower publication counts. This distribution reflects the research trends in fields such as artificial intelligence, computational engineering, supply chain and applied sciences, offering insights into the preferred publication venues for scholars in these disciplines.

This analysis contributes valuable insights for young researchers, highlighting potential avenues for contributing new knowledge related to the SCSA and metaheuristic algorithms in general. The diversity of publication venues and total of citations underscores the algorithm's broad applicability and may encourage interdisciplinary research approaches in this rapidly evolving field.

B. *RQ2. What are the New Variations and Enhancements made to the SCSA since its Inception?*

The Sand Cat Swarm Algorithm (SCSA) is designed to find effective solutions in complex problem spaces. However, to improve its performance and expand its application, several enhanced versions of SCSA have been developed. These new variants focus on balancing two critical processes: exploration (searching new areas) and exploitation (refining known areas). Innovations include introducing advanced search strategies, combining SCSA with other algorithms, adapting it for specific problem types, and adding learning and chaotic behaviors to improve its efficiency. These enhancements enable SCSA to solve a wider range of problems more effectively and make it a versatile tool for complex, real-world applications.

1) Enhanced exploration and exploitation balance: Balancing exploration and exploitation are essential for efficient optimization. For example, [12] introduces a new variant of SCSA which has several mechanisms to optimize this balance, including the Triangle Walk (TW) and Levy Flight Walk (LFW) strategies, which are well-known for their exploratory capabilities. Additionally, the algorithm uses a nonlinear period adjustment mechanism to control the intensity of search behaviors dynamically, adjusting exploration and exploitation phases based on search requirements. Furthermore, a dynamic exponential factor is incorporated to fine-tune the transition between exploration and exploitation over time. Together, these features allow this variant to adaptively navigate complex landscapes, enhancing its ability to locate optimal solutions with fewer iterations.

2) Hybridization with other algorithms: Hybrid algorithms can effectively blend the strengths of multiple approaches, and several hybridizations of SCSA have been developed to address its limitations. For instance, some versions [20], [22], [32] combine SCSA with the Whale Optimization Algorithm (WOA) to enhance convergence, while others integrate it with the Sine Cosine Algorithm (SCA) for improved exploratory behavior. In another instance, the Arithmetic Optimization Algorithm (AOA) has been incorporated to refine the balance between global and local searches. These hybrid approaches allow SCSA to tackle a broader range of optimization problems with enhanced performance, as the combination of strategies improves both efficiency and effectiveness in reaching high-quality solutions.

3) Adaptation for specific problem domains: SCSA has been tailored for specific application domains by modifying the algorithm's structure and parameters. For example, adaptations have been made [24], [27] for software module clustering, where SCSA is adjusted to address the complexities of grouping related software modules. In another application, the algorithm has been customized for optimizing Proportional-Integral-Derivative (PID) controllers, a task requiring precise tuning of parameters to achieve stability in dynamic systems. Additionally, a binary version (bSCSA) has been developed for feature selection tasks, enabling SCSA to select optimal subsets of features in high-dimensional spaces. Other than that, SCSA also indicates well performance in solving Flexible Job Shop Scheduling (FJSP) problem as FJSP is common discrete optimization problems [20]. These domain-specific adaptations highlight SCSA's versatility, making it a valuable tool for solving diverse real-world problems, namely continuous and discrete problems.

4) Integration of learning mechanisms: Integrating learning mechanisms into SCSA allows the algorithm to intelligently guide its search process, reducing the likelihood of becoming trapped in local optima. Techniques such as Lens Opposition-Based Learning (LOBL), pseudo-opposition and pseudo-reflection learning, and Pinhole-Imaging Opposition-Based Learning (PIOBL) have been embedded into SCSA [21] to enhance solution quality. These strategies improve search efficacy by using "opposition-based" concepts that explore the search space from opposite perspectives, thus offering a more comprehensive view of potential solutions. This improved adaptability enables SCSA to achieve better convergence rates and a higher likelihood of finding globally optimal solutions.

5) Multi-objective optimization: To expand SCSA's capabilities in, variants have been created [18], [22] that address problems with conflicting objectives. These adaptations, like Multi-Objective SCSA (MO-SCSA), are designed for complex scenarios, such as electric vehicle (EV) charging and discharging optimization, where multiple goals must be met concurrently. Additionally, some variants incorporate Pareto optimization, enabling SCSA to generate a set of Pareto-optimal solutions for multi-objective problems. This adaptation allows users to select trade-offs among competing objectives, thus extending the algorithm's utility for complex, multi-dimensional problem domains.

6) Chaotic behavior integration: Incorporating chaotic behavior into SCSA can significantly enhance its search capability, allowing for better exploration of complex solution spaces. Chaotic Sand Cat Swarm Optimization (CSCSA) is an example of such an enhancement, where chaotic mappings (e.g., tent mapping) are used to introduce randomness into the algorithm's search strategy [23]. By alternating between chaotic patterns and regular search behaviors, this variant improves the algorithm's ability to escape local optima. In another version, the hybrid of chaotic SCO and pattern search (CSCPS) blends chaos theory with pattern-based search to further optimize exploration [24]. This integration of chaos helps SCSA to achieve a more robust search process, ultimately leading to higher-quality solutions in challenging optimization landscapes.

In conclusion, the Sand Cat Swarm Optimization algorithm has demonstrated its potential as a versatile and effective optimization technique across various domains. Ongoing research focuses on enhancing its performance, adapting it to different types of problems, and exploring novel hybrid approaches to leverage its strengths in combination with other techniques.

C. RQ3. How does the Evaluation of the SCSA Compare with other Swamp Intelligent Metaheuristic Algorithms?

Recent enhancements to the Sand Cat Swarm Optimization (SCSA) algorithm and its variants have led to significant advancements in optimization performance. These developments primarily focus on improving key metrics such as convergence rate, accuracy, robustness computational cost, and others problem specific metrics. Various studies have introduced new variants of SCSA, each optimized for specific problems, including balancing fuel costs, emission reduction, and customer satisfaction, or providing high adaptability in global search performance. This review highlights the evaluation method used in evaluating performance of these SCSA variants.

1) Enhanced convergence and accuracy: Many SCSA variants demonstrate notable improvements in convergence rate and optimization accuracy, consistently outperforming other metaheuristic algorithms. For instance, the CSCPS variant excels in convergence speed, achieving optimal results quickly and efficiently, with a lower computational cost compared to traditional methods [24]. Similarly, ISCOA is particularly effective in minimizing fuel costs and emissions, showing enhanced accuracy and suitability for practical optimization scenarios [25]. Other algorithms like CWXSCSA [11] and ISCSA [26] emphasize not only accuracy but also the capability to escape local optima, allowing them to refine solutions with higher precision.

2) Robustness across applications: SCSA variants have shown exceptional robustness across diverse applications, including optimization problems in engineering, environmental management, and logistics. COSCSA, for example, maintains stability while achieving high accuracy and rapid convergence, making it resilient in complex problem environment [27]. Additionally, IMSCSA 's robust performance is evident in its ability to handle diverse optimization tasks with minimal deviation across multiple test scenarios [15]. In practical applications like delivery cost reduction and carbon emission optimization, SCSA and its variants demonstrate robustness and consistency in maintaining high performance, even when faced with fluctuating problem variables.

3) Reduced computational costs: To ensure practicality in computationally intensive tasks, some SCSA variants emphasize reduced computational costs while maintaining strong performance. For instance, MSCSA optimally balances global and local search operations, lowering the algorithm's computational demands [15]. Likewise, bSCSA has been noted for its cost-effectiveness, which allows it to perform robustly in high-dimensional problem spaces while avoiding unnecessary computational overhead [17]. By efficiently utilizing resources, these variants are well-suited for applications requiring quick, resource-efficient solutions.

4) Exploration and exploitation balance: Improved exploration and exploitation balance is a defining feature of many recent SCSA variants. BMSCSO, for example, achieves a delicate balance, which allows it to avoid local optima and maintain adaptive performance in both global and local searches [17]. The DGS-SCSO variant further demonstrates this balance, showcasing superior convergence rates and stability in complex landscapes by dynamically managing exploration and exploitation phases [21]. This ability to flexibly navigate both broad and fine-grained search spaces enhance these algorithms' adaptability and effectiveness across varied optimization tasks, as evidenced by the consistently high performance of enhanced SCSA variants across different contexts.

In summary, the SCSA and its variants have shown exceptional performance improvements across critical optimization metrics. These versions demonstrate faster convergence, higher accuracy, and robustness, proving adaptable to various complex problems. The advancements in exploration-exploitation balance and computational efficiency make SCSA variants reliable for tackling a wide range of optimization challenges, outperforming traditional metaheuristic approaches in both theoretical and practical applications.

D. RQ4. What are the Evaluation Methods of the SCSA Compared with other Swamp Intelligent Metaheuristic and the Performance Metrics Used?

1) Evaluation method: The assessment method is essential for reviewing a new form of a metaheuristic algorithm, as it dictates the algorithm's usefulness, efficiency, and dependability in addressing optimization challenges[28]. Evaluating the Sand Cat Swarm Algorithm (SCSA) and its variants have consistently employed three methods namely benchmark test function, case study and compare with wide range of competing algorithms. These three methods employed a wide range of performance metrics based on three different types of measurement metrics such as statistical metrics, non-statistical metric and problem specific metrics.

a) Benchmark test function: These benchmark functions typically include standard optimization problems and specialized test suites designed for evaluating metaheuristic algorithms. There are several sets of benchmark instances that are widely used in the literature:

- Standard benchmark functions: These comprise well-known optimization problems such as Sphere, Rosenbrock, Ackley, and others. These functions are widely used due to their known characteristics and ability to test different aspects of algorithm performance [17], [26].
- CEC (Congress on Evolutionary Computation) benchmark suites: Multiple studies referenced CEC test functions, particularly CEC2014, CEC2017, CEC2019, and CEC2020 [11], [27]. These suits are specifically designed for comparing evolutionary and swarm intelligence algorithms on various problem types.
- Real-world engineering problems: Some researchers incorporated practical engineering optimization problems to evaluate algorithm performance in more applied contexts [24], [29], [30].

Researchers generally seek out the original articles describing the CEC benchmark suites or utilize known implementations found in optimization libraries to access these benchmark functions. Standard functions are extensively accessible in mathematical software programs or can be implemented using their mathematical formulations in libraries such as Python and R. The selection of benchmark functions typically hinges on the facets of algorithm performance under assessment, like convergence rate, solution precision, or capacity to navigate diverse problem environments.

b) Case study: Based on the case studies used to compare SCSA performance, several key themes emerge. Engineering Optimization Problems feature prominently, with applications ranging from hydraulic turbine design to vehicle safety optimization. Energy Systems and Renewable Energy form another significant theme, focusing on wind farm optimization and integrated energy systems with electric vehicles [31].

Industrial and Manufacturing Applications highlight SCSA 's practical relevance in areas like e-commerce logistics and equipment operation optimization [32].

Computer Science and Machine Learning Applications include benchmark tests, intrusion detection, and cognitive radio networks. Medical and Biological Applications showcase SCSA 's potential in areas such as brain tumor diagnosis and power transformer fault detection. Benchmark Functions and algorithm comparisons are used to rigorously evaluate SCSA against established standards and other optimization techniques.

This diverse range of themes as shown in Table IV, SCSA's versatility and broad validity of applicability across various scientific and practical domains, from engineering and energy to environmental science motivates all researcher to contribute more critical research on SCSA in the future.

a) Competing algorithm: The research on enhancement of Sand Cat Swarm Algorithm (SCSA) encompasses a diverse range of comparative algorithms, reflecting the multifaceted nature of metaheuristic optimization. The comparison spectrum includes nature-inspired algorithms like Whale Optimization and Grey Wolf Optimization, evolutionary approaches such as Genetic Algorithms, swarm intelligence techniques including Artificial Bee Colony and Firefly Algorithm, and physics-based methods like the Gravitational Search Algorithm as shown in Table V. Researchers have also benchmarked SCSA against hybrid and improved versions of existing algorithms, machine learning-based approaches, and recently developed optimizers.

This comprehensive comparison strategy allows for a thorough evaluation of SCSA's performance across various optimization contexts, highlighting its strengths and potential areas for improvement relative to both established and emerging techniques in the field.

TABLE IV. COMPREHENSIVE OVERVIEW OF THE VARIOUS CASE STUDIES USED TO EVALUATE SCSA

Theme	Case Study	Description	Author(s)
Engineering Optimization Problems	Elbow draft tube optimization	Optimization design of the elbow draft tube of the hydraulic turbine	[29]
	Pressure Vessel Design Problem	Engineering design optimization	[13]
	Car Crashworthiness Design Problem	Optimization of vehicle safety design	[14]
	Various engineering cases	Three-bar truss, Tension/compression spring, Cantilever beam, Pressure vessel, Speed reducer, I-beam vertical deflection, Piston lever	[33]
Energy Systems and Renewable Energy	Wind and PV farm optimization	Optimization of energy storage allocation for wind farm and photovoltaic farm in China	[12]
	Wind farms	Onshore wind farm in Austria and offshore wind farm in Denmark	[22]
	Integrated energy system	Optimal scheduling model for integrated energy system with electric vehicles	[32]
	Intrusion detection	Feature selection for improved intrusion detection	[16]

Theme	Case Study	Description	Author(s)
Computer Science and Machine Learning Applications	Malicious User Detection	Optimal Deep Learning for Spectrum Sensing in Cognitive Radio Networks	[34]
	Cognitive Radio Sensor Network	Application in wireless sensor networks	[35]
Benchmark Functions and Algorithm Comparisons	CEC test suites	CEC2017 and CEC2020 benchmark functions	[27]
	Multiple algorithm comparison	Comparison with Sine Cosine Algorithm, Circle Search Algorithm, Salp Swarm Algorithm, etc.	[9]

TABLE V. COMPETING ALGORITHM BASED ON A CATEGORY OF METAHEURISTIC ALGORITHM

Theme	Algorithms	References
Nature-Inspired Algorithms	Whale Optimization Algorithm (WOA)	[30], [36]
	Grey Wolf Optimization (GWO)	[26], [33], [35]
	Particle Swarm Optimization (PSO)	[10], [25], [33], [35]
Evolutionary Algorithms	Genetic Algorithm (GA)	[17], [33], [37]
Swarm Intelligence Algorithms	Artificial Bee Colony (ABC)	[35]
	Ant Colony Optimization (ACO)	[38]
	Firefly Algorithm (FA)	[25], [35]
Physics-Inspired Algorithms	Gravitational Search Algorithm (GSA)	[12], [23]
	Black Hole Algorithm (BHBO)	[23], [39]
	Sine Cosine Algorithm (SCA)	[14], [17], [21]
Hybrid and Improved Algorithms	Hybrid Whale Optimization Algorithm-Simulated Annealing (WOA-SA)	[11]
	Chaotic Grey Wolf Optimizer (CGWO)	[40]
Machine Learning-Based Algorithms	Support Vector Machine (SVM)	[18], [27], [41]
	Artificial Neural Network (ANN)	[27]
	Long Short-Term Memory (LSTM)	[27], [31]
Recently Developed Algorithms	Harris Hawks Optimization (HHO)	[14], [42]
	Dung Beetle Optimizer (DBO)	[42], [43]
	Aquila Optimizer (AO)	[42]

In conclusion, these themes collectively demonstrate that SCSA is being compared against a wide range of metaheuristic algorithms, spanning from well-established techniques to recent innovations. This comprehensive comparison approach allows researchers to thoroughly assess the performance and capabilities of SCSA in various optimization contexts. The diversity of competing algorithms also reflects the dynamic nature of the field and the continuous development of new optimization techniques. More research comparing SCSA performance with new metaheuristic algorithm are encouraged to obtain the performance of SCSA in solving various optimization problems.

2) Performance metrics: The selection of performance metrics is crucial in effectively evaluating and comparing different approaches to verify the algorithm performance and solution quality in optimization problems [44]. This importance spans across various optimization scenarios, from simple to complex. In single-objective optimization problems (SOPs), the goal is straightforward: to find an optimal solution that either minimizes or maximizes a single objective. This simplicity allows for relatively easy comparison between solutions, with the one yielding better fitness clearly superior. However, as optimization problems become more complex, such as in multi-objective scenarios, the landscape becomes significantly more intricate [28]. The presence of multiple, often conflicting objectives introduces a layer of complexity that makes evaluating solution superiority far more challenging. In these cases, various approaches often yield a set of optimal solutions, each considered equivalent under concepts like Pareto dominance [45], [46], [47], [48].

This complexity underscores the critical need for sophisticated performance metrics across all types of optimization problems. While it's relatively straightforward to compare individual solutions in SOPs, providing a quantitative comparison of different optimal solution sets in more complex optimization scenarios is far from trivial. The challenge lies in developing metrics that can effectively capture and quantify the quality of these diverse solution sets, considering factors such as diversity, convergence, and the balance between different objectives or constraints.

Therefore, the careful selection and design of performance metrics become paramount in general optimization. These metrics must be capable of providing meaningful comparisons between different approaches, guiding researchers and practitioners towards more effective optimization strategies. This emphasizes the importance of ongoing research into performance metric development, particularly for complex optimization scenarios, to ensure that the evaluation of different optimization approaches is both comprehensive and insightful.

Based on the analysis indicates that researchers have chosen a diverse range of performance metrics in their research. These evaluation metrics collectively address the metric used to analyze the performance of SCSA by providing a comprehensive comparison of SCSA with other metaheuristic algorithms. They cover various aspects of algorithm performance as listed below.

- Convergence Rate: Many studies focus on the convergence rate of SCSA compared to other algorithms. This metric is crucial as it indicates how quickly the algorithm reaches an optimal or near-optimal solution. For example, study by [27] noted that the SCSA algorithm converged to the optimal result faster than the Particle Swarm Optimization (PSO) algorithm.
- Accuracy: Accuracy is a widely used metric across various studies. It measures how close the algorithm's

solution is to the true optimal solution or how well it performs in classification tasks. For instance, study by [26] reported that the SCSA algorithm achieved the highest classification accuracy of 93.96% compared to other algorithms.

- Robustness: Robustness is evaluated in several studies to assess how well the algorithm performs across different problems or under varying conditions. Study by [27] noted that the SCSA algorithm effectively avoided falling into local extremum, indicating robustness.

- Computational Cost: The computational cost or efficiency of the algorithm is another important metric. This metric is used to evaluate the algorithm's practicality for real-world applications. For example, study [26] reported that the SCSA algorithm selected the fewest features in the least computational time of 1.91 seconds.

- Solution Quality: Some studies use specific metrics to measure the quality of solutions, such as Mean Square Error (MSE), RMSE, and R-squared (R2). These metrics provide a quantitative measure of how well the algorithm's solutions fit the problem requirements.

- Statistical Measures: Several studies employ statistical measures to compare algorithm performance, including mean, median, standard deviation, and statistical tests like the Wilcoxon rank sum test [23], [49]. These measures provide a more rigorous comparison of algorithm performance across multiple runs or problem instances.

- Problem-Specific Metrics: Some studies use metrics specific to the problem domain. For example, in classification tasks, metrics like precision, recall, F1-score, sensitivity, and specificity are used. In energy optimization problems, metrics like TEPL and TEVD are employed [31].

- Convergence Curves: Visual representations of algorithm performance, such as convergence curves [23], are used to illustrate how quickly and effectively algorithms approach optimal solutions over time.

- Feature Selection Performance: For feature selection problems, metrics such as the number of selected features [26] are used alongside accuracy to evaluate the algorithm's effectiveness in identifying relevant features while maintaining high performance.

- Specific Optimization Performance: Some studies use the best value, worst value, and mean value [50] to evaluate the overall optimization performance of the algorithms across multiple runs.

The comparative analysis demonstrates that the new variants of the Sand Cat Swarm Algorithm (SCSA) exhibit superior performance compared to competing algorithms as shown in Table VI. The enhancements introduced in these variants contribute to improved solution quality, better convergence rates, and enhanced robustness in tackling optimization problems. These findings highlight the effectiveness of the proposed modifications in strengthening SCSA's capability, making it a competitive choice for complex optimization tasks.

In conclusion, in single-objective optimization, evaluating solutions is straightforward since a single best outcome can be identified. However, in multi-objective optimization, conflicting objectives create a more complex landscape where multiple solutions are considered optimal under Pareto dominance [28]. This complexity necessitates specialized evaluation techniques to determine trade-offs and balance competing objectives effectively. Choosing the right evaluation method and performance metrics is crucial in ensuring the reliability and validity of the optimization process. Proper metrics, such as convergence indicators, diversity measures, and statistical tests, help assess solution quality, guide algorithm improvements, and ensure meaningful comparisons across different optimization approaches.

E. RQ5. In Which Domains has the SCSA been Applied, and What are the Outcomes and Benefits of these Applications?

The Sand Cat Swarm Algorithm (SCSA) algorithm has found diverse applications across various domains, demonstrating its versatility and effectiveness in solving complex optimization problems. This analysis highlights the primary application domains of SCSA.

One significant application area of SCSA is in renewable energy systems, particularly in optimizing parameters for solar (PV) models. For instance, a study by [12] proposed a Brownian random walk-based SCSO for parameter identification in various PV mathematical models, showcasing its effectiveness in enhancing the accuracy of parameter estimation. Similarly, the SCSA has been utilized in optimizing the efficiency of photovoltaic thermal systems through advanced artificial intelligence techniques [56], [57], [58] . These studies underline the algorithm's capability to improve energy management and performance in renewable energy applications.

Another prominent domain is in unmanned aerial vehicle (UAV) path planning. A study by [59], [60] demonstrated that an SCSA-based approach significantly improved the convergence speed and accuracy of UAV path planning, indicating its potential for real-time applications in dynamic environments. Furthermore, the research emphasizes the algorithm's utility in enhancing UAV operational efficiency. These applications illustrate the effectiveness of SCSO in optimizing navigation and operational strategies in aerial systems.

SCSA also plays a crucial role in the field of sensor networks, particularly in underwater wireless sensor networks (UWSNs). The multi-objective SCSA has been employed for energy-optimized cluster head selection, which is vital for efficient data transmission and monitoring in underwater environments [60]. This study reflects the importance of SCSA in enhancing the performance and reliability of sensor networks.

In the realm of machine learning and data analysis, SCSA has been effectively integrated into various models to optimize performance. For instance, the algorithm has been utilized to enhance the accuracy of fault diagnosis in rolling bearings by optimizing support vector machine parameters [61]. These applications indicate the SCSA potential in optimizing machine learning models and improving data-driven decision-making processes.

A study by [20] proposes an improved Sand Cat Swarm Optimization (ISCSO) algorithm for solving the Flexible Job Shop Scheduling Problem (FJSP) also known as example of discrete problem. The approach enhances optimization by using chaotic mapping for population initialization, improving diversity and convergence speed. A nonlinear convergence decreasing factor balances exploration and exploitation, successfully enhancing the global search capability. Additionally, integrating a genetic algorithm for agent position updates enables discretization and helps avoid local optima proves that SCSA potentially be applied to discrete problem and effectively solving FJSP.

TABLE VI. OVERALL COMPARATIVE PERFORMANCE OF NEW VARIANTS OF SCSA COMPARED TO THE COMPETING ALGORITHMS

Authors	Overall Performance
[11]	SCSA improved the convergence rate and accuracy of the whale optimization algorithm (WOA) in solving optimization problems.
[27]	The SCSA algorithm has a faster convergence rate, higher accuracy, and improved robustness compared to other metaheuristic algorithms.
[37]	ISCOA showed enhanced performance over other recent approaches in terms of minimizing fuel costs and emissions of generation units.
[25]	The CSCPS algorithm outperformed other methods in terms of convergence rate, accuracy, and robustness. Additionally, the computational cost of the CSCPS algorithm was found to be efficient compared to other commonly used metaheuristic algorithms.
[26]	The SCSA algorithm exhibits strong performance across convergence rate, accuracy, robustness, and computational cost compared to other metaheuristic algorithms.
[51]	The DGS-SCSA algorithm outperforms the original SCSA algorithm in terms of convergence rate, accuracy, and robustness.
[14]	The performance of the SCSA algorithm is compared with other metaheuristic algorithms in terms of convergence rate, accuracy, robustness, and computational cost.
[23]	The results demonstrated that CWXSCSA exhibits superior optimization accuracy, faster convergence acceleration, and better robustness compared to the alternative approaches. However, the comparison did not include computational cost.
[10]	SCSA demonstrates competitive performance in terms of convergence rate, accuracy, robustness, and computational cost compared to other metaheuristic algorithms.
[52]	The results show that the SCSA algorithm demonstrates better performance in several test cases and real engineering problems, indicating superior convergence rate, accuracy, robustness, and computational cost.
[53]	the improved sand cat swarm algorithm (ISCSA) outperforms the SCSA, WOA, and ASO algorithms in terms of convergence speed, number of iterations, and the ability to jump out of local optimums.
[40]	The performance of the Chaotic Sand Cat Swarm Optimization (CSCSA) algorithm is superior to other metaheuristic algorithms in terms of convergence rate, accuracy, and robustness.
[54]	The results showed that the SCSA algorithm demonstrated superior global convergence, consistently yielding the smallest objective function values. It also showed robust stability and was effective in reducing the cost of delivery and carbon emissions while improving customer satisfaction.
[17]	The MSCSA algorithm shows better convergence ability and optimization performance compared to the SCSA algorithm and other comparison algorithms
[12]	The proposed IMSCSA algorithm is evaluated against other state-of-the-art optimizers and is shown to perform significantly better in terms of convergence rate, accuracy, and robustness. However, the computational cost of IMSCSA is relatively higher due to certain mechanisms requiring more computing power.
[43]	The performance of the Improved Sand Cat Swarm Optimization (ISCSA) significantly outperforms competing algorithms in terms of convergence rate, accuracy, and robustness.
[24]	The performance of the MSCSA algorithm has fast convergence speed, demonstrates excellent optimization results, effectively maintains the balance between global and local search performance, and has lower computational costs compared to other metaheuristic algorithms.
[35]	COSCSA converges more rapidly, with higher accuracy, and stays more stable compared to other algorithms.
[42]	The IMSCSA has been shown to have better optimization performance compared to other competitive algorithms in terms of convergence rate, accuracy, and robustness.
[39]	The results showed that the proposed BMSCSA obtained the maximum accuracy in a total of 14 datasets and was rated first solely based on having the best accuracy results in 10 datasets, having the lowest standard deviation values in several datasets and much better than many other rival methods. In terms of convergence rate, the proposed BMSCSA algorithm successfully balances the capacities for exploitation and exploration, and its convergence behavior was superior to that of some of its competitors.
[50]	The improved ISCSA reaches convergence after 15 iterations and has the best adaptivity, outperforming the other four methods in terms of global search performance and convergence speed.
[49]	Demonstrates excellent performance and robustness compared to other advanced algorithms in jumping out of local optima, improving convergence speed, and optimization accuracy.
[16]	The performance of the Binary Sand Cat Swarm Optimization (bSCSA) algorithm was found to be impressive in terms of convergence rate, accuracy, and robustness when compared to other metaheuristic algorithms
[55]	The SCSA algorithm exhibits efficient performance in terms of convergence rate, accuracy, and computational cost when compared to other metaheuristic algorithms. It also shows robustness in maintaining a balance between exploration and exploitation.

Finally, SCSA has been applied in various engineering and control systems, such as in the design of controllers for industrial applications. Shi's research on a modified SCSO-based controller for dicing saw chuck table systems illustrates its effectiveness in improving control accuracy and system robustness [62]. Additionally, the integration of SCSA in optimizing power quality conditioners in microgrid systems further showcases its relevance in enhancing the performance of electrical systems [63]. These applications highlight the algorithm's versatility in addressing challenges in engineering and automation.

In summary, the Sand Cat Swarm Optimization algorithm (SCSA) has demonstrated significant applicability across multiple domains, including renewable energy, UAV path planning, sensor networks, machine learning, and engineering systems. Its ability to optimize complex problems makes it a valuable tool in various scientific and industrial applications.

F. *RQ6. What are the Current Limitations of the SCSA, and What Potential Improvements and Future Research Directions can be Identified?*

The Sand Cat Swarm Optimization (SCSA) algorithm, since its inception, has garnered significant attention in the field of nature-inspired optimization techniques. However, as with any emerging algorithm, the SCSA has been subject to critical examination, revealing several areas that warrant further research and improvement. This section aims to elucidate the key research gaps that have been identified in the literature, providing a comprehensive overview of the challenges that researchers face in enhancing the SCSA's performance and applicability.

1) Current limitations of the SCSA: By synthesizing findings from various studies, we have identified six primary areas of concern: premature convergence and local optima trapping, imbalance between exploration and exploitation, limited population diversity and quality, computational efficiency issues, adaptability constraints to different problem types, and the need for stronger theoretical foundations. Understanding these research gaps is crucial for guiding future developments in the SCSA algorithm and for positioning it more competitive among other optimization techniques.

These themes are interrelated and collectively contribute to the overall weaknesses of the SCSA algorithm. For example, the issues of premature convergence, local optima, and limited exploration-exploitation balance are closely connected and affect each other. Similarly, the lack of population diversity can exacerbate the problem of getting stuck in local optima.

Addressing these weaknesses has been the focus of many subsequent studies, leading to various improvements and hybrid algorithms. However, these gaps also highlight the ongoing need for further research and development in the field of swarm optimization algorithms as summarized in Table VII.

TABLE VII. RESEARCH GAPS

Research Gaps	Authors	Description
Premature Convergence and Local Optima	[26], [33], [51], [53], [64]	SCSA tends to converge prematurely and get stuck in local optima, limiting its effectiveness in complex optimization problems.
Limited Exploration-Exploitation Balance	[12], [53], [54]	The algorithm struggles to maintain an effective balance between exploring new solutions and exploiting known good solutions.
Low Population Diversity and Quality	[12], [53], [64]	SCSA often generates populations with poor quality and lack of diversity, which can lead to suboptimal solutions.
Low Computational Efficiency	[27]	The algorithm can suffer from slow convergence and high computation time, limiting its applicability to large-scale or time-sensitive problems.
Limited Adaptability to Different Problem Types	[25], [33], [65]	Originally designed for continuous optimization, SCSA requires significant modifications to adapt to other problem domains like binary optimization or specific applications.
Lack of Theoretical Foundations	[43], [65]	There's a gap in the theoretical underpinnings of SCSA, limiting understanding of its performance guarantees and broad applicability.

Table VII provides a concise overview of the main weaknesses identified in the Sand Cat Swarm Optimization algorithm (SCSA), along with the relevant citations that discuss these issues that can be defined as research gaps in SCSA scientific research as more research needs to be done to assess and propose new strategies to overcome these weaknesses. There are six key research gaps and areas for improvement in the SCSA have been identified. These gaps highlight potential directions for future research to enhance the algorithm's performance and applicability.

One of the most significant weaknesses of the standard SCSA is its tendency towards premature convergence and getting trapped in local optima. This issue is particularly problematic for multi-peak functions and complex optimization problems, limiting the algorithm's effectiveness in finding global optimal solutions. The root cause of this weakness appears to be an imbalance between the algorithm's exploration and exploitation phases. Improving this balance is crucial for enhancing the SCSA's ability to efficiently search for the solution space while also refining promising solutions [12], [53], [54].

Another critical area for improvement is the quality and diversity of the initial population. The lack of diversity in the initial population can lead to suboptimal solutions and contribute to the premature convergence problem [12], [53], [64]. Addressing this issue could significantly improve the algorithm's performance across a wide range of optimization scenarios.

Computational efficiency is also a concern for some variants of the SCSA. The slow convergence and high computation time reported in some studies suggest that there is room for improvement in the algorithm's implementation and structure. Enhancing SCSA’s efficiency would broaden its applicability to large-scale or time-sensitive optimization problems [27]. The selection of benchmark algorithms (PSO, GWO, etc.) was guided by their widespread use in swarm intelligence research, structural similarity to SCSA, and their established performance in optimization tasks. While additional comparisons with other metaheuristics could offer further insights, this study focuses on widely accepted benchmarks to ensure consistency and computational feasibility. Future research could explore broader comparisons with algorithms such as WOA and HHO to assess performance variations further.

The SCSA's adaptability to different types of optimization problems has been identified as an area needing further research. Originally designed for continuous optimization problems, the algorithm requires modifications to handle binary optimization tasks like feature selection [66]. Expanding the SCSA's versatility to tackle diverse problem domains, such as face recognition and natural language processing, represents a promising avenue for future work.

From a theoretical perspective, the SCSA and its variants currently lack strong foundational guarantees. The inability to ensure finding the global optimum for all optimization problems, as demonstrated by the No Free Lunch (NFL) theorem [67], underscores the need for more rigorous theoretical analysis of the algorithm's properties and limitations.

2) Future research direction of the SCSA: The Sand Cat Swarm Algorithm (SCSA) has shown great potential, but some challenges need to be addressed to improve its performance and applicability. Below are key areas for improvement and suggested future directions.

To prevent premature convergence and getting stuck in local optima, future studies should focus on better exploration-exploitation balancing strategies. Methods such as adaptive adjustments, chaotic maps, or randomization techniques can help SCSA escape local minima and improve global search [68], [69], [70], [71].

To enhance search efficiency, hybridizing SCSA with other metaheuristic algorithms or integrating machine learning techniques can improve adaptability [72], [73], [74], [75]. Using these methods to adjust parameters dynamically and incorporating memory structures could further refine the search process.

Maintaining population diversity is crucial for avoiding stagnation. Implementing self-adaptive [75], [76], [77], [78], [79] parameter tuning, multi-population strategies, or opposition-based learning can help generate diverse solutions and improve overall performance.

For better computational efficiency, SCSA can benefit from parallel processing and high-performance computing techniques. Implementing GPU acceleration, cloud-based optimization, and surrogate-assisted methods could make the algorithm more scalable for large-scale problems [80], [81], [82].

Expanding SCSA's application to different problem types is another important direction. Future studies should adapt it for combinatorial optimization, multi-objective problems, discrete and real-world datasets, making it suitable for tasks such as scheduling, routing, and engineering optimization [20], [48], [83], [84], [85].

Lastly, strengthening the theoretical foundation of SCSA is necessary for wider acceptance [50], [86]. Future work should focus on proving its convergence properties, establishing benchmark performance comparisons, and applying mathematical models to analyze its behavior.

In conclusion, while the Sand Cat Swarm Optimization algorithm has shown promise in various optimization tasks, these identified research gaps provide clear directions for future enhancements. Addressing issues of premature convergence, exploration-exploitation balance, population diversity, computational efficiency, problem adaptability, and theoretical foundations could significantly improve SCSA's performance and broaden its applicability across different domains. Future research efforts focused on these areas have the potential to elevate the SCSA's standing among nature-inspired optimization algorithms.

V. Conclusion

This systematic literature review has comprehensively analyzed the new variant, application area and performance of the Sand Cat Swarm Algorithm (SCSA) across diverse optimization problems. The analysis findings reveal the algorithm's robust performance in a wide range of benchmark functions, including standard optimization problems, CEC benchmark suites, and real-world engineering challenges. The SCSA and its variants have consistently demonstrated competitive performance against state-of-the-art metaheuristic algorithms, particularly in terms of convergence speed and solution accuracy. Key insights from this review include the versatility of SCSA in handling both unimodal and multimodal optimization landscapes, its scalability across various problem dimensions, and successful adaptations for specific domain applications. These findings underscore the potential of SCSA as a powerful tool in the optimization researcher's toolkit.

The analysis also highlights areas for future research, including further exploration of SCSA's theoretical foundations, development of hybrid algorithms leveraging SCSA's strengths, and extended testing on emerging benchmark suites and real-world problems. As optimization challenges continue to grow in complexity, the insights provided by this review offer valuable direction for researchers and practitioners alike. The demonstrated efficacy of SCSA across diverse problem domains suggests its potential for broader adoption and refinement. Future work building on these findings could lead to significant advancements in solving complex optimization problems across various fields of science and engineering. This comprehensive review provides researchers and practitioners with valuable insights into the current state of SCSA, its practical applications, and promising avenues for future research in the field of metaheuristic optimization.

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