Computer Science Review 58 (2025) 100805

Contents lists available at ScienceDirect

Computer Science Review

journal homepage: www.elsevier.com/locate/cosrev

Review Article

Sand cat swarm optimization: A comprehensive review of algorithmic advances, structural enhancements, and engineering applications

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ARTICLE INFO

Keywords:
Metaheuristic algorithms
Combinatorial problems
Engineering optimization
Structural mechanics
Sand cat swarm optimization
Bio-inspired computing

ABSTRACT

Metaheuristic algorithms, as powerful computational tools, play a significant role in solving complex optimization problems in the field of engineering. Among these algorithms, the Sand Cat Swarm Optimization (SCSO) algorithm, inspired by the hunting behaviour of sand cats, has shown considerable potential in addressing combinatorial problems and real-world applications. In this survey paper, a systematic and comprehensive review of the basic structure and extended versions of the SCSO has been conducted. Papers related to SCSO have been collected from 5 major databases (Elsevier, Springer, IEEE, MDPI, and Wiley). Elsevier and Springer contain the largest share of articles, with 32% and 26%, respectively. In this paper, binary, multi-objective, and hybrid versions have been thoroughly reviewed. Also, the application of the SCSO in various engineering fields, including structural engineering, energy systems, biomedical computing, and control systems, has been fully investigated. The field of engineering problems and Electronics-Power include the highest percentage of SCSO usage, with 20% and 24%, respectively. The results of statistical analyses show that the improved versions of SCSO outperform the basic metaheuristic algorithms in stability of results, convergence speed, and final quality of answers.

1. Introduction

Complex optimization problems, often characterized by high multidimensionality and nonlinearity, present formidable challenges. These challenges are further compounded by noise and discontinuities, making it arduous to identify global solutions. Traditional methods for solving such problems, categorized into direct and descending methods, often need to be enhanced in their effectiveness, particularly in discrete, multidimensional, and noisy search domains. Direct methods, also known as zeroth-order methods, rely solely on the value of the objective function and are therefore referred to as non-derivative methods. These methods are better suited for uncomplicated issues with a limited number of variables. In contrast, descent approaches necessitate additional information, such as the initial derivative and, in certain instances, the secondary derivative of the target function [1]. These methods function within a limited scope, necessitate the derivative of the objective function, and, in certain instances, are not efficient for search domains that are discrete, multidimensional, and noisy. Because of these weaknesses, scientists have focused on developing metaheuristic algorithms that can solve challenging optimization problems. They are optimization algorithms inspired by nature and do not depend on derivatives [2,3]. The primary advantages of these algorithms include their resilience, reliable performance, simplicity, and ease of integration. Unlike traditional optimization methods, metaheuristic

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https://doi.org/10.1016/j.cosrev.2025.100805
Received 15 April 2025; Received in revised form 29 June 2025; Accepted 4 August 2025
Available online 11 August 2025

algorithms do not require the objective function to be differentiable or continuous and can be effectively applied to problems involving discrete, continuous, or mixed variables. One of the most important characteristics of metaheuristic algorithms is their capability to find globally optimal solutions [4,5]. These algorithms effectively explore the search space by striking a proper balance between local and global search steps. They often require a large number of parameters, the precise tuning of which has a significant impact on the algorithm's efficiency. These parameters provide the algorithm with the flexibility necessary to adapt to various problems. However, improper tuning of the parameters can lead to reduced efficiency or getting stuck in local optima [6]. Additionally, compared to traditional methods, metaheuristic algorithms are more effective in finding better solutions to complex problems. The intricacy of engineering systems has increased substantially over the past few decades. Several factors, including technological advances, the increasing difficulty of the issues, and the need for sensitive systems in diverse and challenging environments, contribute to the increase in complexity [7]. Consequently, the design and optimization of these systems require metaheuristic algorithms that can effectively manage this complexity.

The most important benefits of metaheuristic algorithms are as follows: 1) Ability to search ample space: It can explore large search spaces effectively and avoid getting stuck in local optima [8]. This feature makes these algorithms suitable for complex problems with ample search space. 2) Flexibility: These algorithms can be easily adapted for different problems with minor changes in their structure and parameters [9,10]. This flexibility allows users to use metaheuristic algorithms to solve different problems [11]. 3) No need for derivation: unlike many classical optimization methods, metaheuristic algorithms do not need to calculate derivatives [12,13]. This advantage makes these algorithms suitable for problems with complex objective functions. 4) Applicability for mixed and continuous problems: metaheuristic algorithms can be used to solve mixed problems as well as continuous problems (such as optimization of numerical parameters) [14,15]. 5) Parallelization: Many metaheuristic algorithms are parallelizable; that is, they can be implemented to use multiple processors or cores to perform calculations simultaneously. This feature increases the speed of running algorithms. 6) Wide applications: These algorithms are used in many scientific and industrial fields [16,17], including engineering [18,19], economic, biology [20,21], and artificial intelligence [22]. Due to their versatility and extensive applications, metaheuristic algorithms are an effective tool for professionals and academics to solve a wide range of complex problems.

The five main classes of metaheuristic algorithms include swarm-based, nature-based, evolution-based, physics-based, and human-based algorithms. Swarm-based algorithms include Sparrow Search Algorithm (SSA) [23], Particle swarm optimization (PSO) [24], Cleaner Fish Optimization algorithm (CFO) [25], Emperor Penguin Optimizer (EPO) [26], Seagull Optimization Algorithm (SOA) [27], starfish optimization algorithm (SFOA) [28], etc. Nature-based algorithms include Artificial Gorilla Troops Optimizer (GTO) [29], Capuchin Search Algorithm (CapSA) [30], Snail Homing and Mating Search (SHMS) [31], African Vultures Optimization Algorithm (AVOA) [32], Arctic Puffin Optimization (APO) [33], Farmland Fertility Optimization (FFO) [34], Moth Swarm Algorithm (MSA) [35], Rat Swarm Optimizer (RSO) [36], Mountain Gazelle Optimizer (MGO) [37], Artificial meerkat algorithm (AMA) [38], Frigate Bird Optimizer (FO) [39], Eurasian Lynx Optimizer (ELO) [40], and Fishing cat optimizer (FCO) [41], etc.

Evolution-based algorithms include Snake Optimizer (SO) [42], Biogeography-based Optimization [43], Biology Migration Algorithm (BMA) [44], etc. Physics-based algorithms include Fibonacci Indicator Algorithm (FIA) [45], Nuclear Reaction Optimization (NRO) [46], Arithmetic Optimization Algorithm (AOA) [47], Gradient-based Optimizer (GBO) [48], Sine Cosine Algorithm (SCA) [49], Lichtenberg Algorithm (LA) [50], etc. Human-based algorithms include the Student Psychology-based Optimization (SPBO) [51], Doctor and Patient Optimization (DPO) [52], Mother Optimization Algorithm (MOA) [53], War Strategy Optimization (WSO) [54], Political Optimizer (PO) [55], etc.

Optimization problems have grown increasingly intricate and varied across many industries and specializations recently [56,57]. Researchers have also expressed interest in resolving these problems [58]. Traditional (mathematical) optimization methods are no longer viable for solving today's optimization challenges. Researchers are increasingly using Metaheuristic algorithms as a non-traditional methodology. Metaheuristic-based optimization algorithms resemble natural behavior and draw inspiration from animal behavior. They mimic observable behavior in nature and are often influenced by animal behavior. They look for the best solution in a randomly chosen domain [59]. Metaheuristic algorithms employ two distinct stages, namely exploration and exploitation, to effectively avoid premature convergence to local optima [60]. It is crucial to execute these stages in a well-proportioned manner.

In 2022, the SCSO [61] was created based on the hunting behavior of sand cats. Its implementation process begins with initializing the issue search space that is limited by upper and lower constraints given by the nature of the optimization problem. The search space is a collection of alternative solutions that is continuously updated by the algorithm to find a solution close to the optimal one. In each iteration, the current solutions are evaluated and replaced with alternative candidates. The SCSO algorithm consists of two stages: exploration, a thorough search is undertaken in the solution space to investigate diverse parts of the problem space and prevent being stuck in the local optimum, and exploitation, the algorithm concentrates on refining current solutions and performing a more extensive optimization based on the knowledge gathered during the exploration stage. The following is a list of the significant contributions that this paper makes:

- In this paper, the binary and multi-objective models of the SCSO have been investigated.
- The SCSO has been meticulously reviewed, encompassing all changes and improvements applied to the algorithm. This comprehensive review ensures that no aspect of the SCSO is overlooked.
- All the combined models of the SCSO have been thoroughly analyzed.
- The advantages and disadvantages of the SCSO have been extensively assessed and compared to those of other metaheuristic algorithms. An extensive analysis is conducted on the performance of the SCSO, providing a fair evaluation of its effectiveness and facilitating a more informed understanding of its potential applications.
- All problems and areas that the SCSO has used have been examined using formulas and results.
- Concepts and practical optimization problem methods are proposed for future work.

The structure of this paper is as follows: Section 2 defines the SCSO and its mathematical model. Section 3 contains the methodology of the paper. In this section, previous works and the development of the SCSO algorithm are analyzed. Section 4 is a comprehensive assessment of all SCSO variations. SCSO approaches can be categorized into four groups: SCSO variations, hybridization, optimization problems, and enhancement. Section 5 reviews the advantages, disadvantages, and capabilities of SCSO. In the final section, a conclusion and future works are discussed.

2. Sand cat swarm optimization

The SCSO was developed based on the behavior of sand cats in 2022 [61]. It incorporates two distinct components, namely search and attack, which effectively manage the exploitation and exploration stages harmonized.

2.1. Initial population

In SCSO, each agent has a specified value for the problem variables based on population and defines the problem space in vector format. In D-dimensional problems, each factor is expressed as a $d \times 1$ array, which indicates the solutions to the problem. In other words, each factor represents a point in the search space where each array element is recorded as the value of a problem variable. This method enables SCSO to simultaneously explore the problem space using a set of agents and approach optimal solutions more closely. A candidate matrix is first created with a population of factors proportional to the problem size $((Npop \times Nd),(pop = 1,\ldots,n))$, so that the population includes from 1 to n. In the SCSO, each agent moves in the search space and seeks to improve its values. This movement is performed according to a specific objective function that determines the degree of fit or optimality for each factor. In other words, agents try to improve their position by using the information available in the environment and according to the objective function.

2.2. Prey search (exploration)

The SCSO search process involves agents that resemble cats, which use emitted and sensed low-frequency noise to seek their prey or ideal solutions. Sand cats, renowned for their exceptional auditory capabilities, have heightened sensitivity to low-frequency noises. These animals can perceive frequencies lower than 2 kHz, a crucial skill for hunting and navigation in their arid habitats. The SCSO agents strive to successfully discover and converge towards optimal solutions by utilizing low-frequency noise emission, similar to the method employed by sand cats. It improves its capacity to explore different sections of the solution space and take advantage of potential opportunities to get the best solutions in optimization challenges by imitating natural behaviors, such as low-frequency sensing seen in sand cats. In SCSO, each solution is shown as $X_i = (x_{i1}, x_{i2}, x_{i3}, \ldots, x_{id})$ where X_i represents the i^{th} factor. With the increase of repetitions, the value of $(\underset{G}{\vec{r}})$ decreases linearly from 2 to zero, according to Eq. (1), w downward trend of getting closer to the prey without losing it. In Eq. (1), $iter_c$ is the current iteration and $iter_{max}$ is the maximum iteration. The value of SM is based on the hearing characteristic of sand cats, which has a value of 2. If the maximum number of iterations is equal to 100, then the value of $\underset{G}{\vec{r}}$ will be larger than 1 in iterations 1–50 and <1 in iterations 50–100. The $\vec{R}^{\to}$ defines a parameter controlling the transition between the exploitation and exploration stages in Eq. (2).

$$\underset{G}{\vec{r}} = S_M - \left(\frac{S_M \times iter_c}{iter_{max}}\right) \tag{1}$$

$$\vec{R}^{\to} = 2 \times \underset{G}{\vec{r}} \times rand(0,1) - \underset{G}{\vec{r}} \tag{2}$$

$$\vec{r}^{\to} = \underset{G}{\vec{r}} \times rand(0,1) \tag{3}$$

The parameter r for operations in the stages of exploration or exploitation is defined according to Eq. (3) and the $\vec{r}^{\to}$ parameter indicates the sensitivity range of each factor, which is different to avoid getting stuck in local optima. In the search stage, each agent's position is updated using a randomly generated position. It enables search agents to discover new areas within the search space whose position is based on the position of the best candidate $\overrightarrow{P_{bc}}^{\to}$, the current position of $\overrightarrow{P_c}^{\to}$, and the sensitivity range r. Additionally, the best position is defined by agents as the optimal location to hunt prey, as per Eq. (4) which provides agents with a new opportunity to discover new local optima within the search area. Agents benefit from the randomness of the search process, and operational costs and complexity are reduced. It is essential to use a sensitivity range for each factor to increase efficiency and avoid getting stuck in local optima. This approach enables each agent to react dynamically and adapt to environmental conditions, continually searching for new optimal points. In the exploration stages, using random positions allows the search space to be fully explored and optimal points to be explored. This increases the chances of finding the best solution and avoids focusing too much on specific points that may be local optima. Finally, by taking advantage of the randomness in the search process, the variety of the search increased, and the computational costs and operational complexities were also reduced.

$$\vec{P}^{\to}(t+1) = \vec{r}^{\to} \times \left(\overrightarrow{P_{bc}}^{\to}(t) - rand(0,1) \times \overrightarrow{P_c}^{\to}(t)\right) \tag{4}$$

2.3. Prey attack (exploitation)

In the SCSO, the sensitivity range of factors is represented as a circular shape, the attack stage refers to the distance between the best position of $\overrightarrow{P_b}^{\to}$, which represents the best solution, and the current position of $\overrightarrow{P_c}^{\to}$. This distance is defined according to Eq. (5). A randomly selected angle establishes the direction of movement (θ) inside this circle. The angle is chosen randomly from a range of 0 to 360 degrees. It utilizes a random angle to allocate to each agent, utilizing a roulette wheel selection technique. The deliberate utilization of angles serves many objectives: 1) Navigating Hunting locations: Agents are guided toward prospective solutions (hunting locations) by choosing random angles inside the sensitivity circle. This method simplifies the exploration of possible options, thereby enhancing the chances of finding the best possible answers. 2) Preventing Local Optima: Using random angles helps agents avoid getting stuck in local optima. This method ensures agents behave differently and stops early convergence to poorer solutions by introducing varied movement directions. 3) Positive Impact on Agent Performance: Using random angles benefits agent behavior by directing them towards potentially fruitful regions of the search space where optimum solutions may be found. Including this stochastic component improves the algorithm's ability to navigate and effectively utilize the search space. Incorporating random angle selection into the SCSO improves its resilience and efficiency in global optimization applications. This technique guarantees that agents explore the search space efficiently, balancing exploration and exploitation to get maximum performance in tackling intricate optimization problems.

P_{rnd} represents a random position that makes the agents closer to the prey. The random angle, determined through the roulette wheel selection strategy, allows agents to search the environment indirectly, avoiding repetitive paths. This increases the diversity in the search for factors and improves the probability of finding global optima due to the random angle selection in each move. P_{rnd} parameter as a random position plays a vital role in search optimization. This randomness encourages agents to leave their current positions and explore new, unknown areas. Such dynamic and unpredictable movement improves the search process and increases the likelihood of finding the optimal solution. In general, the attack stage in the SCSO is defined by combining the distance between the current and best positions, using the random angle and roulette wheel selection strategy, and the random position parameter.

$$P_{rnd} = \left|rand(0,1) \times \overrightarrow{P_b}^{\to}(t) - \overrightarrow{P_c}^{\to}(t)\right|$$

$$\vec{P}^{\to}(t+1) = \overrightarrow{P_b}^{\to}(t) - \vec{r}^{\to} \times \overrightarrow{P_{rnd}}^{\to}(t) \times \cos(\theta) \tag{5}$$

2.4. Exploitation and exploration

The values of $\underset{G}{\vec{r}}$, a key element in the SCSO, is crucial in striking a balance between exploration and exploitation. It enables the algorithm to seamlessly transition between these two stages, ensuring a balanced probability of operation. When the value of $\vec{r}_G$, decreases linearly from 2 to 0, is balanced; the value of R, a random value in the interval $[-2r_G, 2r_G]$, will also be balanced, ensuring a harmonious operation between the two stages of exploration and exploitation. If the random value of R is in the range $[-1, 1]$, then the next position of an agent can be between the current position and the hunting position. If $|R| \le 1$, the exploitation stage is performed. It is one of the effective parameters in hunting attacks. Eq. (6) illustrates the position update for each agent during the exploration and exploitation stages.

In the SCSO process, the parameter $\vec{r}_G$ decreases from 2 to 0, which plays a crucial role in regulating the balance between exploration and exploitation. At the beginning of the process, high values of $\vec{r}_G$ increases exploration in the search space. As the process progresses and the parameter decreases, the best-found positions are increasingly exploited. This dynamic balance between exploration and exploitation enables the algorithm to be both practical and adaptive. If the value of R is in the range $[-1, 1]$, then the agents exploit the nearest positions. Otherwise, they continue to explore the search space. $\vec{r}_G$ and R parameters in SCSO significantly enhance efficiency and accuracy in solving complex problems. These parameters contribute to the balance between exploitation and exploration and enable the adequate updating of the agents' positions, instilling confidence in the algorithm's capabilities.

$$P(t+1) = \begin{cases} \overrightarrow{P_b}(t) - \vec{r} \times \overrightarrow{P_{rnd}}(t) \times \cos(\theta) & |R| \le 1; exploitation \\ r \times \left(\overrightarrow{P_{bc}}(t) - rand(0,1) \times \overrightarrow{P_c}(t)\right) & |R| > 1; exploration \end{cases} \quad (6)$$

When $|R| \le 1$, the R parameter guides the agents to attack the prey, a stage known as exploitation in the SCSO algorithm. Conversely, when $|R| > 1$, the agents are tasked with finding new solutions in the global region, a stage referred to as exploration. Fig. 1 visually depicts the change between these two stages.

The flowchart of the SCSO algorithm is shown in Fig. 2.

The performance of the SCSO algorithm is compared with that of the CSO, WOA, Gravitational Search Algorithm (GSA), Salp Swarm Algorithm (SSA), and GWO, as well as the PSO algorithms. Evaluation of CEC2014, CEC2015, and CEC2019 functions showed that the SCSO algorithm had achieved faster convergence and higher accuracy than other algorithms. CEC2014, CEC2015, and CEC2019 benchmarks are used to evaluate the performance of optimization algorithms. They include a set of complex and different optimization problems designed to measure the efficiency of algorithms in various conditions. SCSO can be used as one of the best options for solving complex optimization problems.

The SCSO demonstrates strong potential. It has also shown better performance on numerous benchmark functions. Furthermore, when compared to BWO, SCSO converges more quickly and achieves superior results on complex optimization problems. Similarly, when pitted against CSO, SCSO has demonstrated a better ability to balance local and global search rates, resulting in improved outcomes in complex issues. SCSO has outperformed GSA in discovering optimal solutions and has consistently found better optima. Furthermore, SCSO has consistently delivered better results in standard CEC functions than WOA. Lastly, in a head-to-head with GWO, SCSO has demonstrated faster convergence and higher accuracy in complex problems.

3. Research methodology

3.1. Existing survey

Anka and Aghayev have reviewed the SCSO algorithm [62] which has critical shortcomings addressed in the current paper. The current paper provides a broader and more informed perspective by analyzing 133 papers. In contrast, the published paper lacks a comprehensive analysis and provides limited evidence regarding the development, application, and impact of the SCSO algorithm. It also lacks a proper

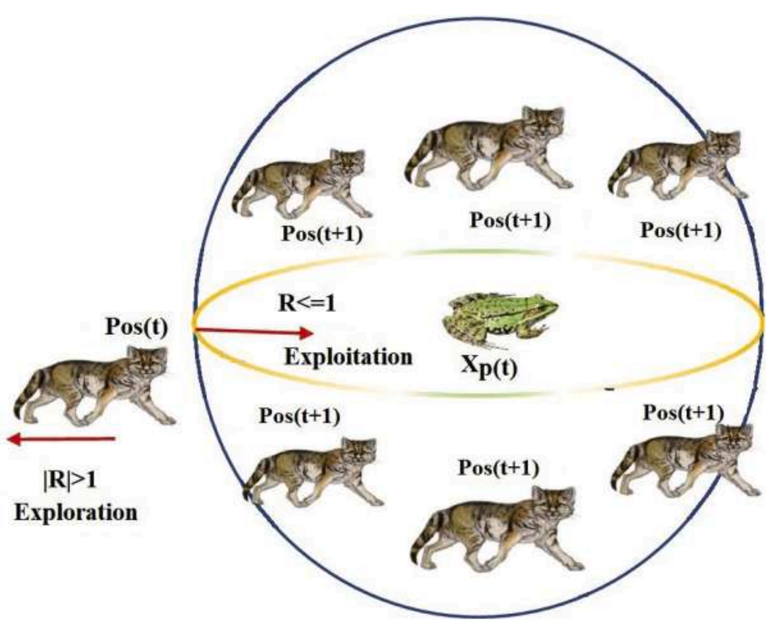

Fig. 1. Searching for prey (exploration) versus attacking prey (exploitation) [61].

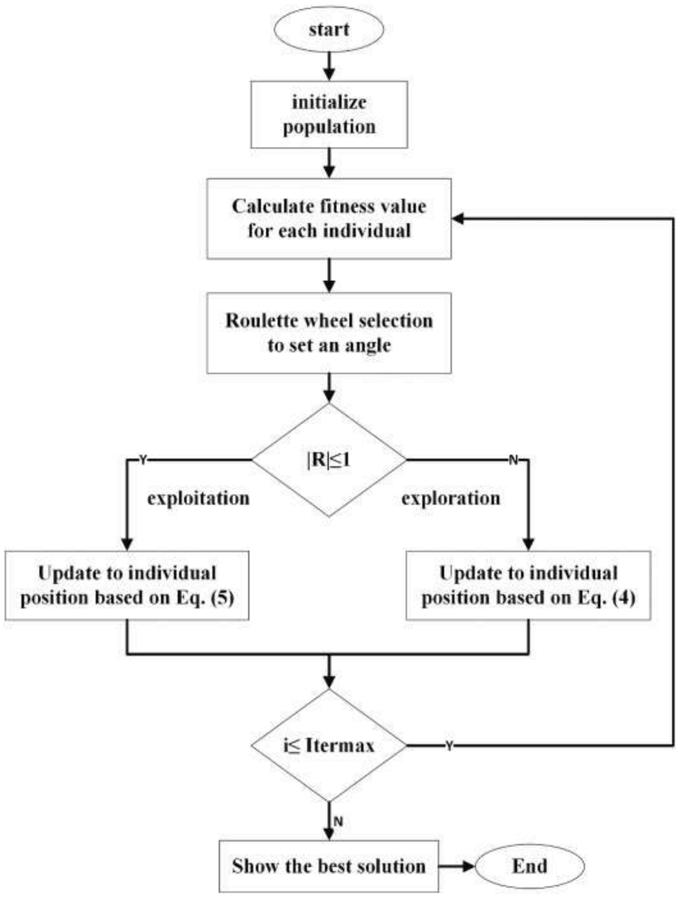

Fig. 2. The flowchart of the SCSO algorithm [61].

classification structure; for instance, concepts such as adversarial learning and reinforcement learning are introduced under the hybrid model section without clear justification. Since these two strategies are dominant in improving solutions, they should be placed in the SCSO improvement section. This paper reviews the applications of the SCSO algorithm across various fields, including networking, industry, energy, and engineering. For example, energy consumption optimization, medical system improvement, and engineering network efficiency enhancement are topics covered in the current paper. The paper provides a detailed structural analysis of the search, convergence, and interaction stages between exploration and exploitation.

3.2. The growth of SCSO in the literature

Recently, the SCSO algorithm has been applied in various scientific and industrial domains. In engineering, it has been utilized for motor tuning to optimize performance, yielding promising results. In the field of robotics, SCSO has been employed for robotic arm path planning, contributing to improved movement efficiency and reduced energy consumption. This algorithm has also enabled the discovery of optimal paths for automated systems and vehicles in path planning. It has been utilized to allocate tasks and balance loads within the Internet of Things (IoT). In sentiment prediction, it has been used to analyze behavioral data and predict user sentiment. Also, in clustering and data optimization problems, using SCSO has increased the efficiency of data mining methods. In network security, it has been used to detect intrusions in wireless sensor networks, and the accuracy of detecting security threats has increased. This algorithm has led to an improvement in the process of selecting essential variables for feature selection in machine learning models. Positioning systems have helped increase positioning accuracy in complex environments. Table 1 shows the growth and development of the SCSO algorithm in various fields in 2025.

Table 1
Development and growth of the SCSO algorithm in various fields in 2025.

Application	Country	Publisher	Journal	Authors
engineering issues and engine tuning [63]	China	Springer	Scientific Reports	Yongliang Yuan et al.
Robotic arm path planning [64]	China	Springer	Applied Intelligence	Zhenkun Lu et al.
Path planning [65]	China	Elsevier	Intelligent Systems with Applications	Yourui Huang et al.
Task Offloading in IoT [66]	India	Springer	Journal of Grid Computing	Veeranki Venkata Rama et al.
Application in metal industries [67]	China	Springer	The International Journal of Advanced Manufacturing Technology	Zheyi Li et al.
video anomaly detection [68]	India	Elsevier	Journal of Visual Communication and Image Representation	Perumal Pitchandi et al.
An intelligent emotion prediction system [69]	India, Saudi Arabia	Springer	Scientific Reports	Amutha Prabakar Muniyandi et al.
Clustering and optimization problems [70]	China	Elsevier	Mathematics and Computers in Simulation	Yanbiao Niu et al.
Intrusion detection in wireless sensor networks [71]	India	Elsevier	Computers & Security	A. Punitha et al.
Dam construction and structure industry [72]	India	Springer	Journal of Vibration Engineering & Technologies	Yugandhara Kasture et al.
Feature selection (FS) [73]	Saudi Arabia	Springer	Scientific Reports	Fatma S. Alrayes et al.
Energy consumption management [74]	India	Springer	Electrical Engineering	C. Pratheeba & P. Sukumar
Optimal scheduling of photovoltaic and battery energy storage in distribution networks [75]	Egypt, United Arab Emirates, Jordan	Elsevier	Journal of Energy Storage	Mohamed A. Elseify et al.
Power system stability [76]	Libya	MDPI	Energies	Mokhtar Shouran et al.
Localization System [77]	China	MDPI	Sensors	Junsong Yu et al.
feature selection [78]	China	Elsevier	Expert Systems with Applications	Li Zhang
Optimization of the steam turbine [79]	China	Elsevier	Energy	Di Liu et al.

The SCSO is used in machine learning for feature selection, model parameter tuning, and data clustering. In the medical field, it is used for medical image analysis and disease diagnosis optimization. In industry, it is suitable for production planning, job scheduling, and energy management. It is also highly efficient in solving routing problems, such as those found in wireless sensor networks and intelligent transportation systems.

Fig. 3 shows the application of the SCSO across various fields, as per

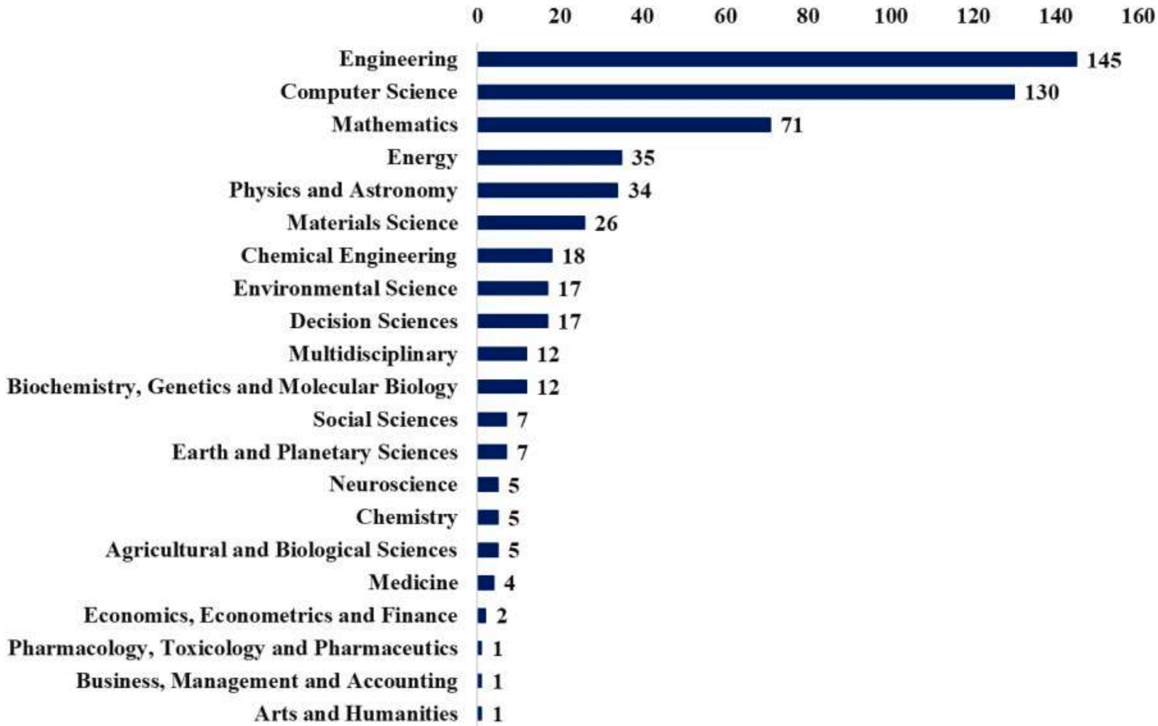

Fig. 3. The application of the SCSO algorithm in different fields according to Scopus (source: https://www.scopus.com).

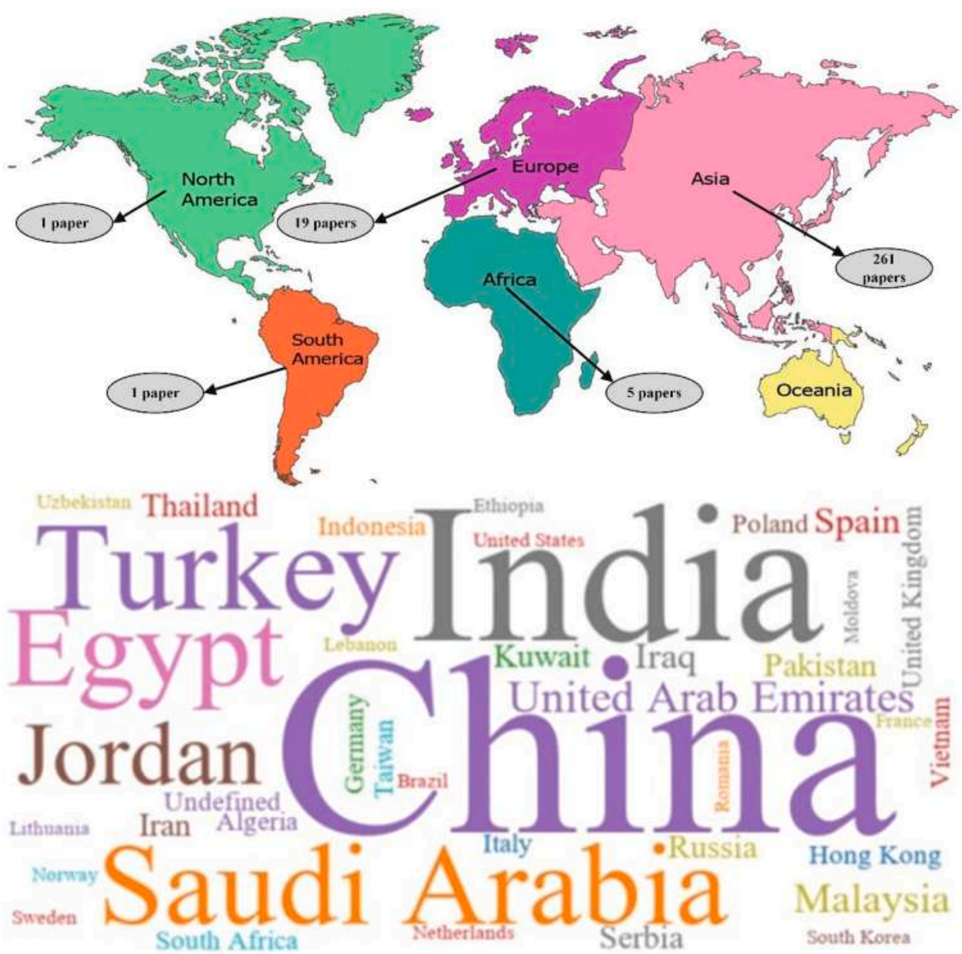

Fig. 4. The application of the SCSO algorithm in different continents according to Scopus (source: https://www.scopus.com).

Scopus. The most widely used SCSO is in the engineering field, with 145 papers, followed by computer science with 130 papers. Mathematics ranks third with 71 papers. Other fields such as energy (35 papers), physics and astronomy (34 papers), and materials science (26 papers) also have a significant share of the use of this algorithm. Chemical engineering (18 papers), environmental sciences (17 papers), and decision sciences (17 papers) are ranked as follows. Some fields, such as the social sciences (7 papers), neuroscience (5 papers), medicine (4 papers), and economics (2 papers), have utilized the SCSO algorithm less frequently. This distribution indicates that the most widely used SCSO algorithm is primarily employed in engineering, computer science, and mathematics. In fields such as the humanities and social sciences, problems are usually qualitative and require fewer mathematical algorithms and optimization.

Fig. 4 illustrates the application of the SCSO across different continents, as per Scopus. In Europe, the total number of papers is 261. In Asia, China ranks first with 122 papers, holding a significant share of scientific research related to the SCSO algorithm in this category. After China, India ranks second with 66 papers, indicating the country's scientific growth in various research areas using SCSO. Turkey, with 17 papers, Saudi Arabia, with 15 papers, and Egypt, with 14 papers, follow, highlighting the role of Middle Eastern countries in producing scientific research. Other Asian countries, including Jordan, the United Arab Emirates, Malaysia, Iraq, Thailand, Pakistan, Kuwait, and Iran, also contribute to scientific production. However, the number of their papers is less compared to China and India.

The total number of papers in Europe is 19, indicating a smaller share compared to Asia. Serbia and Russia have the largest share among European countries, with three papers each. Poland, Italy, and Germany are next with two papers, while other European countries, such as Sweden, Romania, Norway, the Netherlands, Moldova, Lithuania, and France, have only one paper each. The United Kingdom is also on the list with two papers. In Africa, only five papers have been registered, indicating the continent's limited contribution to the production of science using SCSO. South Africa and Algeria are at the top of the list with two papers each, while Ethiopia has published only one. In North America, only one paper has been registered, belonging to the United States. This indicates a minimal contribution of the continent to this particular set of papers. In South America, only one paper has been registered from Brazil, suggesting the region's limited contribution to research in this area.

Fig. 5 shows a graph of the number of SCSO papers with journal names based on Elsevier. Most papers related to the SCSO algorithm have been published in the journals Fuel and Energy Abstracts, as well as Expert Systems with Applications, with a total of 17 papers. Next, Heliyon is in second place with 11 papers. The Journal of Energy Storage is next, with nine papers, followed by Alexandria Engineering Journal and Results in Engineering, each with eight papers. Construction and Building Materials and Applied Soft Computing have also published seven papers. At a lower level, journals such as Energy are represented by six papers, Engineering Applications of Artificial Intelligence by five papers, and Computers and Electronics in Agriculture by five papers. Some journals, such as Biomedical Signal Processing and Control, Ecological Informatics and Sustainable Computing: Informatics and Systems, have only three papers. This distribution indicates that the SCSO algorithm is primarily used in the fields of energy, artificial intelligence, computer science, and engineering. The leading position of journals such as Fuel and Energy Abstracts and Journal of Energy Storage shows that this algorithm plays a critical role in the optimization of energy systems and their storage. Also, journals such as "Applied Soft Computing" and "Expert Systems with Applications", which are related to intelligent systems and soft computing, show that this algorithm also has a wide application in optimization and decision-making.

The widespread use of the SCSO algorithm in the energy field is due to the optimization of energy systems, improving efficiency, reducing costs and managing resources. Energy-related issues, including optimizing energy production and storage, managing smart power grids, increasing the efficiency of renewable power plants and reducing energy losses, require efficient optimization methods. Metaheuristic algorithms such as SCSO are widely used in this field due to their high ability to search for optimal solutions in complex spaces. In artificial intelligence and computer science, metaheuristic algorithms are used to solve

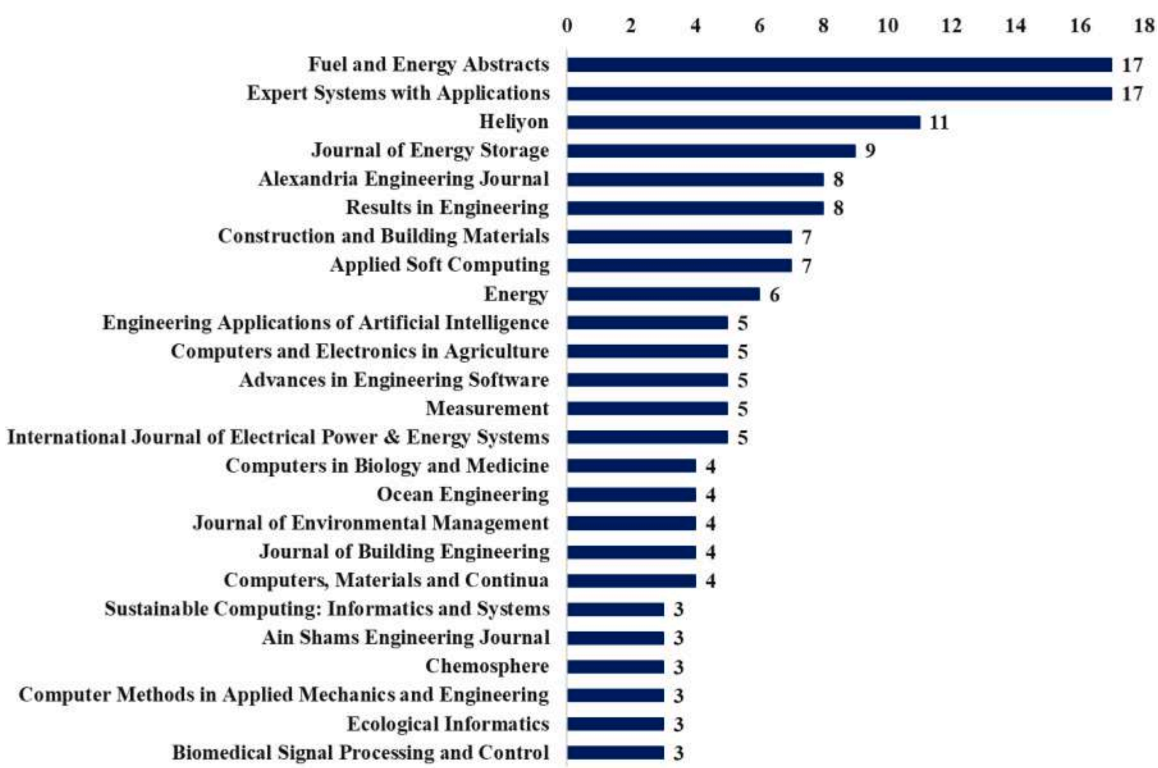

Fig. 5. Graph of the number of SCSO papers with journal names based on the Elsevier (source: https://www.sciencedirect.com).

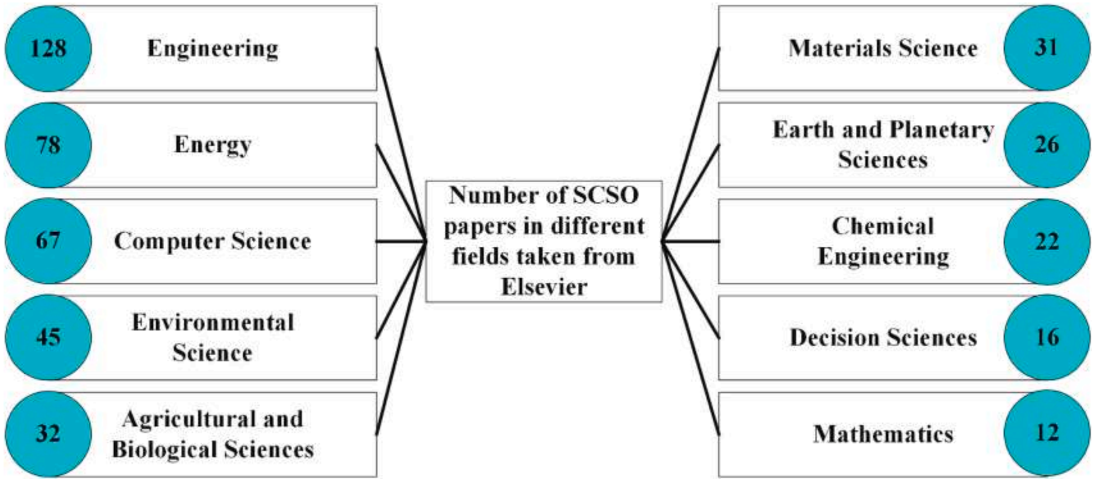

Fig. 6. Graph of the number of SCSO papers in different fields taken from Elsevier (source: https://www.sciencedirect.com).

optimization problems, machine learning, neural networks, big data processing, and optimization of predictive models. Several papers on the SCSO algorithm have been published in the journal "Expert Systems with Applications", which focuses on the application of intelligent systems and decision-making. The SCSO algorithm is widely used in designing artificial intelligence systems due to its ability to find optimal solutions to complex and nonlinear problems.

Journals such as "Construction and Building Materials" and "Computers and Electronics in Agriculture" show that the SCSO has also been used in the optimization of construction and agricultural engineering problems. Journals with fewer papers in this field are primarily found in the fields of life sciences, medicine, and the environment, indicating that this algorithm is less commonly used in these areas.

Fig. 6 shows a graph of the number of papers in various fields, sourced from Elsevier. The most significant number of papers belongs to the engineering field, with 128 papers, indicating that the SCSO algorithm is most commonly used in solving engineering problems and designing optimal systems. Then, the energy field is in second place with 78 papers. Due to the need for optimization in the production, consumption and management of energy resources, the SCSO algorithm has been widely used. Computer science is also in third place with 67 papers, which indicates the role of optimization algorithms in problems related to machine learning, data processing and artificial intelligence. Environmental sciences (45 papers) and biological and agricultural sciences (32 papers) also have a significant share of papers. This shows that optimization methods are used to solve environmental problems, model ecosystems, and optimize agriculture. Materials science (31 papers) and Earth and planetary sciences (26 papers) also use the SCSO algorithm, due to the need for optimization in designing new materials and modeling geological processes. Fields such as chemical engineering (22 papers), decision sciences (16 papers), and mathematics (12 papers) have fewer papers compared to other fields. In these fields, the number of papers is low because traditional mathematical and analytical methods are still prevalent and rely less on optimization algorithms based on collective intelligence.

Fig. 7 illustrates a graph of the number of published papers in different fields from Springer. The most significant number of SCSO algorithm papers is found in computer science, with 65 papers, and engineering, with 59 papers. This means that research in these two fields has the largest share. The fields of earth sciences, with nine papers, and energy and environment, with four papers each, are ranked as follows, indicating the importance of these fields in scientific research. This analysis shows that technical and engineering fields have a higher priority in scientific research. High demand for research in the fields of technology and innovation significantly impacts the distribution of SCSO papers. Additionally, budget and investment in various fields play a significant role in the number of SCSO papers. For example, computer science and engineering typically receive more financial support,

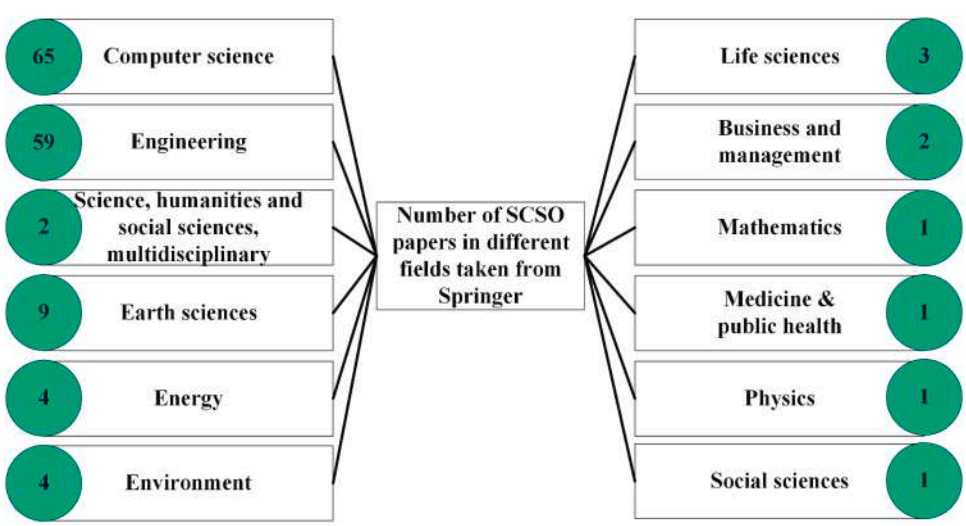

Fig. 7. Graph of the number of SCSO papers in different fields taken from Springer (source: https://link.springer.com).

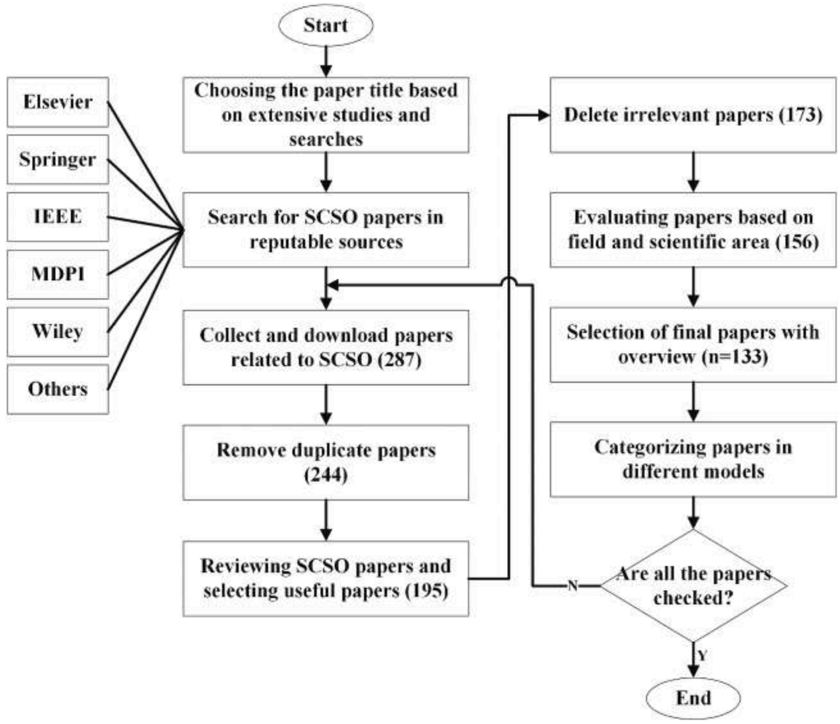

Fig. 8. The procedure for collecting SCSO papers.

whereas other fields, such as the social sciences and humanities, receive less.

Fig. 8 illustrates the procedure for collecting SCSO papers. The process of selecting scientific papers begins with choosing a suitable title, informed by extensive literature reviews and thorough scientific searches. These searches are conducted through reputable databases such as Elsevier, Springer, IEEE, MDPI, Wiley, and other recognized academic sources. Next, papers related to the SCSO topic are collected and downloaded, resulting in 287 papers. After that, duplicate papers are removed, reducing their number to 244. In the next step, the papers are reviewed and useful ones are selected, reducing their number to 195. The papers are evaluated scientifically and in terms of their research area, resulting in a reduced number of 156. Finally, the total number of SCSO papers is 133. The selected documents are categorized based on different models.

Fig. 9 illustrates the most important keywords for extracting and collecting SCSO papers. According to the keywords, it is clear that some words were essential for displaying SCSO papers. "Swarm Optimization" is the most prominent word, indicating the importance and primary focus on swarm optimization methods. "Sand Cat Swarm Optimization" and "Particle Swarm Optimization" also appear in large sizes, indicating the widespread use of these methods in scientific research. PSO is used in most articles to compare with SCSO. Other keywords include "Machine Learning", "Deep Learning", "Feature Selection", "Optimization Algorithms", "Swarm Intelligence" and "Classification", all of which are related to the fields of machine learning and optimization.

Fig. 10 shows the number of citations of the SCSO algorithm from 2022 to March 2025. This data indicates the growth and attention of the scientific community to the SCSO algorithm over time. The total number of citations is 503, indicating the algorithm's relative acceptance within the research community. The number of citations in 2022 is 23, indicating that this algorithm is still in its initial stage, and it has not yet

Fig. 9. The most important keywords for extracting and collecting SCSO papers (source: https://www.scopus.com).

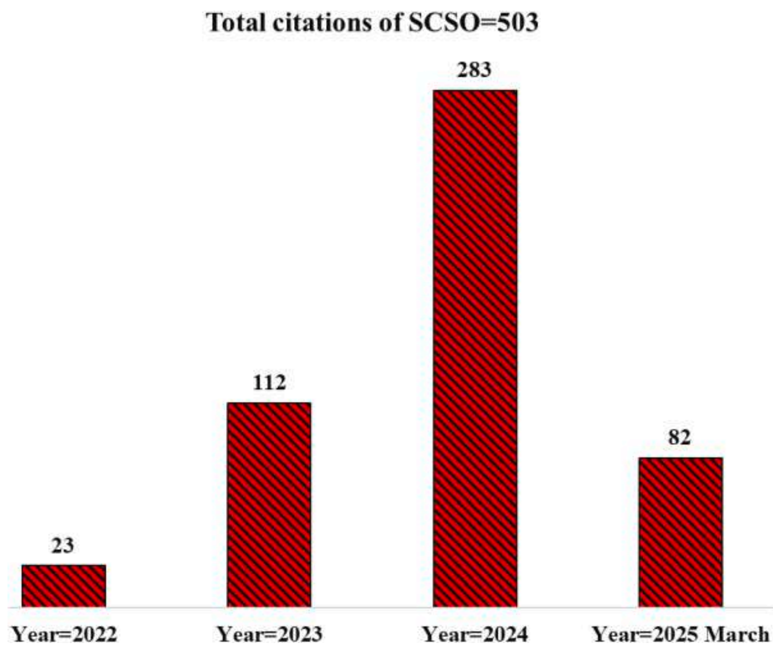

Fig. 10. The number of citations of the SCSO algorithm from 2022 to March 2025 (source: https://scholar.google.com).

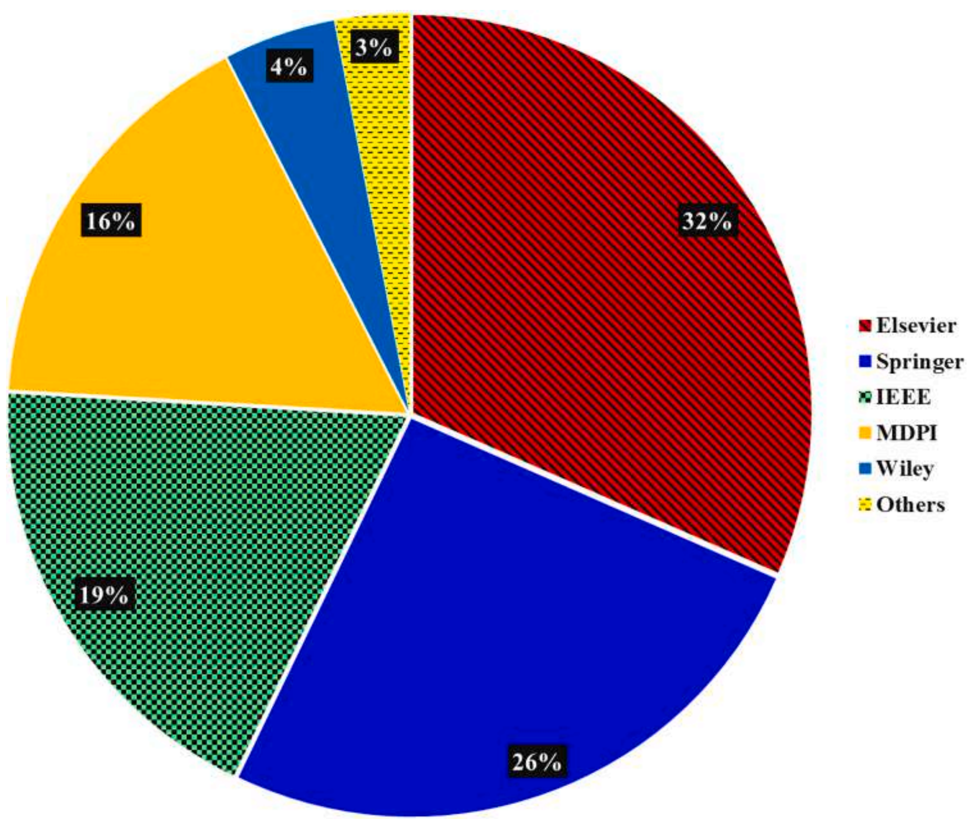

Fig. 11. The number of SCSO papers published from 2022 to 2025 based on publishers.

been widely adopted. The number of citations in 2023 is 112, representing a significant increase compared to the previous year (almost five times). This increase is likely due to researchers' greater awareness of SCSO and its application in various optimization problems. In 2024, the number of citations reached 283, the highest value among the years reviewed. However, in the first quarter of 2025, the number of citations reached 82.

Fig. 11 shows the number of SCSO papers published from 2022 to 2025 based on publishers. This visual representation provides a clear understanding of the distribution of SCSO papers among different publishers, aiding researchers and students in their journal selection process. Other publishers have allocated a distinct share of published papers. Elsevier holds the largest share, accounting for 32 % of the total, with a significant number of papers published under this publisher. After

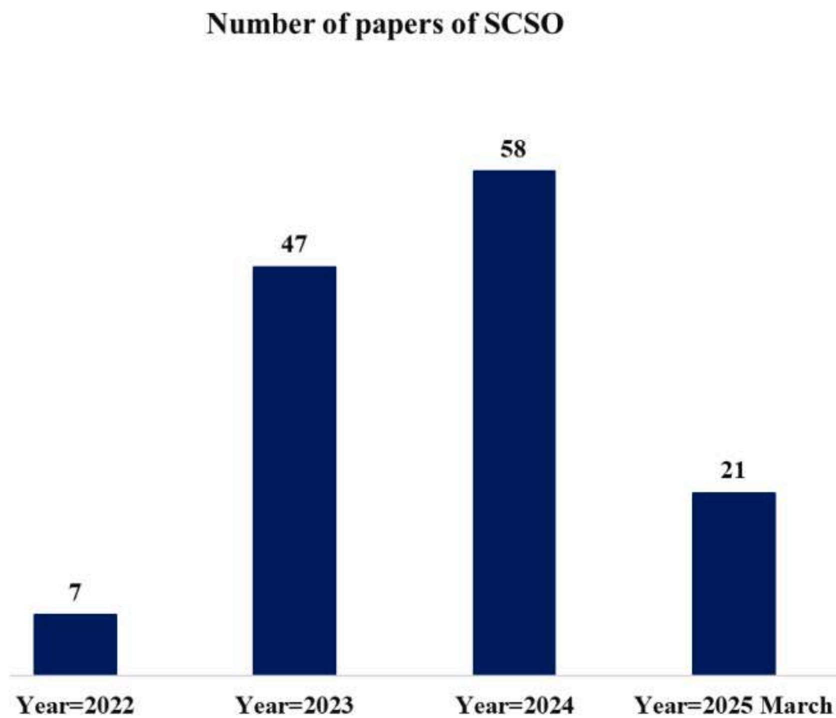

Fig. 12. Number of SCSO papers published per year.

Science, the two publishers, Springer and MDPI, have 26 % of published papers. IEEE Publisher is next with 19 %, representing a significant share of published papers. After that, Wiley's publisher has a smaller share than other publishers, with a 4 % share of published papers. Finally, the "Others" category, which includes other publishers, accounted for only 3 % of the papers. This distribution shows that Elsevier, Springer, MDPI, and IEEE have made the most significant contributions to the publication of scientific papers in this period. In contrast, other publishers have made a minor contribution to this field. This information can be helpful for researchers and students who want to choose journals for publishing their papers, as it shows the strength and breadth of each publisher within the scientific community.

Fig. 12 indicates the number of documents related to the SCSO algorithm in four periods (2022, 2023, 2024, and March 2025). In 2022, the number of published papers was 7. This number has increased significantly in 2023, reaching 47 papers, which indicates substantial growth and greater interest among researchers in this algorithm. In 2024, a total of 58 papers were published. In the first quarter of 2025,

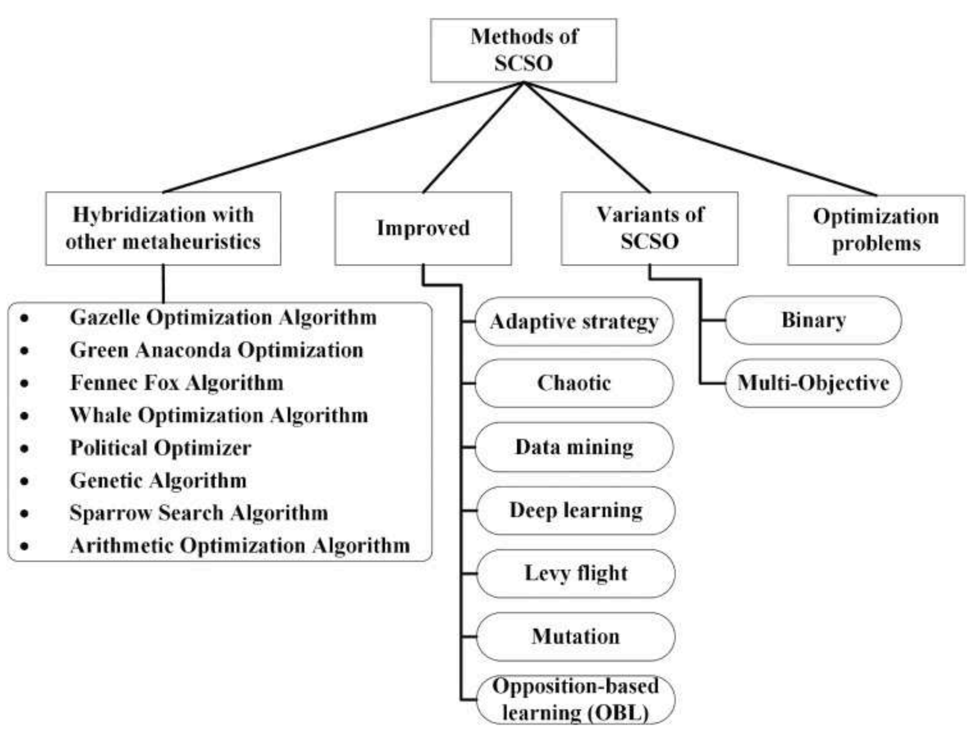

Fig. 13. Classification of SCSO methods.

the number of documents has reached 21, if progress continues in this pattern, the number of records at the end of 2025 is expected to exceed that of 2024. This increase reflects the growing attention and importance of the SCSO within the scientific and academic community.

4. Methods of SCSO

Fig. 13 illustrates the classification of SCSO methods. These methods are divided into four main categories: combination with other metaheuristics, improved, different types of SCSO, and optimization problems. In the section combining with other metaheuristics, various algorithms such as WOA, a Genetic Algorithm (GA), and Gazelle Optimizer Algorithm (GOA) have been introduced. The improved category explores multiple techniques, including adaptive strategies, mutation, opposition-based learning (OBL), Levy flight (LF), chaotic systems, deep learning, and data mining. Different types of SCSO also include two main categories: binary and multi-objective. This diagram clearly shows the extent and variety of SCSO applications in various fields and highlights their importance in optimizing complex problems.

4.1. Hybridization with other metaheuristics

When effectively harnessed, metaheuristic algorithms can tackle a wide range of NP-hard complexity problems, even without prior knowledge of the problem domain. However, their true power is unleashed with other effective search tactics. This hybridization approach allows these algorithms to identify the best possible solutions swiftly and holds significant practical implications. It opens up new avenues for solving complex problems in various fields, demonstrating the potential and effectiveness of our research.

Credit risk, which arises from the default of a party to a contract, is a crucial factor in financial organizations. There are no universally agreed-upon characteristics or indicators for this categorization. In [80], a novel approach to credit risk assessment is proposed. Range control-based class imbalance and Optimized Granular Elastic Net regression (ROGENET) are proposed as innovative methods for feature selection. This research addresses the demand for an intelligent clustering technique in Vehicular Ad Hoc Networks (VANETs) to effectively manage the dynamic network topology and ensure the formation of stable clusters. This problem, known as NP-hard, can be efficiently resolved by employing an intelligent algorithm inspired by nature. The Hybrid Fennec Fox Optimization (FFA) and SCSO (HFFSCOA) based clustering scheme, is robust and considers the dimensions of the grid, the alignment, the density of velocity nodes, and the range of communication to achieve its objective [81]. HFFSCOA plays a crucial role in clustering routes, facilitating the identification of reliable and efficient paths between vehicle nodes to establish and evaluate the network's optimal Cluster Heads (CHs). The outcomes of HFFSCOA highlighted its utility and effectiveness in terms of vehicle count, network scale, adaptable communication ranges, and the construction of clusters within the network.

WOA-SCSO has proposed a new optimization model for optimization problems [82]. The model outperformed other algorithms on the CEC′20 functions, proving its competitiveness. This algorithm was used to optimize the location of Contamination Warning Systems (CWSs) benchmark and a real-world water distribution system (WDS) to reduce contamination. Using the optimization model to determine the optimal pollution control sites in the WDS reduced severe effects by 49 % by strategically deploying at least one sensor in the network. It's efficiency in searching for CWSs' optimal positions inside WDSs.

The Parliamentary SCSO (PSCSO) methodology is revolutionary and improves the SCSO algorithm. The political (parliamentary) system inspires it. The PSCSO model seeks to enhance the identification of worldwide solutions by using interdisciplinary ideas [83]. The PSCSO has been enhanced by incorporating two key additions: exploration and exploitation. The efficacy of the PSCSO is thoroughly assessed by employing 41 benchmark functions derived from the CEC 2015, 2017, and 2019 contests, as well as four conventional engineering problems. It has provided comparative assessments on many cutting-edge algorithms, including SCSO, SE-SCSO, HSCSO, POA, and AOA. The evaluation results indicate that the PSCSO approach outperforms or matches the performance of other benchmark methods. This highlights the effectiveness of the innovative parliamentary-inspired strategy in enhancing the search for global solutions across a broad range of optimization problems. By incorporating techniques inspired by political systems into the SCSO framework, PSCSO provides a viable approach to improving the performance and usability of optimization algorithms in complicated engineering and computer challenges.

Electric vehicles (EVs) are the primary mode of transportation used for urban logistics. Efficient routing optimization and charging arrangement are crucial for the logistics distribution of EVs. A problem-solving approach utilizing a hybrid GA algorithm is proposed to optimize the algorithm. More precisely, the delivery strategy is initiated by the SCSO and enhanced through discrete search and broad neighborhood search [84]. Furthermore, the elite individual migration mechanism is employed to capitalize on the cooperation among the sand cat population, resulting in enhanced operational efficiency while maintaining the elite distribution pathway. An adaptive technique is used to modify the frequency of calls made to the local search module. The experiment findings conclusively demonstrate that the hybrid co-evolution algorithm offers a superior optimal solution to the multi-constrained electric car routing problem.

A lens contrast learning method and SSA named lens OBL and SSA (OBLSSA) is proposed to improve the search capability of SCSO and avoid falling into local optima [85]. To evaluate it, the CEC2005 and CEC2022 test functions are used in different dimensions. The results show that this algorithm has a high ability in optimization. A hybrid SCSO and AOA (SC-AOA) [86] approach is proposed to achieve a good balance between exploration and exploitation. A set of classical functions, such as those used in CEC 2014, CEC 2017, and CEC 2022, are employed to evaluate SC-AOA. The results demonstrate that SC-AOA is capable of finding practical solutions for all engineering cases.

Table 2 presents the advantages and disadvantages of various hybrid models.

Combining SCSO with FFA, WOA, and GA can provide a powerful approach to swarm optimization. As one of the metaheuristic algorithms, FFA delivers capabilities such as effective discovery and high search speed. With the concept of imitating the behavior of whale hunters, WOA can explore and improve the location of optimal points. Also, GA offers optimization capabilities for complex problems through genetic operations such as selection, mutation and crossover. By integrating these operations, GA introduces diversity and robustness, enhancing its ability to reach optimal solutions across various optimization problems. The FFA algorithm can avoid the weaknesses of other algorithms, such as getting stuck in local minima. The hybridization of SCSO and GA increases the suitability and efficiency of solutions for different environments and problems. The GA can leverage the power of genetic operations, which leads to diversity and a mutational search in the search space. WOA and FFA algorithms can help improve the SCSO due to their high search speed and effective exploration capability.

4.2. Improved

Metaheuristic algorithms excel in discovering superior solutions in intricate and unpredictable environments compared to conventional methods. Nevertheless, the SCSO has limitations, including challenges in accurately detecting regions of interest with a high likelihood in complicated scenarios, a deficiency in generating diverse outcomes and a propensity to become trapped in local optimal solutions. Several solutions have been proposed for incorporation into the SCSO to address these limitations and enhance performance.

Table 2
The advantages and disadvantages of various hybrid models.

Refs.	Models	Advantages	Disadvantages
[80]	GENGSO	●The RCSMOTE method, a practical approach to balancing classes and enhancing model performance by generating synthetic samples, has significantly boosted the combined model's accuracy, demonstrating its real-world applicability. ●The combination of sand cat and gazelle swarm-based optimization reduces the number of hyperparameters and minimizes the feature set size.	The hybrid model's computational complexity may be high compared to more straightforward methods, which increases the time and resources required to train it.
[81]	HFFSCOA	●The hybrid model exhibits high scalability and is well-suited for large-scale VANETs. This algorithm efficiently manages a large number of vehicles and responds effectively to the network's dynamic changes, ensuring stable performance under various conditions. ●The hybrid model has improved network stability and reliability by reducing cluster head changes and maintaining stable connections.	Hybrid model capabilities lead to high initial deployment costs. Therefore, advanced hardware and software infrastructure are needed to support the efficient operation of the hybrid model.
[82]	WOA-SCSO	The hybrid model (WOA-SCSO) can find the best points for the sensors and avoid getting stuck in local optima.	The algorithm's success depends on the accuracy of the input data and demand models, which can lead to undesirable results if the data is inaccurate.
[83]	PSCSO	The PSCSO model has enhanced global stage exploration by randomly selecting positions between the optimal solution and the current position.	The PSCSO model may be sensitive to parameter settings. Finding the correct settings for different problem domains may require multiple trials and adjustments.
[84]	GA-SCSO	There is a good balance between exploitation and exploration.	Hybrid models may have computational complexity and cost. This complexity is particularly effective in large logistics environments or real-time decision-making scenarios.
[85]	LSSCSO	Helping to discover the global solution and optimal distribution of agents in the search space	Increasing time complexity
[86]	SC-AOA	Balancing the search steps and finding optimal points	The number of repetitions has increased.

4.2.1. *Adaptive strategy*

The Sequential Contraction and Successive Optimization (CWXSCSO) technique [87] addresses poor convergence precision and local optimality. The CWXSCSO system improves decentralization and uses a crossbar. First, a novel and unique dynamic exponential factor is demonstrated. Additionally, elite decentralization is applied throughout the development process to increase the capacity to exceed the local maximum. In summary, the crossover technique generates new answers and allows the algorithm to explore constrained areas. SCSO improvements include elite decentralization, dynamic exponential factor, and a crossbar method. CWXSCSO has solved six typical engineering optimization problems to demonstrate its efficacy. Upgraded SCSO is more efficient and global in real-world optimization settings.

The weight factor parameter plays a crucial role in the algorithm. Its high value enhances the global search capability by promoting population diversity and enabling exploration across a broad solution space. The technique may perform a local search to find the best answer, effectively speeding up convergence when the comparison size is small. The sand cat engages in local search as part of the local optimization process, as outlined in Eq. (7). As indicated by Eq. (8), when the SCSO approaches a local solution, it becomes restricted to converging only to that local optimum and cannot achieve better local optimization. It can offset the restricted ability to exploit local resources early and enhance the overall search capacity later, preventing the population from settling too soon in a suboptimal solution. Eq. (9) demonstrates the mathematical expression for the exponential factor [87].

$$X(t+1) = r * (X_b(t) - \text{rand}\ (0,1) * X_c(t)) \tag{7}$$

$$X(t+1) = X_b(t) - r * X_{rnd} * \cos\ (\theta) \tag{8}$$

$$\omega = \left(e^{\left(1-\left(\frac{t}{T}\right)^2\right)} \right)^{kt} \tag{9}$$

The variable k follows an exponential distribution and is used as an optimization factor. While the variable t indicates the remaining number, and T denotes the total number of iterations.

Gaps in coverage result from the sensor nodes' initial random placement, which causes them to be positioned away from the ideal location. Hence, to enhance the range of sensor nodes and minimize the areas with no coverage, a virtual force-directed improved SCSO (VF-ISCSO) is suggested, leveraging the impressive capabilities of artificial intelligence [88]. Initially, a non-linear convergence approach is developed to enhance the sensitivity of sand cats. Additionally, the mechanism by which sand cats locate prey is enhanced. The VF-ISCSO maintains superior coverage performance even when there are changes in the size of the monitoring area and the number of sensors.

Multi-dimensional self-learning convolutional computing is used in the proposed heart sound diagnostic method. This novel approach addresses three current limitations: the poor time domain representation of heart sound data, the insufficient feature extraction capabilities of existing models, and the subjectivity of human parameter modifications [89]. It enhances the self-feature expression of cardiac sound samples. This approach enables more thorough feature extraction from heart sound recordings across various domains. The approach may better detect illness-related characteristics by assessing multiple receptive fields and resolutions within each spatial domain. Collaborative computing is used to increase feature extraction depth and complexity. A detailed study of heart sound samples from diverse viewpoints improves the model's capacity to recognize minor differences and patterns across heart diseases. The fundamental hyperparameters of the model are optimized to improve its capacity to extract discriminative features from data. Optimization improves heart sound diagnostic efficiency and accuracy. The suggested model performed well in experiments, obtaining 99 % accuracy. This high accuracy demonstrates the potential of the multi-domain self-learning convolutional computing approach to improve heart sound diagnostics.

The ISCSO algorithm, an enhanced iteration of the SCSO, is specifically developed to efficiently address the challenge of searching for moving targets. It has been proposed as a notable architectural solution that skillfully blends the SCSO's search and attack techniques, achieving a harmonious equilibrium between its global and local search capabilities. Nine distinct search scenarios are generated to validate the performance of the suggested algorithm.

A novel bio-inspired approach, dubbed Boosted SCSOA (BSCSOA), is introduced to tackle the parameter estimation of several solar photovoltaic (PV) models [90]. It is evaluated by comparing it to other renowned algorithms, such as the basic SCSOA, based on statistical metrics and fitness values. The collected findings showed that the BSCSOA outperformed all other algorithms for all cell and module PV models.

SCSO has limits in biological restrictions, local optima, search efficiency, and optimization accuracy, notwithstanding its success. OBL, improved exploration techniques, and biological elimination updates are incorporated into this work to address these issues and enhance SCSO [91]. These enhancements lead to Multi-Strategy Configuring Search Optimization (MSCSO), which uses global optimization and feature selection to improve its robustness and adaptability. It was pretty good at selecting features and optimizing globally. By evaluating and contrasting mathematical and statistical data from several perspectives, MSCSO surpassed alternative algorithms in optimization. It solved several optimization problems, demonstrating its adaptability in real-world applications. In conclusion, MSCSO improves optimizing algorithms by resolving SCSO's flaws and delivering robust global optimization and feature selection solutions across dimensions and datasets.

Two sophisticated wrapper feature selection (FS) methods are built utilizing SCSO. First, binary SCSO(BSCSO) is built by using the S-shaped transform function [92]. It requires an improved search method as it lacks internal memory for storing the optimal position. Hence, the second proposed FS technique focuses on developing an improved version of BSCSO known as Binary Memory-based SCSO (BMSCSO). The implementation and evaluation of the two enhanced feature selection approaches, BSCSO and BMSCSO, were conducted using twenty-one benchmark illness datasets.

Accurate event localization is crucial in WSNs. Determining unknown node placements is challenging. The DV-Hop algorithm is a popular WSN localization method. Network architecture has a significant impact on the accuracy of hop distance estimates in non-uniform areas and regions with irregularly distributed nodes. It convergence speed and accuracy were validated by simulation testing utilizing benchmark functions with different properties [93]. The novel technique outperforms the DV-Hop algorithm in localization accuracy by 58 %, 53 %, and 43 % in the best situation. This significant gain shows the ESCO algorithm's potential to enhance WSN localization, especially in demanding conditions.

Diabetic retinopathy (DR) is a disease that can arise as a result of complications from diabetes. It is characterized by the permanent harm it causes to the blood vessels in the retina. A persuasive image processing technique is suggested for diagnosing DR diseases using retinal fundus images. The proposed approach introduces a novel method for selecting features using a modified SCSO(MSCSO) strategy to eliminate extraneous information [94]. The Lens OBL (LOBL) enhances the algorithm's convergence rate. During location updates, the LOBL algorithm enhances its ability for global exploration by utilizing the MSCSO. The public datasets from APTOS Kaggle 2019 are used to evaluate the system. The trials showed a noteworthy level of specificity, accuracy, and sensitivity.

An Improved SCSO (ISCSO) [95] is proposed to improve the parameters of the double-layer spraying route. The SCSO has limitations, including slow convergence speed, below-average starting population quality, and a tendency to become stuck in local optima. ISCSO offers three upgrade options to overcome these restrictions. First, the general quality of the original population is improved by using the SPM chaotic mapping. A non-linear cycle adjustment technique also accelerates convergence by balancing local exploitation and global exploration. By integrating the immunity algorithm (IA), the ISCSO system may effectively avoid the appearance of local optima and enhance the precision of the solutions. ISCSO was subjected to a comparative analysis with seven others extensively utilized models throughout this procedure. The experimental results demonstrate that ISCSO performs exceptionally well in solving a wide range of functions, delivering greater precision in solutions and achieving a quicker convergence speed.

According to [96], this updated strategy uses stochastic variation and elite cooperation tactics in SCSO. Convergence is accelerated in the SE-SCSO method by balancing local exploitation and exploration through a nonlinear periodic adjustment mechanism. The technique utilizes pseudo-opposition and pseudo-reflection learning within the SCSO framework. These solutions enhance optimization efficiency and the global convergence of the algorithm. Experimental results demonstrate that the improved SE-SCSO technique significantly enhances performance metrics, exhibiting superior convergence accuracy, faster convergence rates, and effective avoidance of local optima. SE-SCSO is more resilient for complicated optimization tasks than regular SCSO because it uses stochastic variation, elite collaboration, and sophisticated adjustment mechanisms. SE-SCSO improves algorithm performance, enabling more dependable and efficient solutions to optimization problems.

To enhance the SCSO, advanced weighting techniques are introduced to assess the contributions of exceptional individuals in updating population positions. Additionally, improving community communication throughout the algorithm's iterations is essential to optimize the results. This technique uses an elite strategy to avoid early convergence to inferior solutions. Random variations based on the t-distribution mitigate concerns about elite cooperation strategies, especially in later algorithm stages when elite positions may become identical. This feature increases approach diversity to retain robust exploration capabilities throughout optimization. Three elite sand cats are picked and assigned specialized duties to steer the hunt. Elite sand cats are selected and weighted based on objective function assessments, giving lower-cost individuals larger weights. This cooperative and weighted method leverages outstanding people's talents while guaranteeing adequate population variety to explore and utilize the search space to maximize SCSO performance. This strategy, by dynamically altering roles and weights based on performance measures, improves the algorithm's capacity to solve complex optimization problems. The weight assignment method is decided by the mathematical expression represented by Eq. (13) [96].

$$w_{gb1} = \frac{1}{2} - \frac{f(X_{gb1})}{2\left(f(X_{gb1}) + f(X_{gb2}) + f(X_{gb3})\right)} \tag{10}$$

$$w_{gb2} = \frac{1}{2} - \frac{f(X_{gb2})}{2\left(f(X_{gb1}) + f(X_{gb2}) + f(X_{gb3})\right)} \tag{11}$$

$$w_{gb3} = \frac{1}{2} - \frac{f(X_{gb3})}{2\left(f(X_{gb1}) + f(X_{gb2}) + f(X_{gb3})\right)} \tag{12}$$

$$X_{lead} = \frac{w_{gb1}\cdot X_{gb1} + w_{gb2}\cdot X_{gb2} + w_{gb3}\cdot X_{gb3}}{3} \tag{13}$$

The variables w_{gb1}, w_{gb2}, and w_{gb3} indicate the weights of various elites, whereas X_{lead} denotes the location of the global best solution following elite cooperation. The locations of the ideal solution vary following elite cooperation, employing a stochastic variation method as indicated by Eq. (14) [96].

$$X'_{\text{lead}} = X_{\text{lead}} + X_{\text{lead}} \cdot t(\text{Iter}) \tag{14}$$

The variable X'_{lead} represents the ideal location of the solution after variation, whereas $t(Iter)$ represents the current number of iterations for the t-distribution (Casey distribution) with the specified degrees of freedom. It is guided by a stochastic variant that employs an elite cooperation method, utilizing X'_{lead} instead of the optimum solution $\overrightarrow{X_b}$. The t-distribution operator is highly likely to produce values that are higher than expected. The algorithm has excellent global exploration capabilities, and the location change significantly affects the step size. In subsequent phases, the t-distribution acts as an approximation to the conventional normal distribution. This approximation is more focused, meaning that the t-distribution tends to have smaller values with a higher likelihood. Additionally, the t-distribution has a smaller step size for location variation, which is beneficial for the algorithm's

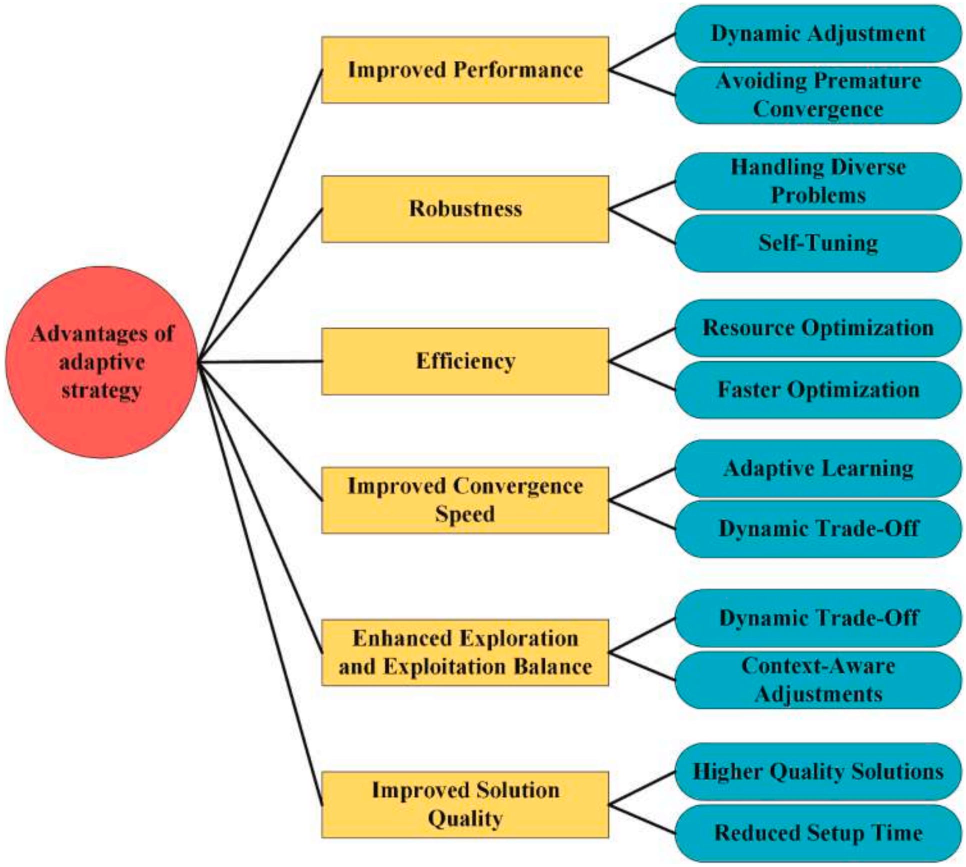

Fig. 14. The advantages of the adaptive strategy on the SCSO algorithm.

convergence.

A scheduling mechanism based on the Multi-Strategy Improved SCSO (MSISCSOA) is proposed to address scheduling challenges in cloud-edge computing environments [97]. The MSISCSOA method incorporates stochastic strategies and elite cooperation, enabling it to strike a proper balance between search and exploitation. This advancement leads to dynamic stochastic search and joint adversarial selection, increasing the convergence speed, improving global optimization, and increasing the search efficiency.

Fig. 14 illustrates the advantages of the adaptive strategy on the SCSO.

4.2.2. Chaotic

A chaotic map is a nonlinear mathematical function that has a dynamic behavior that is very sensitive to initial conditions [98,99]. Chaotic maps, such as the Logistic Map, Sine, and Tent, are among the most famous examples of chaos. It plays a critical role in improving the performance of metaheuristic algorithms [100] due to their dynamic characteristics, such as sensitivity to initial conditions and pseudo-random behavior [101]. These mappings help enhance population diversity, improve global search capabilities within the search space, and prevent premature convergence to local optima. One of the main challenges in metaheuristic algorithms is generating a diverse initial population. Chaos maps can be used as a method to develop an initial population with a broad and diverse distribution, leading to improved initial search [102]. Moreover, chaotic maps can distribute agents or humans throughout the search space due to their pseudo-random structure.

A model optimizes logistics distribution in cross-border e-commerce multimodal transportation to reduce distribution costs, carbon emissions, and customer happiness. The mathematical framework accounts for cargo airplanes and vehicle load limits to achieve these goals. This method utilizes chaotic mapping to determine search agent placements, thereby providing the algorithm with a high-quality initial population. This initialization strategy improves convergence and solution quality. Logistic mapping, a popular method for studying chaotic systems, was employed. It was demonstrated that the mathematical model and enhanced SCSO (ISCSO) were successful through cross-border e-commerce logistics transportation simulations [103]. It makes cross-border e-commerce logistics more sustainable and efficient by using sophisticated optimization approaches in logistical decision-making. It shows how augmented swarm intelligence algorithms may help meet economic, environmental, and customer service goals in real-world applications. Eq. (15) defines the generic form of the logistic mapping [103].

$$\underset{ij}{\overset{\prime}{z}} = \mu \cdot z_{ij}\left(1 - z_{ij}\right) \tag{15}$$

Where zi is a value between 0 and 1, and μ is between 0 and 4, typically set as $\mu = 4$. Using Eq. (16), values for each individual's dimension within the range of (0, 1) are randomly generated to initialize the population of humans via logistic chaos.

$$x_{ij} = low_j + \underset{ij}{\overset{\prime}{z}}\left(up_j - low_j\right) \tag{16}$$

The chaotic initialization strategy in swarm intelligence differs from standard methods by incorporating unpredictability derived from chaotic dynamics. This method provides a unique, nonlinear beginning point for the optimization procedure. In optimizing logistics, where intricate and ever-changing conditions are common, this characteristic offers a distinct advantage in attaining more resilient solutions. Fig. 15 shows a flowchart of the improved SCSO by logistic chaos.

The paper proposes a Chaotic Dynamic Disturbance SCSO (CDD-SCSO) [46] algorithm to identify unknown parameters. This innovative method converts identifying model parameters into an optimization

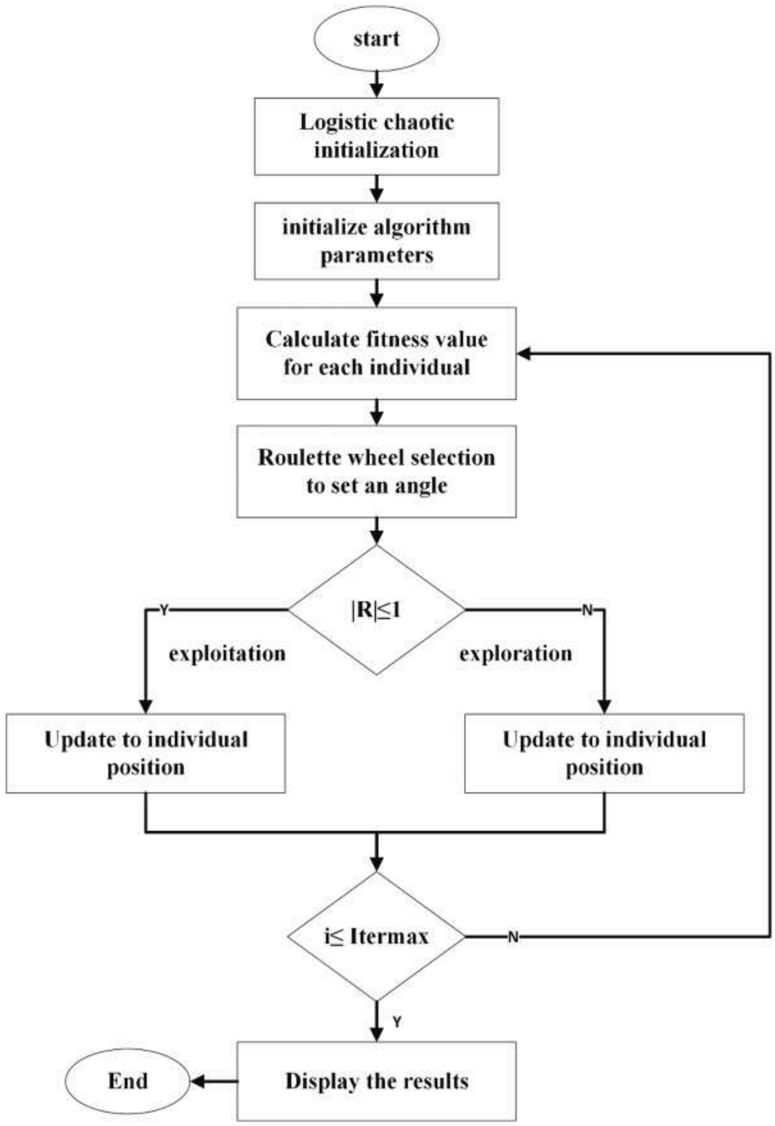

Fig. 15. The flowchart improved SCSO by logistic chaotic [103].

problem involving nonlinear functions. Additionally, it addresses the challenge of linking multiple-input nonlinear parameters by employing a swarm intelligence algorithm. The enhanced swarm intelligence method can efficiently search for optimal values and compute in parallel, identifying the most accurate estimate of model parameters.

The Chaotic SCSO (CSCSO) model is explicitly tailored to tackle the difficulties posed by intricate and restricted optimization issues. The work seeks to showcase the efficacy and supremacy of the proposed CSCSO method in resolving these issues, thereby making a valuable contribution to the optimization and parameter identification [104]. The primary objective of the proposed method is to improve overall search performance and convergence behavior by including non-recurring sites' chaotic features in SCSO's basic search process. Therefore, a chaotic map can substitute for randomness in SCSO, as it exhibits similar random characteristics while offering improved statistical and dynamic properties. Other disadvantages include low population variety, the local optimal trap, ineffective search, and restricted search consistency. To enhance the efficiency of the exploration and exploitation stages, the proposed CSCSO integrates many chaotic maps. The study implemented the suggested approach to 39 functions and transdisciplinary problems. The results showed the most advanced SCSO variant and other metaheuristics based on chaos that were investigated. This comprehensive experiment demonstrates that the CSCSO consistently delivers satisfactory outcomes.

An upgraded SCSO (PSCSO) is proposed to increase the furnace temperature prediction model for an aluminum melting process (AMP) [105]. Initially, a disruptive convergence factor is incorporated into each iteration of the process, altering the algorithm's strategy selection mechanism and enhancing its speed and precision. Furthermore, a population redistribution method is developed. Ultimately, a strategy is proposed to effectively escape local optima during the later iterations of the algorithm. It is applied to AMP and validated using standard benchmark functions. The findings indicate that PSCSO surpasses other optimization strategies. The alteration in the convergence factor dictates the transition to the state of SCSO, denoted as r_G. When the value of r_G is high, the algorithm is in the searching stage. Currently, the algorithm is robust enough to conduct extensive searches throughout the solution space, thereby preventing it from getting stuck in a suboptimal solution. When the value of r_G is small, the algorithm is in the attacking stage. Currently, the algorithm has a robust capacity for local search, which significantly enhances its speed of convergence. Nevertheless, the initial algorithm exhibits a linear decrease from 2 to 0. This causes the method to inadequately represent the predation status of the sand cat, leading to the SCSO being susceptible to local optimization and experiencing sluggish convergence. A suggested enhancement to the SCSO iteration is presented, aiming to increase the algorithm's performance by modifying the convergence factor [105]. The improved convergence factor r_G is defined by Eq. (17).

$$r_G^{'} = 2\left[1 - \left(\frac{t}{t_{max}}\right)^{\frac{1}{2}}\right] + 2|\alpha_t|\left[\left(\frac{t}{t_{max}}\right)^{\frac{1}{2}} - \left(\frac{t}{t_{max}}\right)^{2}\right] \tag{17}$$

where $a_t = 1 - 2(a_{t-1})^2$ and $a_t \in [o, 1], a_0 \neq 0.5$. The enhanced convergence factor may initiate a non-linear and stochastically chaotic descent process.

The proposed method utilizes an improved SCSO with a generalized neural network to detect and notify of faults. The SCSO has been enhanced by integrating a more advanced chaotic mapping initialization strategy, reverse elite strategies, and a Cauchy mutation that is based on adaptive selection [106]. Subsequently, this approach is employed to enhance the performance of the generalized neural network and ascertain its optimal parameters. This methodology significantly improves the precision and dependability of system failure notifications. A chaotic mapping is applied to initialize the SCSO algorithm dynamical disturbance (CDD-SCSO), which is to search for the optimal value of the system parameters with greater accuracy [107].

The benefits of the chaos-based SCSO algorithm are shown in Fig. 16.

4.2.3. *Data mining*

Data-driven models can handle this complexity, but they require more interpretability and depend on the quality of the data. A hybrid technique combines the precision of physical models with the adaptability of data-driven models. A revolutionary two-stage hybrid forecasting method improves wind power forecasts. A power curve-based four-parameter model estimates Wind Power Potentials (WPPs). An error-correcting model using a multilayer perceptron modifies these original findings. A hybrid SCSO and Simulated Annealing method and an upgraded fuzzy C-means clustering algorithm can improve ice risk assessment accuracy. These methods detect icing by identifying power variation and other characteristic data [108]. Our proposed method is validated using real-world sensor data from supervisory control and data acquisition systems, thereby enhancing its trustworthiness. The results demonstrate that the hybrid SCSO-IFCM approach exhibits excellent convergence performance, thereby proving its practicality.

The ANN-SCSO method has been suggested as a means to forecast the temporal variations in tunnel displacements, taking into account the rheological properties of the rock metaheuristic algorithms [109]. It integrates an analytical solution with an artificial neural network (ANN) that has been improved using the SCSO and Chebyshev map. The prediction performance of ANN models is significantly influenced by the model structure, which includes the number of hidden layers and the associated weights and biases. While some optimization techniques, such as backpropagation, have been used to calculate weights and biases to minimize prediction errors, there are considerable obstacles in determining the ideal structure and preventing local optimization issues. Several population sizes were examined during the SCSO optimization process rounds to assess the algorithm's predictive capabilities. To determine the optimal population size of the SCSO, as well as the corresponding optimal weights and biases, the root mean squared error (RMSE) was used as the fitness function. The verification findings indicate that the suggested model's calculation accuracy is marginally inferior to the analytical solutions. Nevertheless, the model remains dependable, given its efficient calculations and acceptable margin of error.

SCSO and Deep Neural Networks (DNN) hyperparameter optimization improve PV/T prediction accuracy [110]. Through complicated calculations, neural networks translate specified inputs into outputs that solve real-world issues like categorization. This study emphasizes feed-forward neural networks. This study presents an input, hidden, and output layer of optimized deep neural network (ODNN) classifiers that seek the ideal number of hidden layers and neurons per layer. Adding hidden layers adds complexity but improves outcomes. ODNN has a default learning rate of 0.15 and a bias parameter of 1. Research indicates that the SCSO algorithm enhances the efficiency and reliability of deep neural networks. Photovoltaic/thermal (PV/T) cooling applications need accurate thermal and electrical efficiency predictions;

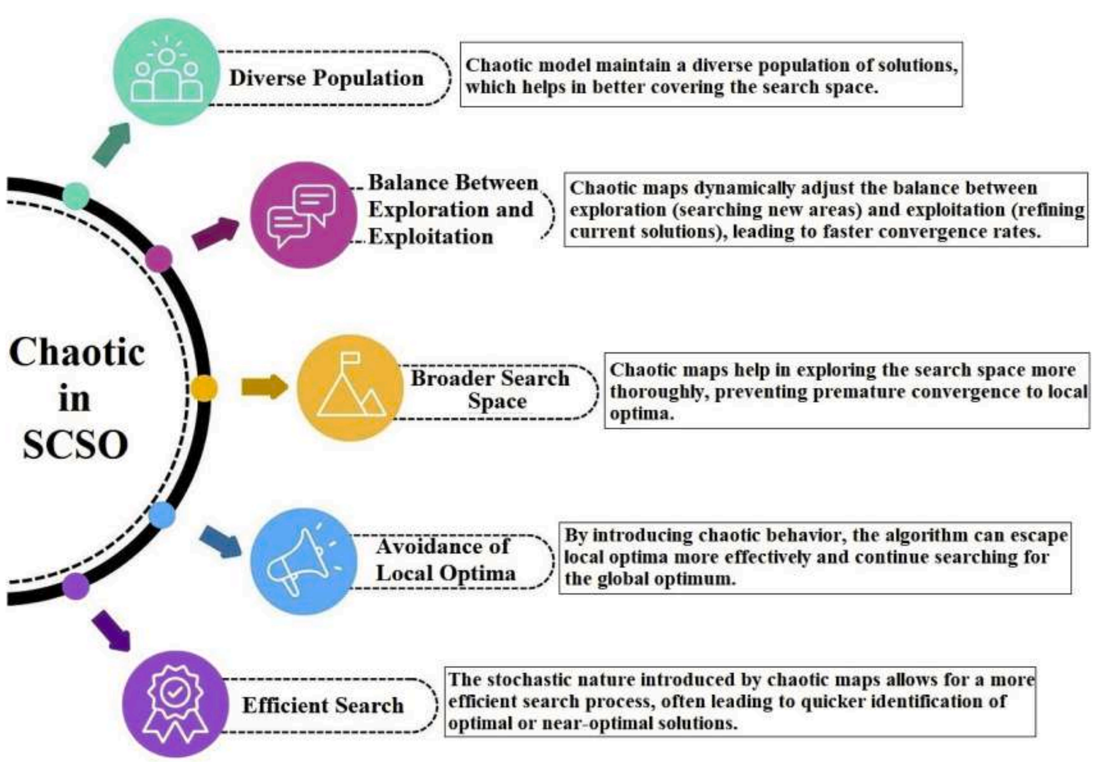

Fig. 16. The benefits of chaotic behavior in SCSO.

therefore, this optimization is beneficial.

Three optimization techniques, namely Manta ray foraging optimization (MRFO), SCSO, and GA, have been developed to enhance the output of biodiesel by drawing inspiration from nature [111]. The MRFO process yielded the maximum expected biodiesel output of 98.63 %, whereas the SCSO process yielded a lower yield of 98.58 %. The algorithms' bio-inspired character allows them to explore the parameter space efficiently, enhancing their potential to outperform standard optimization approaches. By contrast, GA yielded a maximum anticipated biodiesel output of 98.61 %, comparable to the results obtained using innovative methods. Therefore, it emphasized its significance and widespread use in many optimization applications. Notably, the anticipated yields of all the algorithms closely matched the actual biodiesel production of 98.31 %, which is the average result of triplicate trials conducted under optimum conditions. These results are corroborated by prior studies that used similar optimization techniques in disparate domains. For example, MRFO effectively optimizes intricate processes, whereas SCSO has demonstrated the potential to tackle complex optimization challenges. The use of MRFO and SCSO in enhancing biodiesel production processes enhances the current understanding of biodiesel research.

A multiple objectives Self-Organizing SCSO (SOMSCSO) [112]. An approach is proposed to address multiple objective functions like average area rate, energy efficiency, average user rate, and spectral efficiency of 5 G with metaheuristic algorithm MIMO. The performance of PSO, Ant Colony Optimization (ACO), and SCSO is compared with the SOMSCSO approach. The results show that the SOMSCSO approach achieves a significantly better computational time of 25.89 s compared to the existing methods.

Accurate crop evapotranspiration estimations are crucial for efficient irrigation and agricultural water management, especially for maize. Models for maize evapotranspiration often incorporate meteorological data and empirical parameters, which can be inaccurate. It developed a more accurate prediction model using data from multiple locations in Northern China. A Back-Propagation Neural Network (BP) has been used to estimate maize evapotranspiration using soil, meteorological, and crop-specific data [113]. The maize evapotranspiration model improved significantly when meteorological, soil moisture and crop data were included. SCSO-BP performed best among optimized models, followed by GJO-BP and HPO-BP. The findings show that sophisticated optimization may improve crop evapotranspiration models and agricultural water management. Researcher integration of these advanced methods can improve irrigation plans and agricultural sustainability.

The Support Vector Regression (SVR) model and SCSO are suggested as methods for predicting [114]. The historical reliability data is initially subjected to the sliding window approach to produce time series samples. These projected data points were included in the sequence to generate new samples. As a result, the old data was discarded, and continuous reliability prediction was achieved by continually developing new data.

The SCSO method improves backpropagation (BP) neural networks to optimize the elbow inlet channels [115]. The SCSO-BP neural network has four input nodes, nine hidden nodes, and one output node. The output node shows operational efficiency. The GA selected the best parameters from sample space approximation models. The optimal specifications of the elbow inlet channel were determined. The experimental and numerical simulation results were in good agreement. The revised SCSO approach reduced error fluctuation and increased consistency in fluctuation range, thereby improving the approximation prediction model. The updated inlet model reduced intake wall damage and improved input impeller velocity distribution, resulting in a 5 % increase in pump efficiency and a 7.48 % increase in head near the design flow. Additionally, it increased the pump's efficient operating range.

Predicting concrete compressive strength is difficult owing to the complex interactions between affecting elements and strength [116]. These methods utilize Extreme Gradient Boosting (XGB) to forecast the compressive strength of green concrete, which contains fly ash and blast furnace slag, rather than relying on standard testing. Performance criteria such as VAF, R^2, RMSE, and MAE were used to evaluate intelligent prediction models. SSA-Extreme Gradient Boosting (SSA-XGB) exhibits the best prediction power, outperforming the other five hybrid models in all criteria, and thus emerges as the most suitable model for predicting the compressive strength of green concrete. It demonstrates that modern metaheuristic algorithms and machine learning methods, such as XGB, enhance the accuracy and reliability of concrete strength prediction. Researchers can simplify the estimation of concrete properties using these revolutionary methods, enabling more efficient and sustainable construction.

As described in [117], the Reinforcement Learning-based SCSO (RLSCSO) improves SCSO, which determines reinforcement agent behavior in specified settings. Q-Table values determine whether the agent explores new options or exploits knowledge. The reward and punishment systems update the Q-Table depending on agent behavior. The Q-learning algorithm rewards or penalizes states and actions to help the agent learn and adapt. A matrix-based Q-Table captures the agent's experiences and informs its judgments. Initial exploration begins with the agent unaware of its surroundings. It was tested using 20 benchmarks and 100-digit challenge essential test functions. The suggested strategy also solves the NP-hard mobile sensor node localization issue. According to several extensive assessments, the technique solves global optimization issues efficiently and effectively. The RLSCSO method finds optimal solutions while balancing exploration and exploitation, particularly in terms of cost values.

An innovative approach is proposed to enhance surface quality in turning operations by effectively regulating the depth of cut. A piezoelectric vibration sensor provides feedback within a control system that employs a metaheuristic algorithm to precisely control the position of the servo motor driving the cutting tool. Using Q-learning-based SCSO, the PID controller is tuned to provide the best possible cutting depth accuracy and surface finish quality [118]. The findings suggest that the proposed system can effectively manage fluctuations in cutting conditions and tool deterioration. The experimental findings demonstrate that the proposed framework exhibits enhanced resilience and stability compared to a highly optimized traditional PID control.

The rapid expansion of IoT devices has complicated security issues, particularly in the transfer of data across networks. To solve these problems, AI must be used to create sophisticated IDSs. They can respond quickly to changing threats and adjust their techniques accordingly based on prior instances. The vast data network systems generate, and the high computational needs make categorizing network traffic more difficult. Using feature selection (FS) strategies removes less relevant information for the classification objective, thereby reducing data complexity. Classification algorithms become more accurate and efficient using this method. To improve the Extreme Learning Machine (ELM) classifier's performance through feature selection, a hybrid SCSO technique is developed [119]. This hybrid technique integrates SCSO and ELM to expedite feature selection and increase intrusion detection system performance. This improvement is crucial for managing IoT device networks and safeguarding against emerging cyber threats.

Predicting deformation is crucial for ensuring the safety of concrete dams. The random forest (RF) approach has become famous for dam safety monitoring because of its fast calculation and strong generalization. However, discrepancies in measured displacement values and improper RF parameter design can significantly affect RF efficacy. This study uses the Indicator Variable Model (IVM) to detect and minimize observed value discrepancies. For the first time, SCSO is used to improve the RF approach [120]. IVM effectively corrects monitoring data interferences with an accuracy of below 3 %. SCSO optimizes RF parameters better than TAE and PSO. SCSO-RF outperforms TAE-RF, PSO-RF, LSTM, and SVM models in prediction accuracy and stability. IVM with RF augmented by SCSO offers a robust method for reliably forecasting concrete dam deformations, achieving better performance metrics than previous methods.

A novel method using ANN and SCSO for hyperspectral image classification is proposed [121]. In this method, SCSO is first employed for optimal feature selection, and ANN is utilized to enhance the accuracy of classification maps. A new technique using the SCSO algorithm and fully homomorphic encryption is proposed for the security of IoT networks [122]. SCSO is used to tune the MLP network hyperparameters to avoid overfitting optimally.

4.2.4. Deep learning

The application of deep learning has had a profound impact on various domains, offering robust tools for representing complex patterns. Two notable deep learning architectures are Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNNs) networks. CNNs, using convolutional layers, are specifically intended to analyze structured data, particularly for tasks like image processing. In contrast, LSTMs excel in representing sequential data and capturing long-term relationships by utilizing memory cells and gate mechanisms. Efficient optimization is crucial while training deep learning models, with stochastic gradient descent (SGD) and Adam being essential algorithms in this process. Nevertheless, sophisticated optimization methods like SCSO, such as avoiding local minima and effectively exploring intricate search spaces, provide notable benefits. Combining CNN and LSTM with PSO yields a highly effective collaboration, where CNNs can extract the most beneficial features.

Cancer is a dangerous disease that requires improved detection methods. Early identification significantly increases skin cancer survival. Skin lesions vary in appearance, making automated image classification challenging and costly for early detection. According to [123], Skin cancer detection and classification should use an advanced and integrated classifier technique. The suggested approach addresses dimensionality and real-time data streaming prediction. It distinguishes skin lesion features using SCSO-ResNet50. Ensemble classifiers, baseline classifiers, and CNNs outperformed the second layer of skin cancer classification, improving prediction accuracy.

An IDS is crucial for monitoring network activity and spotting unusual or malicious behavior. It necessitates enhancements in both its performance and security. The DL model is the most promising and widely used tool for identifying intrusions. The authors suggest a model for an intrusion detection system based on SCSO, called SCSO-CNN [124]. It is estimated using a database of NSL-KDD. The data is normalized using the Min-Max normalization pre-processing approach. CNN is used for efficient and precise classification of incursion, whereas SCSO is utilized for selecting the attributes. The SCSO-CNN model achieves an exceptional accuracy of 99.85 % when trained on the NSL-KDD dataset. The use of an ID network in this study leads to the attainment of both high network information security and performance.

Software defect prediction (SDP) is crucial for assessing software quality and minimizing development costs. It involves utilizing an optimal deep learning model and an oversampling strategy to predict software defects early, thereby addressing these issues. It is addressed using k-means clustering and the synthetic minority oversampling approach (KMSMOTE). The input is classified into defect or non-defect using the SCSO-Recurrent Neural Network (SCRNN) technique [125]. The SCSO's hyperparameters are carefully selected to provide optimum performance, while the NIPUNA activation function effectively addresses the issue of gradient vanishing. Tests performed on the NASA dataset indicate that the system achieves an average accuracy of 96.21 %, validating the proposed model's effectiveness in accurately predicting outcomes. This model can potentially reduce the cost associated with misclassifications and address the issue of imbalanced sample classes.

Malicious user detection for spectrum sensing in Cognitive Radio Networks (CRNs) is a crucial security measure that ensures the efficient and reliable operation of these systems. Advanced neural network frameworks utilize deep learning to identify and alert to potential risks within a network accurately. Through extensive data analysis, deep learning approaches can identify trends and abnormalities associated with harmful user behavior, system intrusions, fraud, or unusual activity. This approach offers adaptability, enabling a network to acquire knowledge and progress in response to changing threats. A paper titled "An Optimal Deep Learning Empowered Malicious User Detection for Spectrum Sensing (ODL-MUDSS) in the Cognitive Radio Network (CRN)" is introduced in reference [126]. The primary objective of the ODL-MUDSS model is to concentrate on the automatic detection and categorization of malevolent users (MUs) in CRN. The ODL-MUDSS model essentially utilizes the deep belief network (DBN) technology to provide automatic and precise identification of MUs. Furthermore, the use of SCSO may enhance the recognition efficacy of the DBN approach, thereby improving the accuracy of the detection outcomes. The ODL-MUDSS approach is evaluated for performance validation across several processes.

Credit risk prediction is a crucial financial tool for evaluating the default risk of credit applicants. Many credit risk assessments use human audits and statistical methods. Academics and businesses have focused on credit risk techniques enabled by machine learning (ML) to enhance financial AI. Credit risk assessment technique construction hinges on feature selection. The process enhances machine learning by choosing a portion of pertinent material. A novel model for assessing credit risk is called SCSO-based Feature Selection with Hybrid Deep Learning (SCSOFS-HDL) [127]. The political optimizer (PO) approach improves DLSTM-SANN performance through hyperparameter optimization. They were experimentally validating SCSOFS-HDL with credit risk datasets. SCSOFS-HDL performed best on the Australian Credit and German Credit datasets, achieving maximum accuracies of 96.49 % and 96.12 %, respectively. For electric vehicle hybrid energy storage systems (HESS), a new energy management (EM) technique is offered. The SCSO algorithm and recalling enhanced recurrent neural network (RERNN) improve HESS energy allocation and management in the SCSO-RERNN method [128]. This integration stabilizes the DC bus voltage and monitors battery and super-capacitor (SC) states to meet operating criteria under different load scenarios. Comparing hybrid energy management to existing approaches shows its efficacy. The process is carefully validated using MATLAB simulations to ensure its effectiveness. The SCSO-RERNN-based energy management method is a novel approach to enhancing the efficiency and reliability of hybrid energy storage systems in electric vehicles. Its successful application advances electric vehicle energy management and promotes sustainable mobility.

The SCSO-CNN system [129] is designed to categorize email spam, with the primary goal of enhancing performance and accuracy in the classification process. It incorporates three primary enhancements: using numerous feature extraction techniques, implementing feature selection methods, and integrating an advanced hybrid model. These improvements are specifically designed to boost the accuracy of spam identification. The email classification stage establishes a link between the training and testing sets and then utilizes deep learning techniques to extract and classify features. The SCSO technique reduces loss and increases accuracy by optimizing weights for every epoch. The solution provides a comprehensive approach to email security by enhancing its ability to detect phishing attempts within the network.

An RERNN-SCSO microgrid at an Electric Vehicle Charging Station (EVCS) would use a Unified Power Quality Conditioner (UPQC) [130]. This system generates the converter control signal using the SCSO method, and the Recurrent Elman Neural Network (RERNN) technology is employed to forecast it. RERNN-SCSO aims to improve electricity quality. The Point of Common Coupling connects highly inductive and unbalanced non-linear loads. Initializing the UPQC structure in the EVCS requires an extra AC/DC converter. The charging station charges electric cars (EVs) and transfers energy to the grid. The suggested method efficiently charges EVs while addressing power quality challenges, including harmonic currents, voltage disturbances, voltage sags and swells, and voltage imbalances. MATLAB/Simulink was used to compare the RERNN-SCSO technique against current tactics. The

RERNN-SCSO method had a THD of 2.03 % under voltage sag and 2.01 % under voltage swell. They are far lower than those obtained using conventional approaches, proving the suggested system's improved performance. The RERNN-SCSO method improves power quality at EV charging stations and ensures microgrid reliability and efficiency by incorporating sophisticated prediction and control techniques.

A multi-objective SCSO (MO-SCSO) and self-paced extended short-term memory network (SPLSTM) reduce noise and improve wind power prediction [131]. The procedure starts by transforming raw wind power data into a time series format for model input and output. After that, self-paced learning is employed to stabilize the extended short-term memory network training due to noisy input. Next, the enhanced MO-SCSO method optimizes SPLSTM iterative hyper-parameters. Optimization improves the model's wind power prediction. MO-SCSO-SPLSTM is a wind power forecasting composite model. This method was tested using data from Austrian and Danish onshore and offshore wind farms. The experimental findings demonstrate that the proposed technique outperforms typical LSTM models in both accuracy and robustness. The proposed method reduces MAE by 5.44 % for onshore wind generation and 4.96 % for offshore wind production. This novel technique addresses noisy data issues and enhances wind power model predictions. Combining the MO-SCSO with the LSTM network provides a dependable wind power forecasting solution.

A novel strategy called SCSODTL-SCC, which utilizes deep transfer learning, is introduced to detect and classify skin cancer [132]. The main objective of the SCSODTL-SCC model is to classify and diagnose different types of skin cancer using dermoscopic images. The primary methods for removing hair are the dull razor method and median filtering for noise reduction. Furthermore, the U2Net segmentation method is used to identify areas of infected lesions in dermoscopic pictures. Moreover, the classification process utilizes a feature extractor based on NASNetLarge combined with a hybrid deep belief network (DBN) model. The SCSO method may enhance the classification performance by optimizing the hyperparameter tuning procedure, demonstrating the originality of this research. Using the benchmark skin lesion dataset, the simulation parameters of the SCSODTL-SCC model are thoroughly investigated. The comparison results showed that, on a wide range of measures, the SCSODTL-SCC model performed best in classifying skin cancer.

Coverage gaps in WSNs often arise due to the haphazard placement of nodes and the failure of individual nodes. The presence of coverage gaps leads to an increase in the time complexity and power consumption of contemporary protocols. Nevertheless, the use of distributed approaches in recent years to address the coverage hole detection issue has been linked to a significant increase in computing complexity. A novel technique is proposed in [136] for accurately estimating node positions and detecting coverage holes in WSNs. The strategy combines deep learning with cluster-based methods to get optimal results. The first step involves using a modified Lyapunov optimization (MLO) method to calculate the nodes' location, guaranteeing the presence of edge nodes in the network. The following text presents a proposal for designing an ideal clustering approach utilizing an improved SCSO (ISCSO). This technique aims to create efficient and balanced clusters that can accurately calculate the coverage hole area in a network. The findings demonstrate that the suggested technique provides substantial improvements compared to benchmark approaches.

A hybrid neural network and enhanced feature processing have produced a new load forecasting method. A methodology for mapping periodic features extracts repeating patterns in load data. This is essential for reflecting energy consumption's cyclical nature. SCSO-based improved filtering refines data. A smoother and more consistent load profile is achieved by reducing high-frequency noise in load data. Filtered data is better for predicting by avoiding sudden variations. This unique method relies on the SCSO-MHA-GRU (SMG) hybrid prediction model [133]. This model uses a Gated Recurrent Unit (GRU) network with multi-head self-attention. Multi-head self-attention enhances the model's ability to capture and interpret relationships between input features. This innovation enables the model to understand and anticipate complex patterns in load data. The SMG model excels in short-term load forecasting for residential regions with fewer users. This makes it perfect for precisely estimating energy usage in such environments, improving energy management and planning. This innovative load forecasting system uses advanced feature extraction, noise reduction, and hybrid neural network modeling to estimate load well.

Adam, stochastic gradient descent (SGD), MPA, Tuna Swarm Optimization (TSO), Artificial Rabbits Optimization (ARO), SCSO, HBA, and PSO have been used in landslide locations [134]. The study analyzed 945 landslide locations from 2012 to 2022 using Deep Neural Network (DNN) and DNN-hybrid models and 14 conditioning variables. All models have excellent forecast accuracy. These results show that sophisticated optimization methods and deep learning can forecast landslide susceptibility. DNN-hybrid models utilizing MPA, HBA, and ARO algorithms can enhance landslide prediction accuracy and safeguard communities in landslide-prone areas.

Gas-containing coal fracture risk is evaluated using a multi-strategy modified SCSO approach that combines a Parallel Temporal Convolutional Network and Bidirectional Gated Recurrent Unit (PTCN-BiGRU) [135]. This unique approach simplifies gas-containing coal fracture risk calculations by using TCN for feature extraction via kernel entropy component analysis and parallel convolution. The BiGRU model extracts contextual correlations of characteristics more thoroughly, improving prediction abilities. To improve the linearity and generalization of the model, a parameterized exponential linear unit is incorporated into the TCN. To enhance risk projections based on BiGRU network properties, the updated SCSO incorporates an adaptive t-distribution, a chaos reduction factor, and Singer chaos mapping. The ISCSO-PTCN-BiGRU model outperforms other models, achieving a prediction accuracy of 93.33 %. Risk management in gas-containing coal fracture risks is enhanced by this innovative technique, which employs various strategies to improve forecast accuracy and reliability.

Due to a lack of awareness and early diagnosis, breast cancer deaths have increased significantly among women over the past several decades. A federated learning-deep learning approach for illness diagnosis is proposed. It automates and speeds up the process [136]. The recommended study includes image capture, encryption, optimal critical production, secure data storage, and sickness classification. Input medical images are obtained during image collection. Medical samples are also secured to maintain confidentiality using Extended ElGamal Image Encryption (E-EIE). Optimization of keys using the Improved SCSO (I-SCSO) technique improves encryption efficiency. It enables secure communication of medical images. Decrypted images are used to classify illnesses using the convolutional capsule twin attention tuna optimal network model. Parameter adjustments using chaotic tuna swarm optimization (CTSO) lower the classifier's loss. The study uses BreakHis Database for experimental analysis and Python for simulation analysis. Simulation results show that the recommended study performed better in accuracy (95.68 %), recall (95.6 %), precision (95.66 %), F-measure (95.63 %), specificity (95.66 %), and kappa coefficient (95.26 %).

Remaining networks and SCSO are combined to improve multi-labelling text learning accuracy and variety [137]. ResNet-SCSO stresses multi-labeling's diversity and accuracy, unlike existing approaches. Movies, scholarly publications, medical data, birds, and proteins were analyzed separately. Preprocessing was employed to gain accurate and improved data. The ResNet-SCSO model outperforms other algorithms on multi-label datasets with varied dimensions. Comparing the implemented methodology to benchmark methods shows its efficacy.

The authors recommend ISCSO-BiGRU, which improves the BiGRU model, using L-Isomap and ISCSO [138]. Initial feature extraction from DGA feature data uses the L-Isomap technique. Additionally, ISCSO BiGRU parameters should be optimized to create an optimal diagnostic model utilizing BiGRU. Four ISCSO improvement techniques are offered.

Logistic chaotic mapping, water wave dynamic component, adaptive weighting, and golden sine augment the classic SCSO approach. Next, benchmarking functions analyze ISCSO and the four methods' optimization performance. These results demonstrate the superior optimization accuracy and convergence speed of ISCSO. The technique for fault diagnosis was created using ISCSO-BiGRU and L-Isomap. The fault diagnostic model's simulation findings indicate that filtering and downscaling model inputs with L-ISOMP may enhance model performance. The outcomes are contrasted with the fault diagnostic models for GWO-BiGRU, WOA-BiGRU, SCSO-BiGRU, and PSO-BiGRU.

Stock price prediction was performed using an LSTM model and the SCSO algorithm [139]. The results show that the LSTM-SCSO model outperformed all other models in all evaluation criteria. Detecting malicious activities in the field of smart city cybersecurity is crucial for maintaining the integrity and stability of urban systems. A novel method is proposed to detect malicious activities by integrating optimization algorithms and deep learning [140]. The ISCSO algorithm is used to select an optimal set of features.

4.2.5. Levy flight

Real-time dynamic route planning using an improved ANN and Interfering Fluid Dynamical System (IFDS) improves path quality and computational efficiency. Path planning using IFDS overcomes low sample quality and quantity. This method generates and simulates sufficient sample data for ANN training. Enhanced SCSO (ESCSO) improves sample quality [141]. ESCSO improves sample quality using an adaptive social neighborhood search mechanism and the LF method. It extracted data to feed the ANN. The ESCSO method optimizes weights and biases offline to train the ANN. The trained neural network continuously processes sensor input to generate real-time IFDS parameters. Real-time, obstacle-avoiding pathways are generated from these parameters. Experimental findings in complex simulated settings demonstrate that the proposed technique meets real-time requirements and generates more effective pathways than competing methods. The IFDS's adaptable capabilities and the ANN's advanced learning mechanism enable real-time route planning efficiency.

An enhanced SCSO is used to optimize energy storage system (ESS) capacity allocation to increase reliability and minimize energy consumption in combined wind-solar storage systems [142]. An energy storage configuration optimization model is developed from a structural examination of the integrated system. This approach minimizes ESS investment cost, load loss, and abandonment of new energy sources. A k-means clustering technique clusters renewable energy power and load data to obtain average daily data for optimization. Triangle wandering, Lévy flight, and lens image reverse learning improvement improve the multi-objective optimization model in this technique. Local search algorithms may escape local optima by using local fitness, improving their optimization capabilities [143]. This improves ESS capacity allocation, making the combined wind-solar storage system more efficient and dependable. According to experiments, this new SCSO-based optimization method reduces costs and energy loss while boosting system dependability. By optimizing the energy storage system architecture and using advanced clustering and search algorithms, the suggested approach provides a reliable solution for wind-solar energy resource management.

Table 3 shows the advantages of LF with SCSO.

Table 3
The advantages of LF with SCSO.

Benefits	Description
Avoiding getting trapped in local optima	LF motion causes large and unexpected jumps that help the SCSO to escape from local optima and search for a larger space. This feature is particularly useful in problems with complex, multidimensional search spaces, as it enables the SCSO to quickly move away from less critical regions.
High diversity in search	The combination of short and long movements of LF leads to diversity in search and more effective coverage of the search space. This diversity allows the algorithm to scrutinize nearby areas and jump to more distant points. As a result, the possibility of finding better solutions and avoiding undesirable points increases. Also, this diverse approach helps improve the quality of the final results.
High speed of convergence	LF enables the SCSO to reach optimal points and converge more quickly. This feature allows the algorithm to get acceptable results in a shorter period. In time-consuming problems, this high speed is a significant advantage. Additionally, fast convergence enables the algorithm to consume fewer computational resources.
Balanced exploration and exploitation ability	A balance between exploration (searching for new areas) and exploitation (using optimized areas) is established. This balance enables the algorithm to explore new and previously unknown regions while utilizing existing information effectively. In this way, the overall efficiency of the SCSO increases. This feature makes the algorithm better able to face different optimization problems.
High flexibility	The SCSO algorithm's ability to employ LF makes it simple to modify for various optimization issues. Due to its adaptability, the SCSO can be applied across multiple disciplines, including data science, artificial intelligence, and engineering. In addition, the ability to adapt to different problems helps the SCSO to perform multi-objective optimizations effectively. For this reason, the SCSO is considered a powerful and versatile tool in optimization.

4.2.6. Mutation

The SCSO exhibits slow convergence, poor convergence accuracy, and a tendency to become trapped in local optima. COSCSO, an adaptive SCSO that makes use of optimum neighborhood disturbance and Cauchy mutation, is proposed as a solution to these problems [144]. The Cauchy mutation operator disrupts search, accelerating convergence and enhancing search efficiency. Disrupting the neighborhood boosts population variety, search options, and exploitation. COSCSO was compared to CEC2017 and CEC2020 algorithms to evaluate its performance. COSCSO also addresses six engineering optimization issues. Experimental data show that the COSCSO is competitive and can solve numerous practical challenges.

Maintenance is one of the costliest stages in the software lifecycle. However, having access to the software's structural models can significantly simplify the maintenance process. The main objectives of software module clustering are to maximize intra-cluster connectivity, minimize inter-cluster dependencies, and improve overall clustering quality. For effective software source code clustering, a method known as discretized SCSO has been proposed [145]. The proposed method uses the source code's dependency chain to generate the best clusters. The proposed method is superior to the previous heuristic approaches when comparing success rate, modularization quality, and convergence speed. The SCSO approach, which is based on mutation, is shown in Fig. 17.

4.2.7. OBL

OBL is an approach in the field of optimization that attempts to increase the convergence speed and improve the efficiency of the algorithm by considering the opposite solution [146]. The main idea of this method is based on the simultaneous examination of a point and its opposite point in the search space to increase the probability of reaching the optimal solution [147,148].

The SCSO algorithm's drawbacks are addressed by the innovative DGS-SCSO optimizer [149]. The optimizer avoids local optima, early convergence, and slow convergence via Dynamic Pinhole Imaging and the Golden Sine Algorithm. OBL increases algorithm population initialization, while Dynamic Pinhole Imaging improves optimizer global search space exploration. OBL searches for an unknown global optimum by exploring a direction and its reflection. Golden Sine

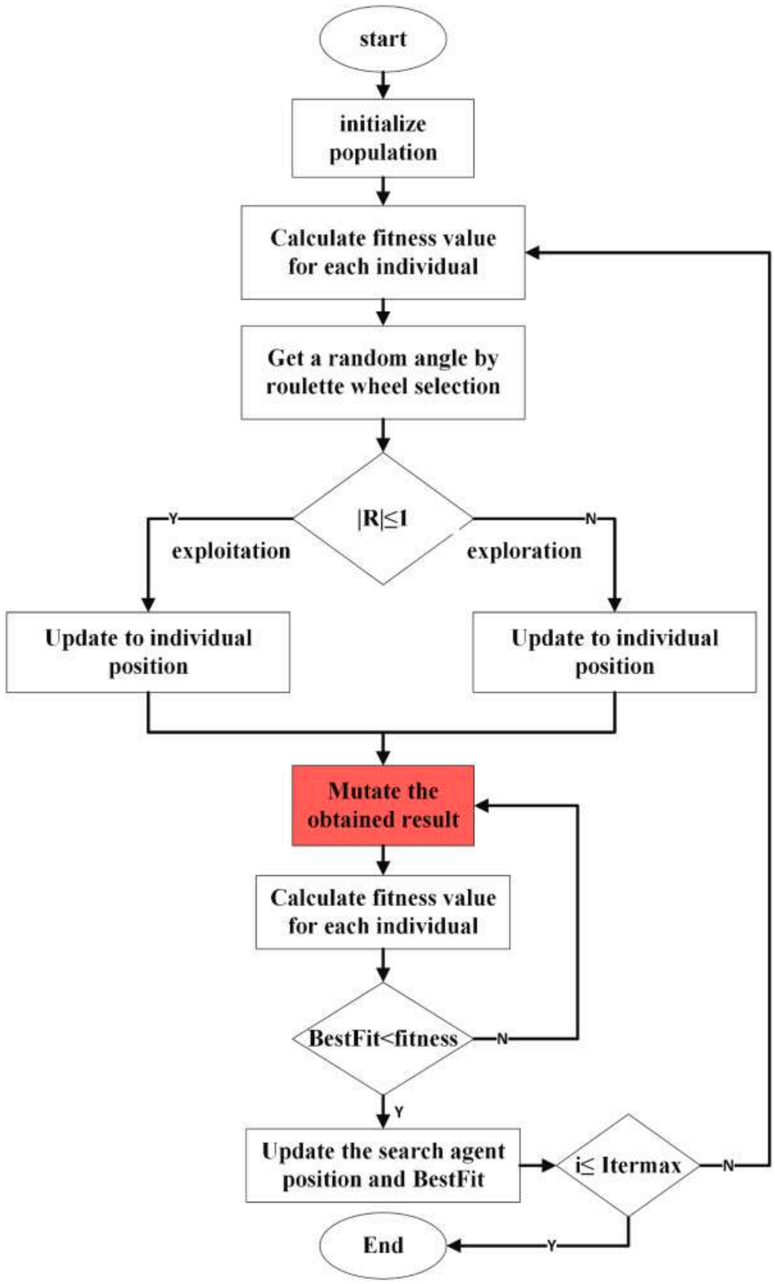

Fig. 17. SCSO algorithm based on mutation [145].

Algorithm improves resource utilization and optimum solution convergence. The DGS-SCSO method was assessed by carefully examining 20 benchmark functions, CEC2019 test functions, and two actual engineering problems. SCSO performs worse than DGS-SCSO (original algorithm). The Wilcoxon Rank Sum and Friedman Test show that DGS-SCSO is more efficient than other algorithms. SCSO struggles to balance exploration and exploitation, slowing convergence. This constraint is particularly noticeable in complex problems where finding the global optimum is challenging. An upgraded SCSO method using numerous strategies addresses this problem [150]. The Intensified Multi-Strategy SCSO (IMSCSO) method improves performance using dynamic random search, hybrid OBL, and joint opposite selection. Testing the IMSCSO algorithm with 23 CEC 2017, 2019, and 2020 benchmark test functions and suites was thorough. Experimental results demonstrate that IMSCSO outperforms or performs comparably to other state-of-the-art optimization techniques. Statistical analyses using the Wilcoxon signed-rank test and the Friedman test confirm that IMSCSO significantly outperforms its counterparts. The algorithm's optimization capabilities were evaluated across seven common engineering problems. The suggested IMSCSO method solves real-world optimization problems, according to empirical data.

The SCSO's powerful exploitation capabilities are due to each sand cat's systematic and steady approach to its target. By the time the SCSO algorithm reaches its latter stages, every sand cat has a chance of becoming stuck in a local optimum and never moving on to a better spot. A new SCSO variant called MSCSO has been unveiled [151]The MSCSO takes advantage of meandering. When sand cats are out hunting, they take long walks. Wandering tactics can enhance the MSCSO algorithm's global exploration and improve the mobility of the sand cat. The next step in improving the algorithm and achieving faster convergence is applying lens OBL. The MSCSO method enhanced test exploration with a walking approach and lens position-based learning. The engineering usefulness of the MSCSO technique was demonstrated by its evaluation of seven engineering challenges.

A hybrid multi-strategy version called HSCSO is proposed to solve optimization problems [152]. In the first step, an elite-based learning strategy is defined to generate complementary solutions. A more diverse set of initial solutions is generated, and the distribution of individuals' positions is improved. A random inertia weight is used for the search step size and optimization direction. This feature makes the algorithm avoid local optima more effectively. The experimental results on CEC2019 and CEC2021 show that HSCSO has a higher convergence speed and better optimization accuracy in most functions.

4.3. Variants of SCSO

To solve binary problems, the positions of the cats are represented as binary (0 and 1). The multi-objective version of SCSO is intended to solve multiple objective function issues. It seeks to produce a collection of Pareto-optimal answers.

4.3.1. Binary

WSNs detect and monitor things in realistic security settings. Most WSN clustering methods focus on selecting energy-efficient Cluster Heads (CHs). Estimating node trust enhances communication, security, and reliability. For WSNs, a safe and energy-aware clustering algorithm called SEACDSC is proposed, which is extended for SCSOs [153]. Among WSN nodes, a specific method in SEACDSC is employed to identify safe and energy-efficient CHs. Discrete SCSO, a variant of the original SCSO algorithm, is proposed for secure and effective CH selection. The fitness function is designed to consider the nodes' remaining energy and trust levels, ensuring efficient CH selection. Additionally, the exponentially weighted moving average (EWMA) dynamically adjusts threshold values according to network conditions. SEACDSC outperformed RCH-LEACH, BAT-Based, Improved-Leach, MG-LEACH, and Enhanced-LEACH in simulations.

Feature selection and hyperparameter optimization are two NP-hard problems that are core to the machine learning field. A more sophisticated version of the previously suggested SCSO has been developed to address these difficulties. The modification includes the integration of ELM hyperparameter adjustment and feature selection [154]. The recommended methodologies were evaluated by comparing them to other well-established swarm intelligence algorithms in terms of accuracy, precision, recall, and F1 score. Empirical evidence demonstrates that the

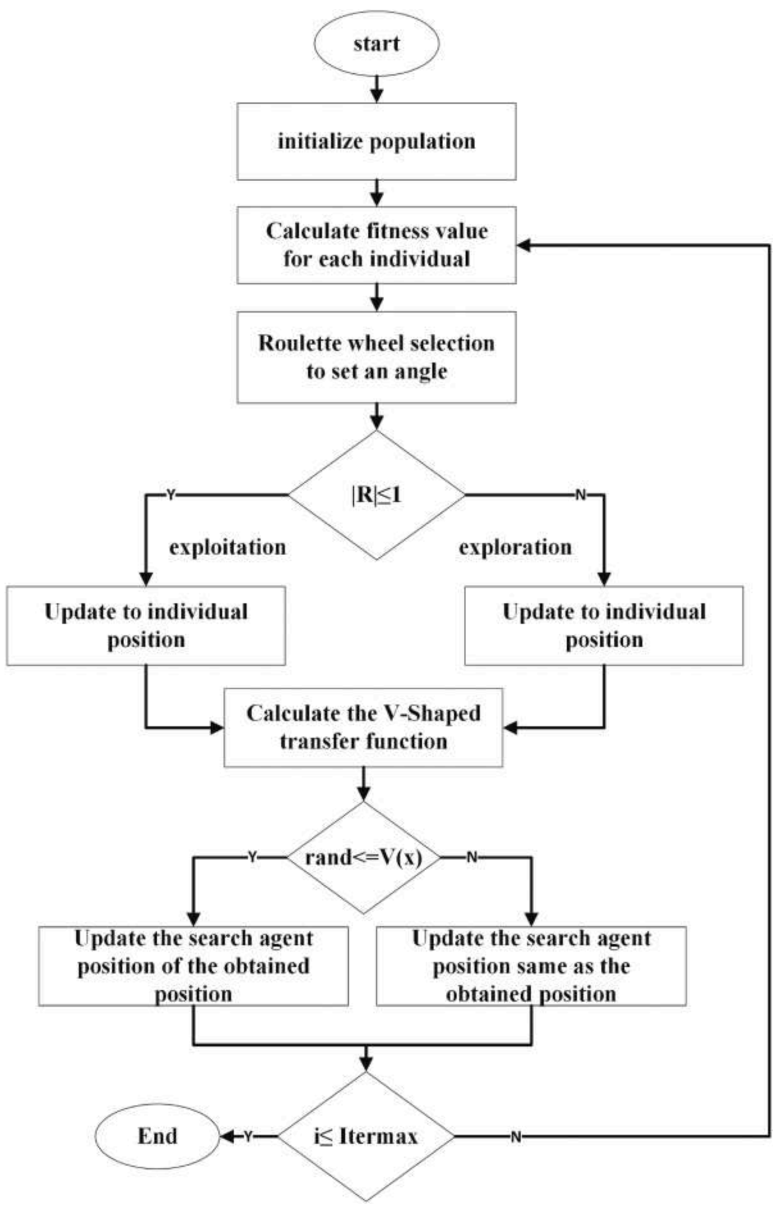

Fig. 18. The flowchart of the binary SCSO [155].

upgraded SCSO algorithm surpasses other algorithms in efficiency.

Feature selection is a practical preprocessing method that selects a limited number of significant or pertinent characteristics to enhance classification performance [155]. It is crucial to acknowledge that because feature selection has NP-hard properties, the search agent might become stuck in local optima, resulting in significant time and complexity expenses. A highly proficient and successful worldwide search technique is required to address these issues. SCSO is a recently developed metaheuristic algorithm designed to address global optimization problems. The binary SCSO algorithm, or BSCSO, is designed to analyze and solve discrete issues, such as feature selection. Ten well-known biological datasets were used to evaluate the BSCSO approach to determine its effectiveness. The binary SCSO flowchart is shown in Fig. 18.

A crossover operator and a learning approach based on pinhole imaging were added in PILC-BSCSO, an upgraded version of Binary SCSO [156]. Improving the selection of the most valuable features is the goal of this new edition. At first, BSCSO's search skills are enhanced with the help of the crossover operator. The pinhole-imaging learning method improves the exploration capacity and the ability to avoid early convergence. A linear kernel is used by the Support Vector Machine (SVM) classifier to evaluate classification accuracy. When tested on three publicly available medical datasets, the PILC-BSCSO technique outperforms eleven state-of-the-art algorithms in terms of classification accuracy and feature selection. Also, regarding colon cancer, PILC-BSCSO gets a perfect score.

4.3.2. Multi-objective SCSO

Multi-objective optimization is a branch of optimization that simultaneously optimizes more than one objective function [157]. In these problems, the objectives are usually in conflict with each other and finding a single optimal solution is not possible. For this reason, a set of optimal solutions, known as the Pareto front, is presented, which exhibits a certain balance.

Multi-objective algorithms are powerful tools for solving complex problems that have conflicting objectives [158]. Considering the broad applications and the increasing need for multi-objective optimization, the development and improvement of these algorithms is still an active and dynamic research field [159]. Current research in this field includes improving the efficiency of algorithms, developing new methods to preserve diversity, and new applications in various scientific and industrial fields.

Sensor node energy savings are best achieved by integrating clustering and routing algorithms. Cluster heads (CHs) are carefully chosen for load balancing during clustering. To enhance WSN energy efficiency, multi-objective SCSO (MSCSO) is suggested [160]. The network's best cluster heads are chosen, and MSCSO finds their paths. The suggested MSCSO maximizes WSN data transfer while reducing node energy consumption. MSCSO outperformed LEACH, DEEC, and T-DEEC in alive nodes, energy consumption, throughput, and life expectancy for 100 nodes. The MSCSO is compared against FAL, SHO, ECMOSSA, whale-based tunicate swarm, and Aquila optimizer algorithms. Results reveal that MSCSO reduces energy usage and enhances performance.

For an electric thermal hydrogen integrated energy system (ETH-IES) incorporating EV vehicle-to-grid (V2G), a hierarchical stochastic optimal scheduling model is proposed [161]. The EV charging and discharging control layer decreases the load curve volatility and dissatisfaction of V2G EV owners. The MSCSO algorithm solves EVs. To reduce operation costs, ETH-IES performs daily stochastic economic scheduling. The simulation findings demonstrate that the MSCSO approach can better establish a win-win scenario between EV owners and microgrid operators.

Fig. 19 shows the vital features and mechanisms of MSCSO. The MSCSO algorithm uses Pareto dominance to evaluate and compare

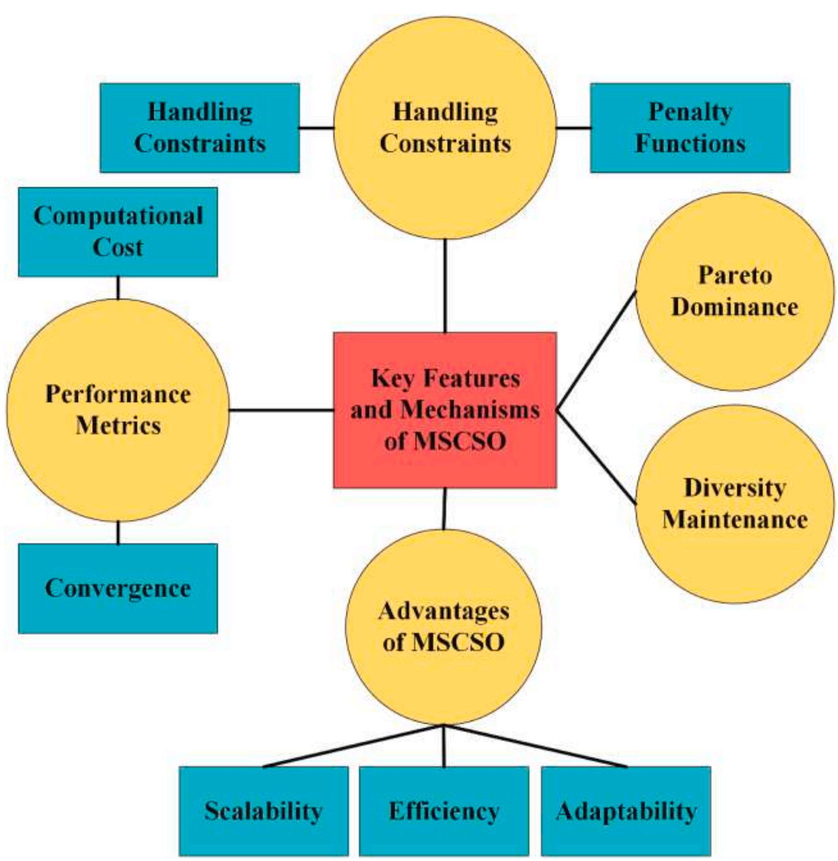

Fig. 19. Key features and mechanisms of MSCSO.

solutions. Its algorithm uses techniques to preserve diversity in the population, prevent premature convergence, and ensure an extensive search of the solution space. Also, penalty functions avoid infeasible solutions, directing the search towards the feasible region. The MSCSO algorithm handles large and complex problems with multiple scalable objectives.

4.4. Optimization problems

Optimization of complex problems is one of the primary challenges in engineering sciences (mechanics, electricity, civil engineering) and mathematics, which requires advanced and combined methods to improve the accuracy and efficiency of the presented solutions [162]. One of these new methods is the SCSO, which utilizes intelligent and flexible behaviours to find the optimal solution within the problem space. By combining local and global search methods, this algorithm seeks to find the most optimal solutions in the problem space. SCSO, with its unique capabilities, can play a crucial role in advancing scientific and industrial research and projects.

The SCSO has attracted the attention of many researchers in recent years. Among the successful applications of SCSO has been in the field of photovoltaic systems (PVS), which has improved energy efficiency and optimized the optimal performance of converters. It has also helped to optimize communication paths and energy-aware routing protocols in wireless sensor networks (WSNs). In the field of radio wave amplification and parameter optimization, the approach has contributed to reduced energy losses and improved signal quality. It has also been applied in diabetes diagnosis for optimal feature selection in medical data processing, resulting in higher accuracy of machine learning models. It has performed well in solving nonlinear and complex optimization problems, such as the economic load distribution (ELD) problem. It has also been utilized as an efficient method in the fields of fault diagnosis, recognition, classification, and feature selection in high-dimensional problems. In IoT networks, this method has been very effective in optimizing routes, reducing energy consumption, and increasing equipment efficiency. The overall overview of SCSO in the optimization sector is displayed in Table 4.

WSNs are vital in advancing the IoT and are used in various applications such as smart agriculture, environmental monitoring, and security systems [193,194]. These networks consist of numerous small sensors that are wirelessly connected, collecting and transmitting data. One of the significant challenges in these networks is energy management and extending the network’s lifetime, as sensors typically have limited batteries and are challenging to replace in remote or inaccessible environments. Clustering is one of the effective methods to improve efficiency and energy management in WSNs [195]. This reduces the number of direct transmissions to the base station and optimizes the energy consumption of the sensors. However, choosing the optimal headgroup is a critical issue that directly impacts network performance. Using the SCSO, optimal cluster heads can be selected, and energy-efficient paths can be determined for data transmission, leading to increased network lifetime and improved overall performance of IoT-based systems.

Fig. 20 illustrates the application of the SCSO in various areas, based on the percentage used. The application of the SCSO has been analyzed across 14 different sectors in multiple fields. The electricity and energy sector, with 24 percent, constitutes the largest share in the application of the SCSO algorithm. The SCSO algorithm has been widely used in solving complex optimization problems related to energy generation, distribution, and management. Its applications include load balancing, power system planning, energy network optimization, and demand forecasting. The field of engineering optimization problems, with 20 percent, constitutes the second largest share in the application of the algorithm. The SCSO algorithm has been used in solving engineering problems such as structural design, industrial process optimization, and performance improvement of mechanical and structural systems. This

Table 4
The general review of SCSO in the field of optimization.

Refs.	Application	Advantages	Weaknesses	Publisher
[163]	Electricity and energy	Faster convergence speed and higher accuracy compared to the other methods	high computational cost	Elsevier
[164]	Electricity and energy	Improved convergence speed and solution quality		Elsevier
[165]	Wireless networks	Faster convergence	The success of SCSO may depend on parameter tuning	Springer
[166]	Wireless networks	Improved convergence speed and solution quality		Springer
[167]	Engineering optimization problems	Faster convergence	The success of SCSO may depend on parameter tuning	Springer
[168]	Engineering optimization problems	Exploration and Exploitation Balance	Need for Precise Parameter Tuning; High Computational Complexity	Elsevier
[169]	diabetes detection	Increase detection accuracy	High Computational Complexity	Springer
[170]	Electricity and energy	The number of iterations and the initial population are proportional to the problem space.	Sensitivity to Initial Conditions	Elsevier
[171]	Engineering optimization problems	Exploration of the problem space based on the best position	Need for Precise Parameter Tuning; High Computational Complexity	Springer
[172]	Smart networks	Adaptable to Problem Size Exploring Uncharted Areas	Stagnation and Premature Convergence	Elsevier
[173]	Engineering optimization problems	Efficient for a large space	Sensitivity to Initial Conditions Low Convergence Speed	Springer
[174]	Electricity and energy	The number of iterations and the initial population are proportional to the problem space.	Sensitivity to Initial Conditions	Springer
[175]	Engineering optimization problems	Enhancing solution vectors by generating random values	Need for Precise Parameter Tuning High Computational Complexity	Springer
[176]	Electricity and energy	Exploration and Exploitation Balance	High Computational Complexity	Elsevier
[177]	recognition and classification	Adaptable to Problem Size Exploring Uncharted Areas	Stagnation and Premature Convergence	Elsevier
[178]	Electricity and energy	Exploration and Exploitation Balance	High Computational Complexity	Springer
[179]	Wireless networks	Exploration of the problem space based on the best position	Need for Precise Parameter Tuning High Computational Complexity	IEEE

(continued on next page)

Table 4 (*continued*)

Refs.	Application	Advantages	Weaknesses	Publisher
[180]	Electricity and energy	Adaptable to Problem Size Exploring Uncharted Areas	High Computational Complexity	MDPI
[181]	nonlinear systems	Enhancing solution vectors by generating random values	Stagnation and Premature Convergence	Elsevier
[182]	Electricity and energy	The number of iterations and the initial population are proportional to the problem space.	High Computational Complexity	IEEE
[183]	Electricity and energy	Exploration of the problem space based on the best position	Low Convergence Speed	Wiley
[184]	Engineering optimization problems	Efficient for a large space	Sensitivity to Initial Conditions Low Convergence Speed	Elsevier
[185]	Engineering optimization problems	Enhancing solution vectors by generating random values	High Computational Complexity	Springer
[186]	Wireless networks	The number of iterations and the initial population are proportional to the problem space.	Stagnation and Premature Convergence	IEEE
[187]	Electricity and energy	Adaptable to Problem Size Exploring Uncharted Areas	Low Convergence Speed	Elsevier
[188]	Electricity and energy	Exploration of the problem space based on the best position	Sensitivity to Initial Conditions Low Convergence Speed	IEEE
[189]	feature selection	Selection of optimal features with the least number of iterations	High Computational Complexity	Elsevier
[190]	feature selection	Exploration of the problem space based on the best position	High Computational Complexity	Elsevier
[191]	Robotic	Adaptable to Problem Size Exploring Uncharted Areas	Sensitivity to Initial Conditions Low Convergence Speed	IEEE
[192]	Smart networks	Enhancing solution vectors by generating random values	Low Convergence Speed	MDPI

indicates the high capability of the algorithm in dealing with multidimensional and complex problems. The forecasting and modeling sector with 8 percent, constitutes the third largest share in the use of algorithms. The SCSO algorithm has been used in issues related to data prediction, modeling of various phenomena, and optimization of complex systems. The wireless sensor networks section with 7 percent shows the use of algorithms in the optimization of wireless sensor networks. Its applications can include managing energy resources, optimizing data transmission paths, and increasing the life of networks. The Electronic Medical Systems segment with 5 percent, shows that the SCSO is used in the field of electronic medicine. This can include optimizing medical systems, managing medical data, and predicting diseases.

Fig. 21 shows the number of SCSO papers in different fields based on other publishers. Elsevier has more documents in the areas of engineering optimization problems, Electricity, and Image processing. Springer has more documents in the areas of engineering optimization problems, Electricity and energy, clustering analysis, Forecasting and modelling, and IoT. Elsevier and Springer have a wide range of scientific journals in various fields. These journals encompass a diverse range of subjects, including the natural sciences, technology, engineering, humanities, and medicine. Elsevier and Springer are reputable publishers in the world of science and engineering. Their journals have high Impact Factors and are well-known in scientific maps (Scopus, Web of Science).

5. Discussion

Metaheuristic algorithms display shared traits. The initialization step of these algorithms starts with the generation of a population in a random manner [196]. They exhibit a repetitive pattern and adhere to instructions for a particular generation specified using mathematical functions. The search process consists of two separate parts. The algorithm examines various areas within a specified search range in the first step, known as global search or exploration. This movement aims to thoroughly and randomly cover the entire search area. The second stage, called local search or exploitation, identifies favourable solutions or solutions within the vicinity revealed in the initial stage. Attaining equilibrium between these two stages is crucial in formulating optimization techniques, as the algorithm's efficiency is enhanced by effectively controlling the interaction between exploration and exploitation.

Metaheuristic algorithms often utilize wrapper-based methods to address various optimization problems, including feature selection. They are particularly advantageous for solving computationally intensive tasks and can identify near-optimal solutions by employing heuristics and stochastic processes to explore the search space. Metaheuristic algorithms offer a significant benefit in feature selection since they are capable of effectively managing high-dimensional data and big datasets [197]. Metaheuristic algorithms can efficiently examine multiple potential feature subsets, detecting significant features even in high-dimensional data. While metaheuristic algorithms have been used to describe feature subsets, they are not entirely immune to intrinsic limitations, such as being trapped in local optima. This is mainly because they rely to some extent on the underlying characteristics of the datasets.

As the total number of iterations increases, the population of sand cats will eventually converge on the best individuals. This might reduce population diversity and make it more difficult for the algorithm to find the best answer globally. To address this issue, the SCSO employs the horizontal crossover technique, as detailed in reference [87]. This method conducts a comprehensive search of the population, minimizing areas where the search is ineffective and addressing the issue of global optimization. Furthermore, the technique employs vertical crossover as the best solution to avoid premature convergence, in addition to horizontal crossover. This helps the algorithm surpass local optima and preserve population diversity. The Crossbar technique, as outlined in reference [90], enhances the global search capability by addressing intricate optimization challenges, resulting in improved algorithm precision and accelerated convergence rates.

Fig. 22 shows the percentage of use of different simulators in SCSO papers. MATLAB is the most widely used, with 46 %, indicating that many papers utilize MATLAB for numerical analysis, control, or signal processing. Python is in second place with 32 %, indicating its popularity in areas such as artificial intelligence, machine learning, and data analytics. The share of specialized simulators (network, security, systems) is 22 % in total.

The BMSCSO [92] incorporates a memory-based technique into the SCSO placement update process, utilizing the most optimal options for additional exploitation. It includes two primary stages as the foundation of BSCSO: during the initial stage, a novel random operator is introduced to the SCSO to enhance exploration. In the second stage, the SCSO method includes a memory component that maintains the connection between the coordinates in the solution space and the sand cat's best solution (i.e., fitness score) achieved. Therefore, this inclusion technique guarantees the opportunity to explore at an early stage and exploit at a

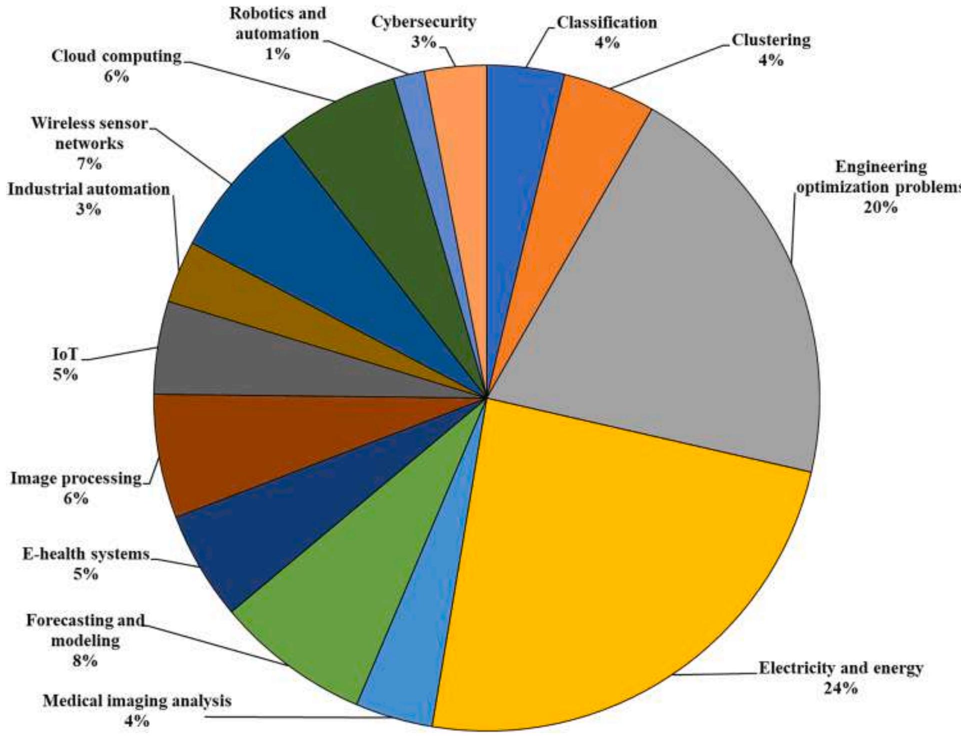

Fig. 20. The application of the SCSO algorithm in different areas based on the used percentage.

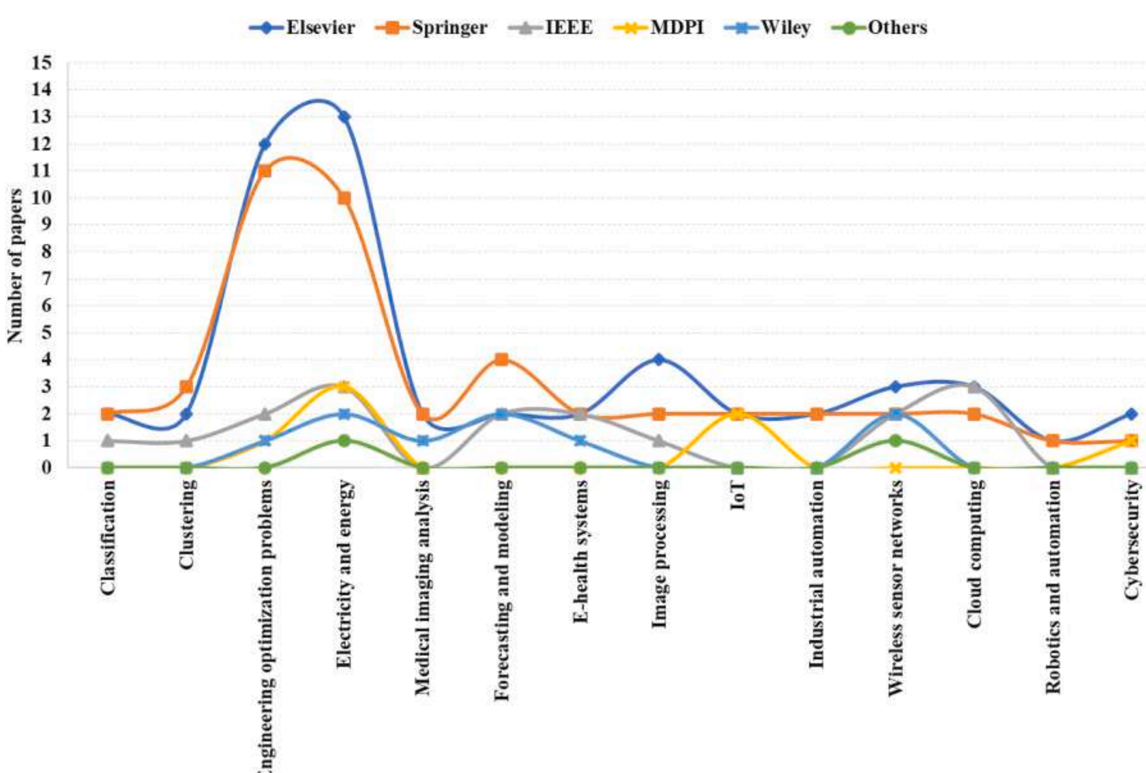

Fig. 21. The number of SCSO papers in different fields based on different publishers.

later level, leading to the accomplishment of the global optimum with improved performance. The SCSO has to make minor adjustments to a few parameters. Adapting these swarming features helps achieve an optimal equilibrium between local and global search capabilities. However, the SCSO does not have an internal memory for information about previously attempted solutions. Throughout its iterative process, SCSO does not record the potential solutions that might lead to the global optimum and disregards any fitness values that surpass the current best global solution. The SCSO's ability to effectively utilize the search space is diminished, resulting in a sluggish convergence rate and

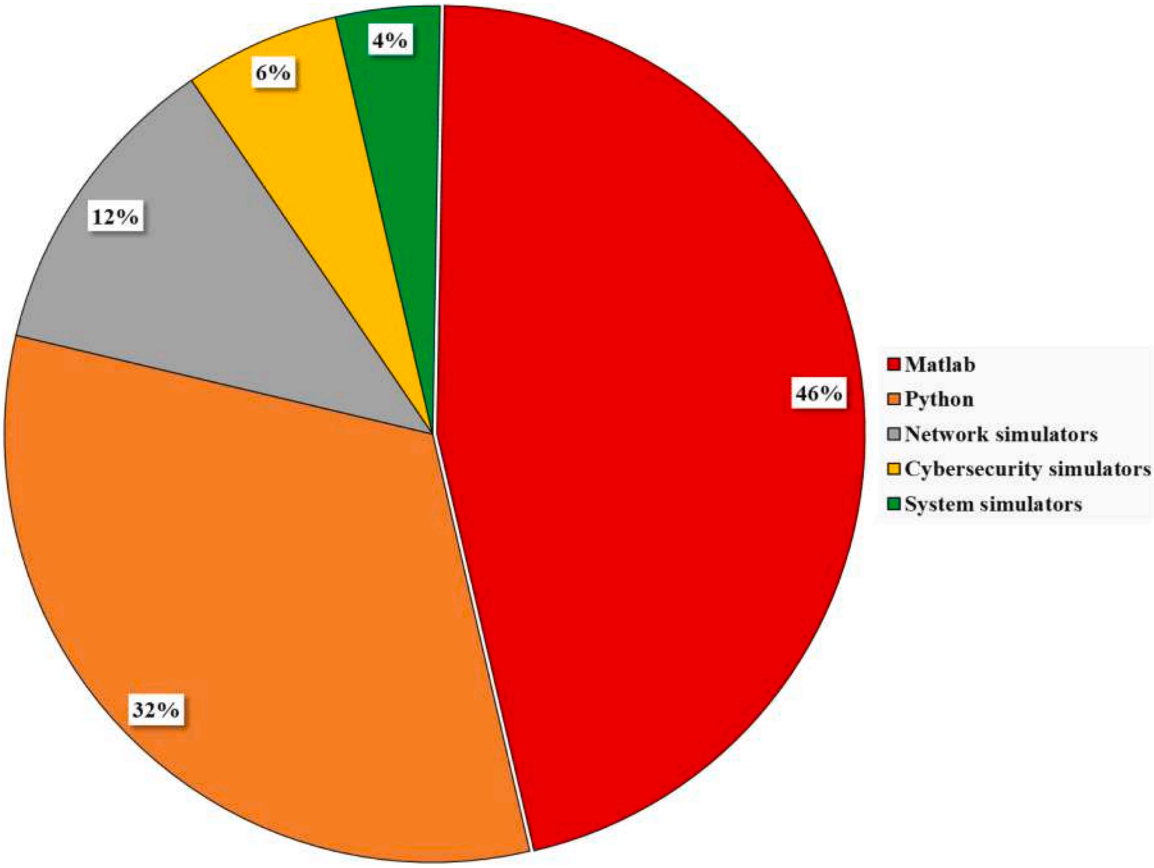

Fig. 22. The percentage of use of different simulators in SCSO papers.

a tendency to become stuck at local optimums. To solve this issue, a proposal was made to enhance SCSO's exploration and exploitation behaviors using a memory-based technique.

The SCSO method has shown remarkable performance in several domains, especially in intrusion detection systems (IDSs) and medical diagnostics, highlighting its capacity to adapt and be versatile [106]. Furthermore, the algorithm's resilient capacity to search globally, influenced by biological symbiosis mechanisms, enables the quick discovery of the best possible solutions in complex problem domains. This reduces the likelihood of being trapped in suboptimal answers. Additionally, by actively exploring different possibilities and adjusting parameters, the algorithm successfully avoids becoming stuck at local maximum or minimum points, thoroughly exploring potential solution areas and increasing the chances of finding the best possible answers globally. SCSO outperforms other metaheuristic algorithms, such as PSO, GWO, and WOA, in many test scenarios and real-world engineering applications. Several studies have proposed hybrid metaheuristic algorithms as a way to improve the performance of current metaheuristic algorithms [198]. Usually, metaheuristic algorithms are combined with two or more other methods. By combining the advantages and disadvantages of each separate algorithm, hybrid metaheuristic algorithms aim to enhance efficiency. The development process is being improved by hybrid methods more and more, as they lower costs, enhance precision, facilitate convergence, avoid local traps, and strike a balance between exploitation and exploration. Many times, hybrid metaheuristic algorithms maximize the delicate balance between exploitation and exploration [199]. Some metaheuristic algorithms may establish an equilibrium between these two stages; hence, hybrid metaheuristic algorithms have been developed [200]. One must have many metaheuristic algorithms to avoid becoming stuck in a local optimum. This hybrid metaheuristic algorithm can offer more options in the search arena. Still, this variation ought not to harm the algorithm's efficiency.

Fig. 23 illustrates the percentage of improved SCSO achieved through various methods. The largest share, at 32 %, belongs to the deep learning technique, which highlights the high importance of this method in improving the SCSO algorithm's performance. The SCSO enables deep neural networks to process complex optimization problems, significantly increasing accuracy. After that, the data mining technique ranks second, with 26 %, indicating its significant role in extracting valuable patterns and optimizing complex problems. The adaptive strategy is ranked third, with a 19 % share, and is widely used for dynamic adjustment and algorithm optimization. Other techniques include chaotic systems with a 10 % share, Levi's flight with a 3 % share, mutation with a 3 % share, and OBL with a 7 % share each. This distribution illustrates the diverse range of improvement methods employed in SCSO and the significance of each technique in enhancing and optimizing the algorithm's efficiency. Deep learning and data mining focus on complex patterns. Therefore, the SCSO has a significant impact on the optimization and training of these models. Combining the SCSO with deep neural networks enables the SCSO to select search paths more intelligently and avoid unnecessary calculation repetition. By combining the SCSO with deep neural networks, the parameters of the neural network are adjusted in a way that enables faster and more accurate convergence. This combination also helps reduce problems such as getting stuck in local optima, allowing the algorithm to discover global optimal regions more accurately.

Table 5 illustrates the general advantages and disadvantages of the SCSO.

GWO and SCSO algorithms are inspired by animal social and biological behaviors and are used to solve optimization problems. One common point between these two algorithms is their inspiration from social interactions and the group behaviours of animals. In GWO, grey wolves hunt in packs and use three types of leader wolves (Alpha, Beta, and Delta) to guide other wolves. This hierarchical structure helps the

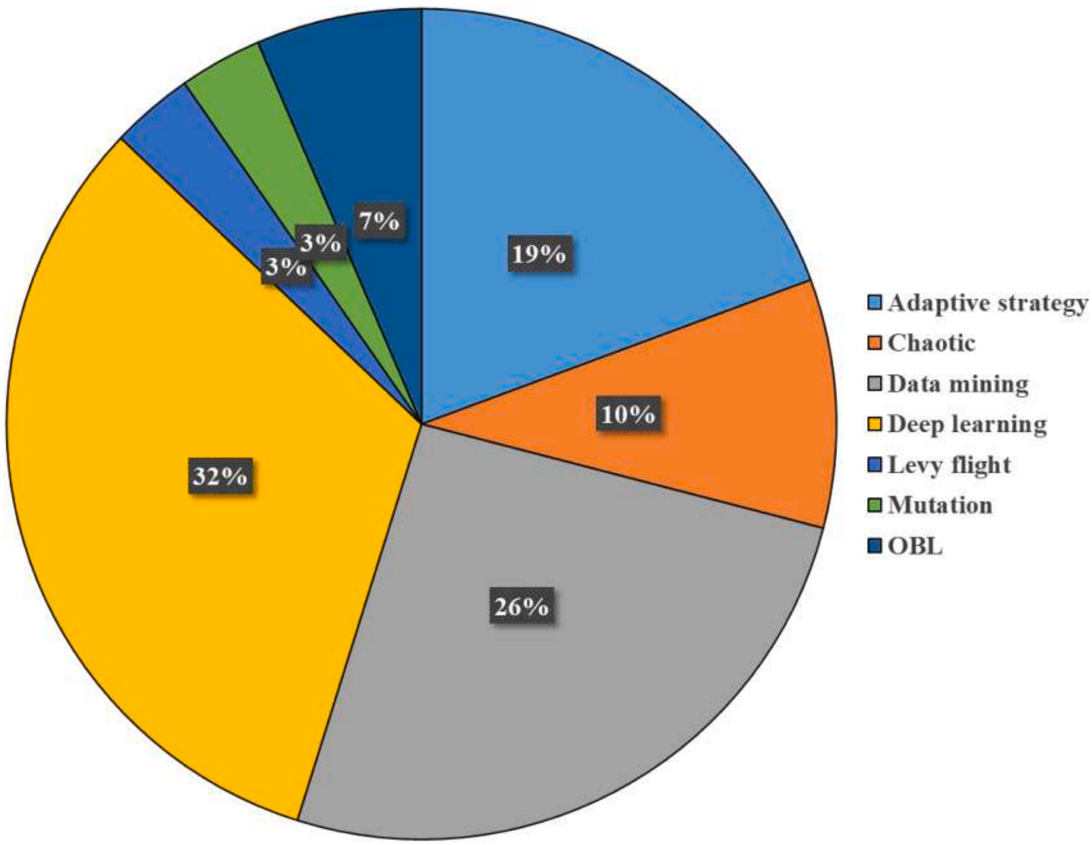

Fig. 23. Percentage diagram of improved SCSO based on different methods.

Table 5
Advantages and disadvantages of the SCSO.

	Factors
Advantages	✓ The SCSO has fewer parameters and operators than other metaheuristic algorithms, which makes its implementation simpler. ✓ SCSO successfully finds optimal solutions in complex optimization problems. ✓ SCSO applied to solve various kinds of real-world optimization problems. ✓ SCSO is appropriate for the solution quality and accelerates the convergence speed. ✓ The SCSO balances the exploitation and exploration stages, increasing the success rate. ✓ The implementation of the SCSO is more straightforward than other algorithms and does not require complex settings. ✓ The SCSO algorithm can avoid getting stuck in local optimality traps and continue searching for global optimality. ✓ Compared to other metaheuristic algorithms, SCSO performs better in various problems. ✓ Population diversity is maintained, ensuring that individual information is fully utilized. ✓ The SCSO is extended to solve multiple high-dimensional
Disadvantages	× The tuning parameters may strongly influence the results of the SCSO algorithm and need to be fine-tuned. × In some complex problems, the SCSO requires many calculations and more time. × In some cases, the SCSO may not thoroughly search the problem space and not may reach complete optimization

wolves move towards the goal in a coordinated manner. Similarly, in SCSO, sand cats search for resources and optimize their positions through social interactions and group coordination. Both algorithms employ similar mechanisms for information exchange and enhancement of both individual and collective decision-making, thereby improving the efficiency of finding optimal solutions. The GWO and SCSO algorithms consist of two primary stages: global search (exploration) and local search (exploitation). In GWO, global search is performed through random movement and initial dispersion of wolves to explore different regions of the search space. In the next step, the wolves move towards the leaders' positions and improve their positions locally. In SCSO, in the exploitation stage, cats improve existing solutions with more detailed and localized changes. This structure balances exploration and exploitation in both algorithms; therefore, falling into local optima is avoided.

6. Conclusion and future works

A novel metaheuristic algorithm that strikes an appropriate balance between exploration and exploitation is the SCSO, inspired by the hunting behaviour of sand cats. Studies conducted between 2022 and March 2025 indicate that enhanced versions of SCSO may yield more optimal solutions at a faster rate compared to both the original algorithm and conventional methods. With its simple and flexible structure, the SCSO has performed well in solving problems such as continuous optimization, feature selection, classification, and clustering. The use of improvement mechanisms, such as chaos mapping and OBL, to enhance the search and prevent getting stuck in local optima has improved the performance of the SCSO compared to traditional methods. Combining the SCSO with other metaheuristic algorithms, such as WOA, GA, and FFA, has yielded favourable results. Combining metaheuristic algorithms by taking advantage of each algorithm's strengths has improved performance in solving complex optimization problems. For example, combining SCSO with WOA yields an extensive search and increased exploitability of SCSO. Additionally, combining SCSO with GA yields improved solutions due to genetic diversity and evolution. The development and improvement of the SCSO are crucial for combined optimization and metaheuristics. According to the positive results presented in this paper, it can be acknowledged that SCSO has become a standard

Algorithm 1
Demonstrates the pseudocode of the SCSO algorithm.

Algorithm 1: SCSO pseudocode [61]

```
N population size, T maximum iterations
  Objective function-based fitness function calculation
  Initialize the R, r, and r_G
  While (t≤ maximum iteration)
  For each search agent
  Get a Roulette Wheel Selection-based random angle (0° ≤ 0 ≤ 360°)
  If(abs(R)≤1)
      For (each agent (Xi)) do
          Update the location agent using Eq. (5)
      End for
  Else
      For (each agent (Xi)) do
          Update the location agent using Eq. (4)
      End for
  End for
  End
  t = t++
  End
```

tool for solving complex optimization problems and has been widely used in both research and industrial applications. The investigations in this paper have shown that the improved SCSO has been applied more frequently in the fields of deep learning, data mining, and adaptive strategies. The SCSO has been utilized for the structure of deep networks and data mining to facilitate accurate prediction. The SCSO requires various combinations to increase efficiency. For example, combining metaheuristic algorithms with SCSO results in fast convergence and the discovery of optimal points. The direction of this paper for future works is as follows:

Combining SCSO with Advanced Algorithms: Combining SCSO with algorithms such as SFOA and FCO results in greater search power and higher productivity. Using SFOA can help search more widely and precisely in the search space. Additionally, the FCO method can accelerate convergence and improve local search performance.

Design of parallel and distributed versions of SCSO: Parallel and distributed versions of SCSO optimize the utilization of computing resources in supercomputers and cloud computing environments. These versions help reduce calculation time and increase the efficiency of the SCSO algorithm. Using parallel and distributed versions also helps parallel processing and improves convergence speed.

Development of dynamic versions of SCSO: design and development of versions of SCSO that can optimize dynamic problems. These versions help improve the SCSO algorithm's performance in dynamic environments. Using the dynamic version can lead to improved response to environmental changes and increased flexibility of the SCSO.

Funding

The result was created through solving the student project "Wireless networks security focusion on IoT" using objective oriented support for specific university research from the University of Finance and Administration, Prague, Czech Republic.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

Authors thank Zdenek Truhlar, Manuel Rosinus, Patrick Mini, Jenna Aurelie Huppertz for their help with the research connected with the topic of the article.

Data availability

No data was used for the research described in the article.

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