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SURVEY ARTICLE

Advances in Sparrow Search Algorithm: A Comprehensive Survey

Farhad Soleimanian Gharehchopogh[1] · Mohammad Namazi[2] · Laya Ebrahimi[1] · Benyamin Abdollahzadeh[1]

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Abstract

Mathematical programming and meta-heuristics are two types of optimization methods. Meta-heuristic algorithms can identify optimal/near-optimal solutions by mimicking natural behaviours or occurrences and provide benefits such as simplicity of execution, a few parameters, avoidance of local optimization, and flexibility. Many meta-heuristic algorithms have been introduced to solve optimization issues, each of which has advantages and disadvantages. Studies and research on presented meta-heuristic algorithms in prestigious journals showed they had good performance in solving hybrid, improved and mutated problems. This paper reviews the sparrow search algorithm (SSA), one of the new and robust algorithms for solving optimization problems. This paper covers all the SSA literature on variants, improvement, hybridization, and optimization. According to studies, the use of SSA in the mentioned areas has been equal to 32%, 36%, 4%, and 28%, respectively. The highest percentage belongs to Improved, which has been analyzed by three subsections: Meat-Heuristics, artificial neural networks, and Deep Learning.

1 Introduction

The necessity for meta-heuristic algorithms has grown in recent decades as the complexity of diverse issues has increased. Previously, academics employed mathematical strategies to handle local optimization's deterministic and difficult-to-trap optimization issues. Because the search space in actual optimization issues increases exponentially and the problem perspective shifts in a multidimensional fashion, standard optimization methods frequently generate less-than-optimal solutions [1–3]. These techniques are inefficient in solving real optimization problems, which has increased interest in metaheuristic algorithms in the last two decades. Due to intrinsic complexity constraints and many design variables such as nonlinear and convex, most real-world optimization issues, such as text processing, community detection, feature selection, optimization issues, setting machine learning parameters, etc., require meta-heuristic algorithms. Therefore, solving these optimization problems is complicated due to many local minimums. In addition, there is no guarantee of finding a universal solution. Many researchers have used meta-heuristic strategies to find the optimal solution to achieve the global optimal [4–6].

Meta-heuristic algorithms have solved many optimization problems, most of which can solve high-dimensional optimization problems well. Large-scale global optimization issues are widespread in scientific research and engineering applications and have attracted much attention in recent years. The high-dimensional optimization problem is expressed as a two-dimensional d minimization problem according to Eq. (1). Where $X = [x_1, x_2, \dots, x_D]$ represents the decision vector, and $F(X)$ is the fitness function.

$$\min F(X), X = [x_1, x_2, \dots, x_D] \tag{1}$$

As the number of dimensions increases, many metaheuristic methods become "dimension traps", meaning that performance decreases rapidly and is easily optimized locally as the number of dimensions increases. Therefore, hybridization operators must strike a balance between exploitation and exploration in the optimization process, and search efficiency must be improved. In general, solutions with better fitness have higher growth performance, while solutions with poor fitness can maintain population diversity and strengthen their exploration ability. As a result, to strike a balance between exploration and exploitation, the population must be separated into two groups: the main population and the sub-population, using

✉ Farhad Soleimanian Gharehchopogh
bonab.farhad@gmail.com

1 Department of Computer Engineering, Urmia Branch, Islamic Azad University, Urmia, Iran

2 Department of Computer Engineering, Maybod Branch. Islamic Azad University, Maybod, Iran

a multinational concept. People in the main population can boost exploitation capacity and solution accuracy, whereas individuals in the subpopulation can assure population variety and exploration ability. This method ensures the ability to exploit while avoiding the local optimum. During the exploration phase, the subpopulation is adjusted by directing individuals in the exploitation population, which can increase exploration efficacy [7].

In meta-heuristic algorithms, graceful exploration means the ability to search optimally globally. The entire population is allowed to explore the whole solution space to find a promising area. In contrast, good exploitation demonstrates good local search capability. The population can use the valuable points to refine the search for a more accurate optimal solution. The balance of exploration and exploitation is essential in improving optimization performance. Excessive attention to exploration leads to wasting evolution in search of some parts of the solution space, and as a result, the convergence rate is reduced.

On the other hand, paying more attention to exploitation risks losing diversity in the early stages of evolution. As a result, the initial population will likely be trapped in the local optimal. Therefore, achieving the right balance between exploration and operation in meta-heuristic algorithms improves performance in solving complex optimization problems [8–13].

Engineering optimization issues have been researched and solved using a variety of methodologies. Meanwhile, meta-heuristic algorithms have performed well. Unlike traditional optimization methods, Meta-heuristic algorithms do not require gradient information and can avoid local optimization. As a result, they can be used to solve engineering optimization challenges.

They can find an optimal solution regardless of the physical nature of the problem. Most of them are inspired by physical or natural phenomena. Examples include Farmland Fertility Algorithm [14], African Vultures Optimization Algorithm (AVOA) [15], Starling murmuration optimizer [16], Sparrow Search Algorıthm [17], and Artificial Gorilla Troops Optimizer [18].

SSA is a population-based meta-heuristic algorithm developed by Xue and Shen in 2020 to solve continuous optimization problems [17]. The evaluation of the SSA algorithm is performed with 19 known mathematical functions. This algorithm has demonstrated its ability to address computational complexity and solution convergence difficulties. The SSA algorithm outperforms the GWO, Particle Swarm Optimization(PSO), and GSA algorithms in performance. The main contributions of this paper are as follows:

- SSA algorithm analysis based on schematic and pseudocode
- Investigations of SSA methods from the aspects of Hybridization, Improved, Variants of SSA, and optimization issues.
- Improved SSA analysis by different methods
- Analysis of SSA performance in solving diverse problems based on convergence rate, exploration, and exploitation factors.
- Focus on outlook works in line with the SSA algorithm

The general structure of this paper is as follows: The SSA algorithm and its operators will be explained in Sect. 2. In Sect. 3, SSA approaches will be divided into four categories: hybridization, improvement, SSA variations, and optimization concerns. In Sect. 4, we'll talk about discussions and comparisons; in Sect. 5, we'll wrap things up and look forward to future projects.

2 SSA: Sparrow Search Algorithm

SSA Algorithm [17] is a new nature-inspired algorithm inspired by the behaviour of sparrows in 2020. Many animals search for cuisine and avoid predators with their swarming intelligence in the wild. The population of sparrows is no exception. They are separated into two categories depending on their fitness, determined by each sparrow's unique posture. The person who has a better fit belongs to the producers. The remaining sparrows are explorers. In the whole population of sparrows, different people have different eating behaviors. In addition, several sparrows are responsible for avoiding predators during the forage search process among the population. To cope with the dangers, they choose to fly farther or closer to other sparrows. In short, the sparrow colony can search for more low-risk cuisine by constantly updating its position.

For simplicity, sparrows' behaviour and related laws are described below.

- Producers often have a lot of energy reserves and offer regions or forage search routes to all explorers. They are in charge of locating cuisine-rich locations. Individual fitness determines how much energy is stored in the body.
- When a sparrow detects a predator, individuals start chirping with warning signals. When the alarm value exceeds the safety threshold, manufacturers must direct all explorers to a safe area.
- Each sparrow can be a producer if it seeks a better cuisine fountainhead, but the ratio of producers to explorers in the whole population is unchanged.
- Producers are sparrows with more vigour. Several hungry probes are more inclined to fly to other locations in search of cuisine to replenish their energy levels.

- Explorers are looking for a producer who can provide the best cuisine in search cuisine. Meanwhile, some explorers may constantly monitor producers and compete for cuisine over prey.
- The group sparrows move quickly to a safe area to find a better position if they are aware of the danger, while the sparrows in the middle of the group walk randomly to get closer to others.

SSA is suggested by imitating the search behaviour of the sparrow and anti-hunting group. This algorithm has fewer parameters, a more robust search capacity, and faster performance. The main stages of SSA can be explained as follows:

Step 1 Create and initialize the solution. At this stage, the population size, maximum number of replicates, producer ratio (PD), and the ratio of sparrows in intensive care (PV) are all determined. The initial position of the sparrow population is shown in Eq. (2). They are produced randomly.

$$X = \begin{bmatrix} x_{1,1} & x_{1,2} & \cdots & \cdots & x_{1,d} \\ x_{2,1} & x_{2,2} & \cdots & \cdots & x_{2,d} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ x_{n,1} & x_{n,2} & \cdots & \cdots & x_{n,d} \end{bmatrix} \tag{2}$$

The number of sparrows in Eq. (2) is n, and the dimension of choice variables is d. Each person's suitability for the following procedure is determined using Eq. (3). In Eq. (3), n defines the number of sparrows, and the value of each row in FX represents each person's fit.

$$F_X = \begin{bmatrix} f[x_{1,1} & x_{1,2} & \cdots & \cdots & x_{1,d}] \\ f[x_{2,1} & x_{2,2} & \cdots & \cdots & x_{2,d}] \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ f[x_{n,1} & x_{n,2} & \cdots & \cdots & x_{n,d}] \end{bmatrix} \tag{3}$$

Step 2 In the SSA, producers with higher fitness values are given preference over those who produce cuisine. Because producers are in charge of finding cuisine and directing the entire population's movement, producers can search for cuisine in a broader range compared to the position of the explorers. According to steps (1) and (2), during each iteration, the manufacturers update their status with Eq. (4).

$$X_{i,j}^{t+1} = \begin{cases} X_{i,j}^{t} \times \exp\left(\frac{-i}{\alpha \times iter_{max}}\right) & if\ R_2 < ST \\ X_{i,j}^{t} + Q \times L & if\ R_2 \geq ST \end{cases} \tag{4}$$

In Eq. (4), $iter_{max}$ is a constant with the highest number of iterations. t is the current iteration, and $j = 1, 2, \ldots, d$, $X_{i,j}^{t}$ represent the next value of jth sparrow in the iteration of t. α is a random number between 0 and 1. R_2 (alert value) is a number in the range of 0 to 1, and ST (safe threshold) is a value of 0.5 to 1.0. Q is a random number based on a normal distribution. L represents a $1 \times d$ matrix in which each element is 1. If it is $R_2 \geq ST$, some sparrows have discovered the hunter, and all the sparrows must fly quickly to other safe areas. When $R_2 < ST$ means no hunter is around, the manufacturer enters the extensive search mode.

In the case of explorers, Rules 4 and 5 must be followed. As previously said, some explorers keep tabs on most manufacturers. They leave their current place to compete for cuisine when they learn that a producer has discovered delicious cuisine. If they win, they can eat right away; otherwise, Rule 5 will apply. Position updating for explorers is defined according to Eq. (5). In Eq. (5) x_p does whether the manufacturer occupy the optimal position. *Xworst* represents the worst place in the world right now. A means a $1 \times d$ matrix that is randomly assigned 1 or -1 to each element inside $A^+ = A^T(AA^T)^{-1}$. If $i > \frac{n}{2}$ This indicates that the i probe with a worse fit value is more likely to go hungry.

$$X_{i,j}^{t+1} = \begin{cases} Q \times \exp\left(\frac{X_{worst}^{t} - X_{i,j}^{t}}{i^2}\right) & if > \frac{n}{2} \\ X_P^{t+1} + |X_{i,j}^{t} - X_P^{t+1}| \times A^+ \times L & otherwise \end{cases} \tag{5}$$

Step 3 After updating the position of the whole population, several sparrows are selected as scouts (exploration) responsible for identification and warning. They usually make up 10 to 20% of the total population. Updating their position is defined according to Rule 6 according to Eq. (6).

$$X_{i,j}^{t+1} = \begin{cases} X_{best}^{t} + \beta \times |X_{i,j}^{t} - X_{best}^{t}| & f_i > f_g \\ X_{i,j}^{t} + K \times \left(\frac{|X_{i,j}^{t} - X_{worst}^{t}|}{(f_i - f_w) + \varepsilon}\right) & f_i = f_g \end{cases} \tag{6}$$

In Eq. (6) X_{best} is the current global optimal position. ε is a small constant to avoid a zero-division error. β acts as a control parameter for step size and the normal distribution of random numbers with mean value 0 and variance 1. f_g and f_w are the current best and worst overall suitability values, respectively. K is a random number in the range 1 and − 1. f_i is the current value of the sparrow. $f_i = f_g$ indicates that sparrows in the middle of the population are aware of the hazard and should approach the rest. If $f_i > f_g$ then the person is at the edge of the group. X_{best} indicates the central location of the population and is safe around it. K represents the direction in which the person moves and the step size's control factor.

Step 4 Each person's current position is compared to the last repetition. The update is done if the new position is better than the previous one and saves the best position. The survival of some sparrows may improve after the last two steps.

Step 5 If the number of repetitions is less than the maximum number, move on to step 2. Otherwise, the algorithm stops, and the best solution is obtained.

```
Input:
G: maximum number of iterations
PD: the number of producers
SD: the number of agents (sparrows) alerted to the risk
R2: the alarm value
n: the number of agents
Create a population of n agents and describe its essential parameters.
Output: Xbest, fg.
While (t < G)
Rank the fitness values to determine the current best and worst individual.
R2 = random(1)
For i in (1, PD)
Using Eq. (4), upgrade the agent's position;
Out of For
For i in ((PD + 1), n)
Using Eq. (5), upgrade the agent's position;
Out of For
For l in (1, SD)
Using Eq. (6), upgrade the agent's position;
Out of For
Get the current fresh position;
if the fresh position is better than formerly, upgrade it;
t= t + 1
End While
Return Xbest, fg.
```

Fig. 1 Pseudo-code of SSA algorithm [17]

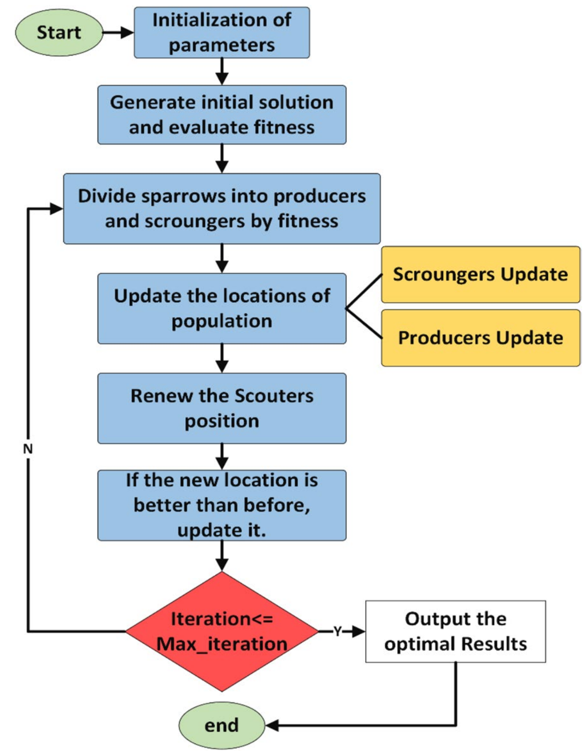

Fig. 2 Flowchart of SSA algorithm [17]

Figure 1 shows the pseudocode of the SSA algorithm.

The primary implementation of meta-heuristic algorithms usually has a sequential approach. Sparrow positions are typically recorded in a $n \times d$ matrix, where n is the number of sparrows and d is the number of dimensions in the search space. Using For-loops, the members of this matrix are changed one by one based on their value in the previous iteration and some random sample numbers. For search agents or various dimensions, all matrix components are simultaneously updated. Figure 2 shows the flowchart of the SSA algorithm.

Since 2020, various researches have been conducted to solve optimization problems with SSA. All the papers worked by SSA are downloaded to calculate the number of SSA papers. Then a grouping based on the percentage of papers in various journals and the number of publications of SSA papers per year is reviewed. Figure 3 shows the rate of papers published by SSA in multiple publications. The majority of publications belonged to IEEE journals (39%), followed by Elsevier (28%), Springer (11%), Hindawi (9%), Others (7%), and Tandfonline and Wiley (3%). Figure 3 shows that the highest percentage of papers published belong to the IEEE. At first, we downloaded all the papers belonging to SSA. Then the papers were categorized based on different publishers. We used the Google search engine and reliable sites such as Springer, Elsevier etc., for searching. We also used other databases in the field of indexing papers.

Figure 4 illustrates the number of SSA papers printed per year. The number of SSA papers printed in 2020 is 7. As shown in Fig. 4, the use of SSA has increased over time.

Papers are collected based on the title, keywords and abstract. Each paper has been thoroughly reviewed in terms of text and type of algorithm. Finally, the papers belonging to the SSA algorithm were grouped. Figure 5 shows the search steps and the number of papers in different steps.

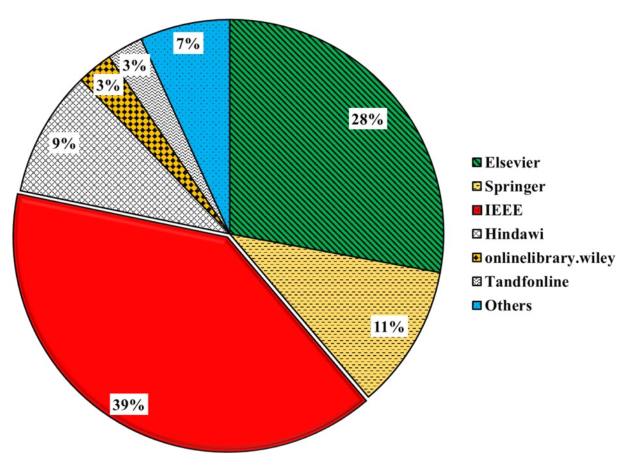

Fig. 3 Percentage of papers published with SSA in various journals

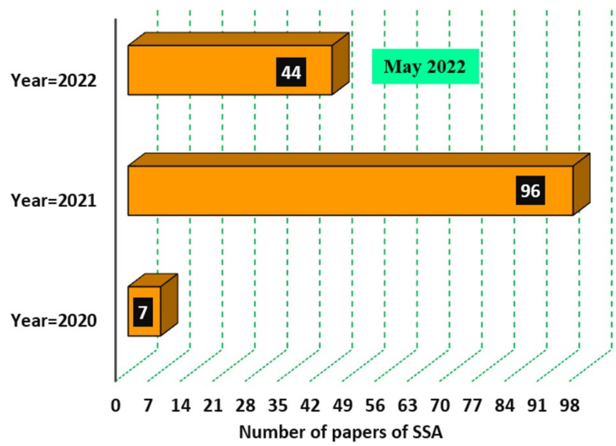

Fig. 4 Number of SSA papers published per year

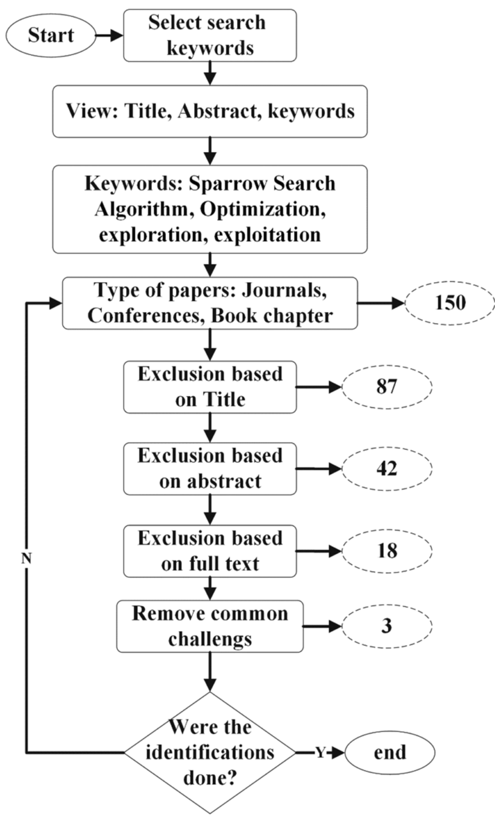

Fig. 5 Review of papers belongs to the SSA algorithm

3 Methods of SSA

Figure 6 shows the taxonomy of SSA methods. Classification is based on Hybridization, Improved, Variants of SSA, and Optimization issues. In hybridization, the combination of SSA with other algorithms is used. Improved uses various subcategories to improve solutions. In Variants of SSA, the Binary subcategory is used, and optimization issues are used to solve diverse optimization issues to find the best answer.

3.1 Hybridization

3.1.1 Meta-Heuristics

According to the performed classifications, the SSA algorithm in the field of meta-heuristics is combined with PSO, water wave optimization (WWO), sine cosine algorithm (SCA), firefly algorithm (FA), differential equation (DE), whale optimization algorithm (WOA), topographical global optimization (TGO), and BSS algorithms.

PESSA [19], a hybrid approach based on PSO and an enhanced SSA (ESSA), has been presented. The ESSA strengthens the producer's random jump to ensure global search ability, each scrounger continues to learn from the producers' optimal experience, and the difference between the best and worst individual will be imposed on the sparrow with the optimal position when it detects danger to speed up the search process. Ten fundamental functions validate PESSA's performance, and the experimental findings reveal that PESSA outperforms the other twelve methods. Finally, the suggested PESSA is tested in four situations, two of which are 2D settings and 3D environments. The findings revealed that the PESSA could obtain a more viable and effective route than the other models.

The WWO-SSA [20] was designed to combine the benefits of the WWO and SSA algorithms while avoiding their limitations. WWO and SSA have been integrated to achieve good performance by continually modifying the parameters to increase WWO's capabilities in development and exploration. Using CEC2017's benchmark features, the hybrid algorithm's performance is compared to WWO and SSA's original methods. WWOSSA is more efficient, according to the findings of the experiments.

A hybrid SSA-PSO [21] model has been developed to speed up convergence before individual SSA updates. In addition, a novel fitness function based on maximum likelihood parameter estimate was created and utilized for parameter initialization. The optimization performance of this algorithm was superior to that of a single method, with more incredible convergence speed and more stable, accurate outputs, according to the findings of five sets of actual datasets. Furthermore, it efficiently handled the difficulties of sluggish convergence speed and low solution accuracy with the help of the new fitness function. The experimental findings revealed that the hybrid SSA-PSO could acquire a superior solution, convergence speed, and stability in software defect estimation and prediction than a single SSA and PSO.

The SCA was initially created to increase the global search capacity of the SSA algorithm because it has the

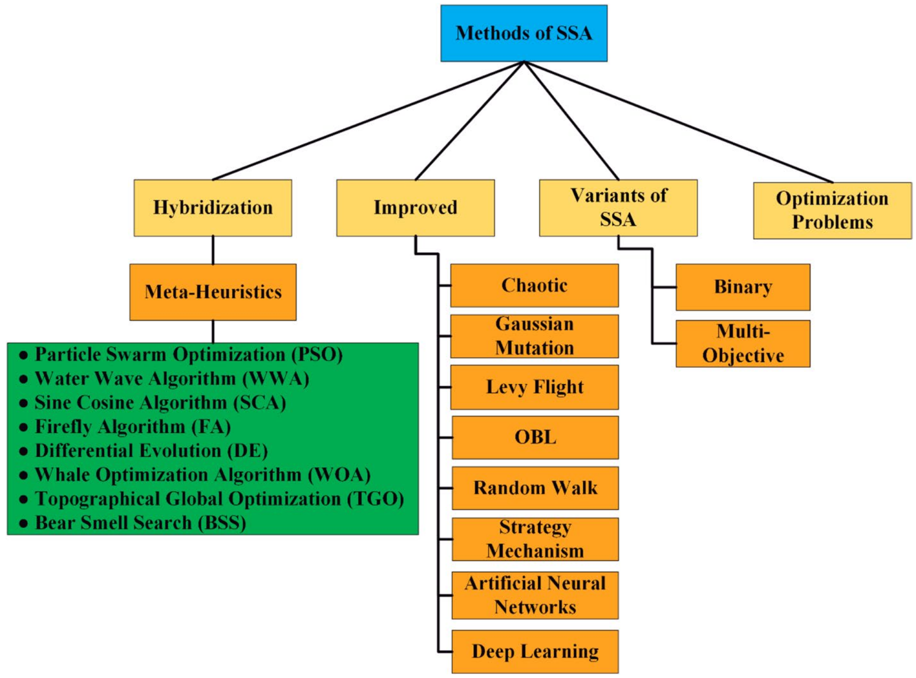

Fig. 6 Classification of SSA methods

qualities of attaining high search and avoiding local optimization. Additionally, the labour collaboration structure of the sparrow in the SSA algorithm is redefined to improve the algorithm's convergence ability. Finally, the enhanced cooperative SSA based on the sine cosine algorithm (SCA-CSSA) is developed [22] based on the new labour cooperation structure and SCA algorithm. The SCA-CSSA approach is used to adjust the weight of AdaBoost-S4VM and the critical parameters of S4VM to improve the precision of the AdaBoost-S4VM model for semi-supervised lung CT classification. The suggested AdaBoost-ISSA-S4VM model was compared against several hybrids and popular approaches on CEC2017 tasks and 12 benchmark tasks, including unimodal and multimodal tasks, to see how effective it was.

The SSA is used to improve the starting weights and thresholds of the BP-ANN, addressing the problem that the BP neural network is sensitive to beginning weights and thresholds. The firefly algorithm (FA) technique with FASSA [23] is presented to alleviate the weakness of SSA that it is easy to slip into the local optimum. Finally, China's big battery manufacturing firm is chosen for the empirical study. Comparative tests are conducted on the FASSA-BP, BP, SSA-BP, and PSO-BP regarding the accuracy, stability, and other factors. The FASSA-BP model was shown to be more accurate in the study.

Because buildings play a significant role in energy efficiency, it is critical to implement sustainable energy source (SES) systems globally, especially given the rising interest in near-zero energy structures. Because of their significant influence on energy usage and pollution, SES must be entirely used in buildings to promote renewable energy and efforts to develop a green future. As a result, getting the best results is critical. A novel multiple-objective optimization approach called SSA-DE [24] is used to get the best SES level. SSA-purpose DE is to determine the best value for system resource parameters.

In Wireless Sensor Networks, a hybrid SSA with DE is designed to alleviate the energy efficiency issue by cluster head selection [25]. The proposed approach combined the SSA's high-level search efficiency with DE's lively potential, extending node lifespan. The hybrid model performs well in the number of alive nodes, throughput, and residual energy. Compared to comparable algorithms, the Improved SSA employing the DE model to find the best potential cluster head demonstrated residual power and throughput development.

Due to sluggish convergence speed, low accuracy, and optimum local distance, the WOA algorithm is merged with the SSA and golden sine leading strategy (SGSWOA) [26]. The producer's position update rule in the SSA is integrated into the encircling prey stage of WOA to extend the algorithm's search space and escape from the local optimum. Then, when used with the golden Sine leading technique, it may balance exploration and development capabilities while improving the WOA algorithm's performance. Finally, the experimental findings showed that the SGSWOA method has superior convergence accuracy, convergence speed, and resilience after optimizing 16 benchmark functions and applying it to actual engineering optimization situations.

A new greedy genetic SSA (GGSC-SSA) based on the SCA method has been suggested [27]. The greedy method is first implemented to initialize the population and boost its diversity. Second, GA operators are utilized to balance global search and local development capacities to update the population. Finally, adaptive weight is added to the routine upgrade to improve the algorithm's flexibility and maximize the solution quality, and the SCA approach is used to update the scroungers. On TSP datasets, the GGSC-SSA is also tested against the genetic algorithm (GA), simulated annealing (SA), PSO, grey wolf optimization (GWO), ant colony optimization (ACO), and the artificial fish algorithm (AFA). The results showed that the GGSC-SSA significantly enhanced the solution precision, optimization speed, and perseverance.

For Unmanned Aerial Vehicle Path Planning, a unique SPSA is suggested [28]. PSO improves the discoverer position updating rule to improve the search along the start–end line. When impediments are encountered, adaptive variable speed escape search is employed to increase path search efficiency. Adaptive oscillation optimization increases path smoothing and lowers path fluctuations. Finally, reducing the nodes and smoothing procedure increases the path smoothness, making it more acceptable for path planning in the actual world. It's also been proven that the SPSA has a faster convergence time and uses less energy than other algorithms.

SSA and TGO [29] have been proposed for network security situations to improve the accuracy and performance of the scenario prediction model [30]. TGO-SSA is used to optimize neural network scenario prediction model structural hyperparameters. The TGO-SSA technique outperforms the standard scenario prediction model to improve neural network model accuracy and reduce training loss. Python was used to test the suggested technique. The findings revealed that the approach could perform better at situation prediction.

The Improved Bear Smell Search (IBSS) and SSA are presented [31]. The BSS is included in the proposed work through crossover and mutation functions, thus the designation IBSS-SSA. The grid created the multi-objective function with reactive power variations dependent on the available resource power. The SSA procedure ensures that online control signals are detected utilizing a parallel implementation against active and reactive power variations. Under power flow changes, the control technique based on the suggested methodology enhances the power controller's control parameters. The proposed approach, based on fluctuations in the resource and load side characteristics, is used to regulate the power flow management of the smart-grid system. The proposed model manages energy resources to meet the grid's power needs, including renewable energy and energy storage devices.

Figure 7 shows the advantages of hybridization SSA with different algorithms. SSA combines SCA, PSO, DE, and BSS algorithms to solve optimization issues.

In the hybrid SSA-PSO model, the SSA algorithm uses the gbest agent to update the agents' position. By choosing the best optimal points, the SSA algorithm ignores the

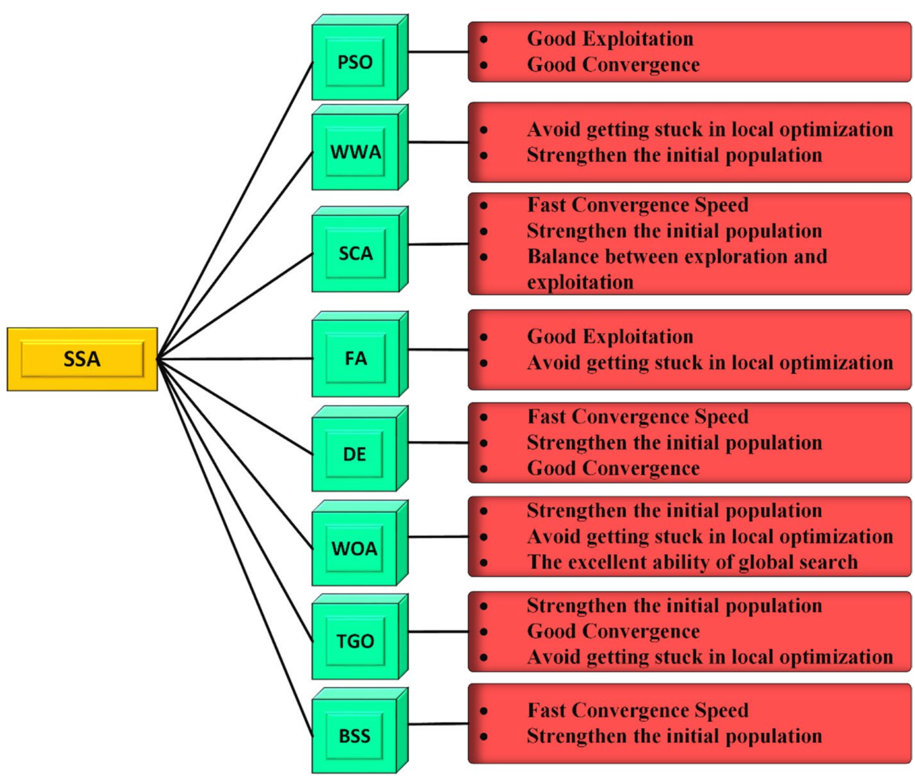

Fig. 7 Advantages of hybridization SSA with different algorithms

problem of premature convergence in the PSO algorithm. The SSA-PSO model prevents premature convergence by enhancing group search capabilities. In the optimization process, the SSA-PSO model reduces premature convergence by determining the optimal value for the parameters.

3.2 Improved

All SSA restrictions are slow convergence, optimum local entrapment in certain circumstances, and exploration and exploitation phases that can't cope with the extensive dimensions. Due to the limitations of SSA, numerous approaches have been developed in recent years to enhance SSA, including chaos, Gaussian, Lévy flight, OBL, Random Walk, Strategy mechanism, artificial neural networks (ANNs), and Deep Learning. Improved strategies for boosting population variety and speeding convergence by hybridization operators have shown to be beneficial.

3.2.1 Chaotic

Turbulent systems are distinguished by their unpredictability, periodicity, and parameter sensitivity. Turbulent mapping can be used to produce rough numbers between 0 and 1 instead of pseudo-random number generators to optimize the parameters of metaheuristic algorithms. Experiments have demonstrated that using chaotic sequences for initialization influences the entire algorithm process and that chaotic sequences produce better results than quasi-random numbers. Chaotic mapping improves the variety of the sparrow population's starting state. Chaotic mapping prevents premature convergence and increases global optimization accuracy and convergence. Figure 8 shows the most critical chaotic targets in SSA.

Table 1 shows the improvement of SSA by the chaotic method. Items such as the advantages and disadvantages of chaotic SSA have been analyzed.

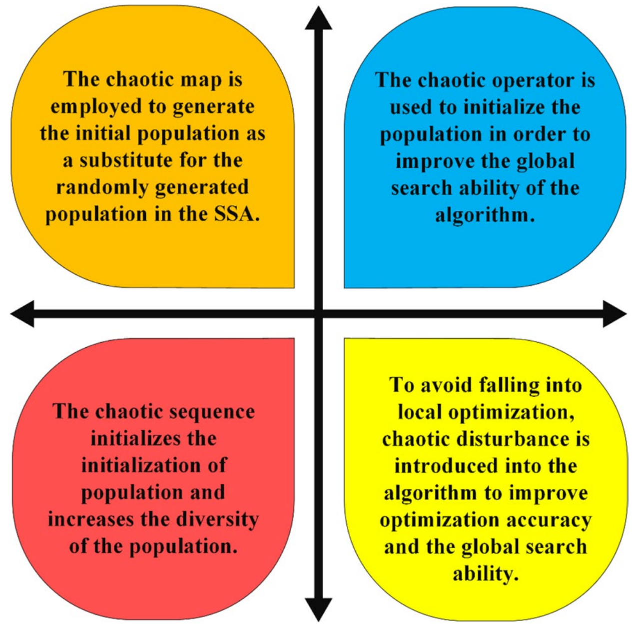

Fig. 8 The most critical chaotic targets in SSA

3.2.2 Gaussian

A modified SSA termed CASSA [51] was used for an uncrewed aerial vehicle (UAV). The route planning challenge is changed into a multi-dimensional task optimization issue once the 3D task space model and UAV route planning cost functions are established. Second, the chaotic approach is used to broaden the algorithm's population, while an adaptive inertia weight is used to balance the algorithm's convergence rate and exploration capabilities. Finally, the Cauchy-Gaussian mutation technique improves the algorithm's capacity to overcome stagnation. According to simulation data, the CASSA-generated routes are superior to the SSA, PSO, ABC, and WOA.

A crack segmentation approach based on adaptive T-distribution is utilized to enhance the selection of clustering centres and make the cracks more accurate and comprehensive segmentation [52]. The simulation demonstrates that incorporating an adaptive t-distribution mutation mechanism into SSA improves its ability to resist getting caught in local optimization. Second, the improved TSSA is utilized as the K-means algorithm's starting clustering point. After verification, the suggested technique considerably enhanced complicated crack pictures' segmentation accuracy and fitness. The Gaussian function's objective is to keep you from slipping into the local optimum.

A multi-objective scheduling model based on an ISSA has been developed to increase the efficiency of Micro-grid combined heat and power (MCHP) [53]. The objective and economic advantage objectives are initially defined to minimize total operating costs and environmental pollutant discharge. Then, a dynamic adaptive weight is used instead of a single weighting technique, and the SSA is combined to create a multi-objective optimum timetable model for comprehensive energy. Finally, multiple optimization scenarios are constructed to test a typical day operation's suggested scheduling optimization model. The results demonstrated that the multi-objective configuration outperformed the single-objective setup to meet power grid dispatching criteria. The proposed optimization approach improved the economic and environmental advantages of the integrated energy system. As a result, the Cauchy-Gaussian mutation method chooses the current best fitness person for mutation,

Table 1 Improvement of SSA by Chaotic method

Refs	Models	Objective	Advantages	Disadvantages
[32]	Improved chaotic SSA (ICSSA)	Using an enhanced chaotic SSA, identify parameters of robot manipulators with unknown payloads	Population diversity*	Slow convergence rate*
			Strong global searchability*	High execution time*
			Good convergence*	
[33]	CSSA	Fault diagnosis	Good convergence*	High execution time*
[34]	IHSSA-ICMIC	Optimization of engineering problems	Faster convergence*	Achieve a solution in the final iterations*
			Strong global searchability*	
[35]	Logistic chaotic-SSA	The chaotic time series prediction method	Balance between exploration and exploitation*	High execution time*
			Good convergence*	
[36]	Sin chaotic-SSA	Scheduling strategy of regional integrated energy model	Good convergence*	Achieve a solution in the final iterations*
			Prevent useless search*	
			Global optimization capability*	
[37]	CM-SSA	Energy optimization in microgrid	Population diversity*	Slow convergence rate*
			Good convergence*	
			Prevent useless search*	
[38]	Chaotic sine mapping-SSA	Predicting and optimizing network weights	Population diversity*	Achieve a solution in the final iterations*
			Strong global searchability*	
			Good convergence*	
			Prevent useless search*	
[39]	CM-SSA	Optimal dispatch strategy of microgrid energy storage	Faster convergence*	High execution time*
			Strong global searchability*	
			Short running time*	
[40]	CSSA	Position recognition problem	Balance between exploration and exploitation*	Achieve a solution in the final iterations*
			Global optimization capability*	
[41]	CMSSA	Global optimization	Strong global searchability*	High iterations*
			Good convergence*	
			Prevent useless search*	
[42]	CSSA	Dynamic path planning	Balance between exploration and exploitation*	High execution time*
			Good convergence*	
			Prevent useless search*	
[43]	CSSA	Solve continuous optimization problems and continuous dimensions	Short running time*	Achieve a solution in the final iterations*
			Balance between exploration and exploitation*	
			Global optimization capability*	
[44]	NCSSA	TSP problem	Prevent useless search*	Slow convergence rate*
			Update the situation without getting lost*	
			Faster convergence*	
[45]	CSSA	Solve continuous optimization problems and continuous dimensions	Balance between exploration and exploitation*	High iterations*
[46]	CSSA-SCN	Solve continuous optimization	Strong global searchability*	High execution time*

Table 1 (continued)

Refs	Models	Objective	Advantages	Disadvantages
			Short running time*	
			Balance between exploration and exploitation*	
[47]	CSSA	Solve optimization problems and strengthen the antenna	Update the situation without getting lost*	Achieve a solution in the final iterations*
			Population diversity*	
[48]	CWTSSA	Solve continuous optimization problems and continuous dimensions	Update the situation without getting lost*	Slow convergence rate*
			Population diversity*	
			Strong global searchability*	
[49]	CMISSA	Solve continuous optimization	Balance between exploration and exploitation*	Slow convergence rate*
[50]	CSSA	Solve continuous optimization	Update the situation without getting lost*	High iterations*

The asterisk (*) indicates the number of items

compares the positions before and after the mutation, and chooses the better position to move on to the next iteration.

ISSA-SVM is an ISSA that solves the problem of SVM hyperparameter selection and constructs the mid-long term load prediction model [54]. A novel dynamic adaptive t-distribution mutation improves the ISSA. The ISSA offers greater convergence precision, stability, and speed than the SSA, evidenced by a comparison test using six benchmark functions. The simulation results demonstrated that the ISSA-SVM successfully enhanced prediction accuracy compared to the original SVM, BP neural network, multiple linear regression, and other methods. The Gaussian function has always detracted from local optimism and population variety.

3.2.3 Levy Flight (LF)

The LF technique improves the multi-objective SSA's capacity to jump out of the local optimum. The simulation results confirmed the upgraded multi-objective SSA's efficacy. The wind–solar-diesel–storage micro-cost grids and loss were reduced using a multi-objective function. The correct step size for an LF is crucial since a big step size might make individuals meander around the local optimal amount and be unable to find the ideal answer. An extremely tiny step size, on the other hand, may render the ideal value unachievable and result in merely a local optimization. On the other hand, LF's search approach in SSA is fully random.

A DV-Hop method is suggested to optimize using the improved SSA (ISSA) [55]. The maximum hop distance error is utilized to adjust the hop distance from the unknown node to each anchor node to decrease the estimated distance error. Second, LF is used to improve the capacity of the SSA to leap out of local optimums, and Powell local search is used to improve the method's convergence. Finally, the simulation results indicated that the revised algorithm's positioning error is considerably decreased compared to the original DV-Hop method, and positioning accuracy is effectively enhanced in irregular regions.

Bernoulli's chaotic mapping, LF, mutation, crossover, competition, and enhanced SSA are designed to obtain an ideal energy configuration [56]. The results of several test functions and assessment indicators illustrate the superiority of the upgraded SSA. The suggested method's usefulness is demonstrated by solving and assessing the best configuration of an energy management model. The case study results reveal that an active distribution network with a multi-micro-grid system offers significant economic and environmental benefits under many scenarios. The proposed solutions are critical for a multi-microgrid dynamic distribution network's effective operation and environmental conservation.

The LF operation is added to the original SSA's producer's search process to improve the algorithm's ability to hop out of the local optimum and optimize performance [57]. The opposition-based learning (OBL) technique produces better SSA solutions, which helps to speed up the algorithm's convergence speed. On the one hand, numerical tests based on traditional benchmark functions assess the LOSSA's performance. On the other hand, the Support Vector Machine (SVM) hyper-parameter optimization task is used to verify LOSSA's capacity to tackle actual situations. The LOSSA is feasible and successfully handles machine learning algorithms' hyper-parameter optimisation problem. This study proposes an improved SSA based on LOSSA. The LOSSA's overall performance is good, according to the experimental data. The LOSSA surpassed the SSA and other natural heuristic algorithms in search accuracy, convergence speed, and stability.

Reverse learning and the LF random step are used in the SPISSA [58]. In the initialization stage, this model increased the variety and quality of sparrows, and in the subsequent iteration stage, it improved the global search capabilities. Finally, the technique is integrated with the Spark distributed computing framework to account for network incursion traffic's high-dimensional and large-scale aspects. The population is estimated in parallel in the Spark framework based on the data partition. Experiments have shown that SPISSA can identify the best subset from the public data set. At the same time, the algorithm's computation time has been significantly lowered.

In the WSN, DV-Hop is a frequently utilized positioning method [59]. An ISSA is provided based on DV-Hop wireless sensor network positioning technology. There are two critical factors to DV advancement. The double communication radius method modifies the minimum hop count between nodes to reduce the estimated distance error; second, instead of using the least-squares method. This improved algorithm employs SSA to evaluate nodes' positions; simultaneously, SSA employs the Lévy flight strategy to improve performance further. Finally, simulation is used to assess the method's placement accuracy, and the results show that ISSA-LF is superior.

3.2.4 Opposition-Based Learning (OBL)

DV-Hop is a widely used placement strategy in the WSN [60]. Based on DV-Hop wireless sensor network positioning technology, an ISSA is supplied. DV progress is dependent on two variables. The double communication radius method modifies the minimum hop count between vertices to reduce the estimated distance error; second, instead of using the least-squares method. This enhanced algorithm utilizes SSA to calculate node positions; simultaneously, SSA uses the Lévy flight strategy to improve performance even further. Finally, simulation is used to evaluate the method's accuracy in terms of placement, and the findings demonstrate that ISSA-LF is superior. A new defect diagnostic technique based on *LightGBM* optimized by the elite opposite SSA(EOSSA) [61] is proposed. The change in data distribution is frequently ignored by dimension reduction methods based on Euclidean distance.

In the case of mobile robot route planning, population variety is insufficient in later rounds, making it simple to settle into a locally optimum solution. Using the sparrow search method, an enhanced SSA is presented to address these issues in mobile robot path planning. First, the algorithm optimizes the initial population of sparrows using OBL, which increases the quality of the initial solution and improves the system's local search capabilities. Second, it incorporates the Metropolis criteria into the simulated annealing (SA) process, allowing the system to accept new solutions by determining whether to take them, allowing the algorithm to escape the local optimum and improve global search capacity. OBL is utilized to construct a reverse solution to create a new sparrow population, increase population variety, and enhance population quality [62]. Simultaneously, the OBL can be utilized to direct the algorithm away from the local optimum. Finally, the ISSA's performance is tested using 2D grid maps of various specifications created on the MATLAB platform. The simulation results demonstrate that the ISSA outperforms the SSA, PSO, and other standard intelligence algorithms in optimal performance and can successfully jump out of the local optimum.

An improved SSA (ISSA) is used to suggest a distributed maximum power point tracking (DMPPT) [63]. First, the population was initialized using the centre of gravity reverse learning technique, resulting in a superior spatial solution distribution. Second, the learning coefficient was added to the discoverer's position update section to increase the algorithm's global search capability. Simultaneously, the mutation operator was employed to improve the joiner's position update and prevent the algorithm from sliding into the local extreme value. The initial sparrow population is generated using random initialization in the conventional SSA. The quality of the starting population influences the end convergence accuracy for the intelligent algorithm of population iteration. The initial population of the SSA is generated using centroid OBL (COBL), which assures the initial population's homogeneity and variety while also improving its fitness. The model's findings revealed that the ISSA could track the maximum power point (MPP) more precisely and fast than the perturbation observation technique (P&O) and the PSO and has superior steady-state performance.

The ROSSA model [64] is based on SSA paired with Random OBL (ROBL) and a linear decreasing approach. The path planning challenge for mobile robots may theoretically turn into an optimization problem that intelligent optimization systems can handle. An SSA-based optimization technique is presented in light of this assumption. The declining linear approach balances the algorithm's capacity to search worldwide and exploit locally by altering the algorithm parameters. ROBL increases the variety of the population and improves the algorithm's exploration capabilities. Trials demonstrate the ROSSA's superiority with three conventional algorithms for 11 benchmark test functions and comparative studies with PSO and SSA on the path planning issue.

A learning SSA (LSSA) [65] is introduced in the discoverer stage. The random reverse learning technique promotes population variety and flexibility in the search process. An upgraded sine and cosine guiding mechanism is added at the follower stage to make the discoverer's search approach more thorough. Finally, we suggest a differential-based local search. The method updates the best solution acquired each time to avoid omitting high-quality solutions throughout the search process. In 12 benchmark functions, LSSA was compared against CSSA, ISSA, SSA, BSO, GWO, and PSO to ensure the method was feasible. According to the simulation results, LSSA has a high degree of universality. Finally, robot route planning is used to verify LSSA's practicability, and LSSA has high path planning quality and reliability.

3.2.5 Random Walk

An enhanced SSA employing the random walk approach (RWSSA) [66] is presented to maximize the distribution and signal coverage of 5G base stations in open-pit mines. RWSSA is compared to SSA, MS-ALO, and PSO. In comparison to other models, the convergence speed and accuracy are good. Finally, the RWSSA is superior to previous algorithms in numerous ways, making it more appropriate for 5G base station distribution optimization in open-pit mines. In the 5G base station deployment optimization challenge, RWSSA achieved superior performance and application.

An RW technique is presented to enhance the SSA [67]. The SSA, the grey wolf optimization algorithm, and the WOA are all contrasted and studied. It is confirmed that the ISSA has a quick convergence speed and good optimization precision after a benchmark test function experiment. The RW strategy improvement sparrow search method's exact solution is employed as the starting neuron connection weight and threshold information of the BP neural network, which is then used to categorize dangerous URLs and further evaluate the updated technique's viability. The findings demonstrated that optimising the BP network by optimising the RW strategy optimization SSA might increase hazardous URL classification accuracy.

For optimal model parameter identification of proton exchange membrane fuel cell (PEMFC) stacks, a new optimization approach termed Adaptive SSA (ASSA) [68] is suggested. The sparrows' locations in the solution space are scattered randomly. An RW technique is used when no nearby sparrows surround the present individual. The ASSA is used to minimize the sum of squared error (SSE) between the empirical and estimated stack voltages in the PEMFC stack by optimally selecting the parameters in the PEMFC stack. The approach is used in three case studies: Horizon H-12, Ballard Mark V, and NedStack PS6 under various operating circumstances, yielding SEE values of 0.82, 5.14, and 0.097, respectively. The ASSA significance is demonstrated by comparing the algorithm's outputs to CGOA, GRA, and simple SSA. According to the final data, the proposed ASSA is the most efficient compared to the others.

3.2.6 Strategy Mechanism

A strategy mechanism combines local and global search by strengthening the update of individuals in the community to search more in the problem space. This method makes it possible to move towards a global optimizer faster, even for algorithms with heavy computational fitness functions. The strategy mechanism helps to change the control parameters in different optimization stages, or even for various optimization problems, the parameters are adjusted according to the ongoing search feedback. This approach selects an adaptive parameter and thus balances exploration and exploitation (Table 2).

3.2.7 Artificial Neural Networks

ANNs are used to predict and classify various issues such as time series, price estimation, weather forecasting, estimating the accuracy of industrial devices, etc. If the structure of ANNs is improved, then their efficiency and accuracy will increase. In this section, the combination of SSA with ANNs is examined. The SSA algorithm is used to optimize radial-basis function (RBF), extreme learning machine (ELM), generalized regression neural network (GRNN), and Elman networks. The ELM network is a feed neural network used for statistical classification, regression analysis, clustering, approximate spars, comparison, and training. The limitation of the ELM network is that initial weights and thresholds are determined using traditional trial-and-error or network search methods. Traditional methods do not work well with inaccuracy, so SSA has been used to solve ELM problems. Each hidden node has a return edge of its connection in the Elman network. Figure 9 shows the SSA schema on ANNs.

Table 3 shows the advantages and disadvantages of SSA with ANNs.

Recently, neural networks have been widely used to predict various issues in artificial intelligence. In ANNs, a parameter called weight needs to be updated frequently to avoid significant errors. Since the learning process of an ANN is strongly related to optimizing a target function, choosing an optimization algorithm is a crucial step in designing the structure of an ANN. Figure 10 shows the steps of SSA-BP synthesis. The purpose of SSA is to optimize the weight of the BP network.

3.2.8 Deep Learning

Deep learning (DL) has demonstrated advanced performance on various issues. Hyper-parameter settings are vital in deep learning performance and machine learning models. Deep neural networks have one or more hidden layers between the input and output layers. They typically apply nonlinear transformations or activation functions

Table 2 Improving SSA with strategic methods

Refs	Models	Strategy	Results	Global convergence	Exploration vs exploitation	Complexity
[69]	EEMD-Tent-SSA-LS-SVM	Tent chaotic mapping, t-distribution	Wind power prediction	Moderate	Tuning dependent	Moderate
[70]	Mixed Strategy SSA (MSSSA)	Non-linear adjustment, random distribution	Increase positioning accuracy	Slow	Moderate	High
[71]	ISSA-gradient boosting regression tree technique (ISSA-GBRT)	gradient boosting regression tree, t-distribution	Optimization issues in the engineering industry	Tuning dependent	Tuning dependent	Moderate
[72]	ISSA	Neighborhood search strategy	Path planning approach for mobile robots	Slow	Less diverse solutions	Moderate
[73]	ESSA-DELM	Trigonometric substitution strategy and Cauchy mutation	Optimization of engineering and continuous issues	Fast	Good	Moderate
[74]	ISSA	Mutation, random distribution	Optimal reactive power dispatch and distributed generation placement	Slow	Less diverse solutions	High
[75]	ISSA	Position updating strategy	Solve engineering and dynamic problems	Fast	Tuning dependent	Moderate
[76]	LLSSA	Inverse learning strategy, spiral search strategy	Optimization of engineering and continuous issues	Slow	Good	Low
[77]	ISSA	Iterative local search strategy, a greedy strategy	Optimization of engineering and continuous issues	Fast	Tuning dependent	High
[78]	IMSSA	Position updating strategy	Sequential quadratic programming for solving the cost minimization	Tuning dependent	Moderate	Moderate
[79]	SSACBR	t-distribution mutation operator, memetic algorithm, Case-based reasoning	Prediction of statistical data	Tuning dependent	Good	Low
[80]	EMSSA	Hazard-aware transferring strategy, dynamic evolutionary strategy, uniformity-diversification orientation strategy	Continuous optimization problems	Slow	Less diverse solutions	Moderate
[81]	adaptive spiral flying SSA (ASFSSA)	Variable spiral search strategy	Optimization of engineering and continuous issues	Tuning dependent	Tuning dependent	Moderate
[82]	ISSA	Position updating strategy	Optimization of engineering and continuous issues	Moderate	Tuning dependent	Low
[83]	ISSA	Mutation, random distribution	Water quality prediction	Slow	Tuning dependent	Moderate

(logistics, tanh, or ReLU). In DL, hyperparameters include the number of layers, the neurons in each layer, the activation function, the learning rate, the deletion rate, and the batch size. There is no optimal general configuration for hyperparameter optimization. These parameters can be optimized manually but are time-consuming and require specialized knowledge. Automated optimization of meta-parameters can be done using meta-heuristic algorithms. GRU, LSTM, and CNN are the most important deep learning networks. Table 4 shows the combination of SSA with deep learning algorithms.

Figure 11 shows the percentage of Improved SSA based on different methods. The Chaotic and Strategy models' percentage is higher than Gaussian, LF, OBL, and Random

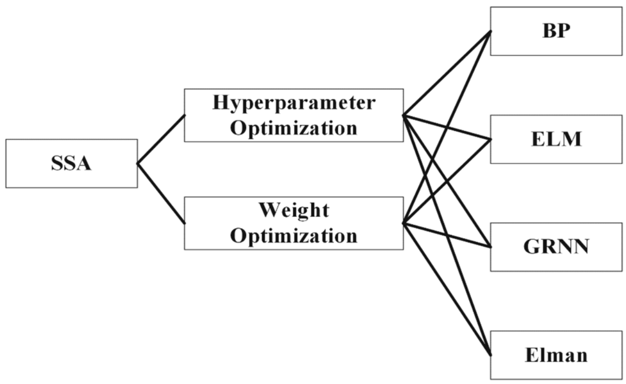

Fig. 9 SSA schema on ANNs

Walk models. The percentage of using the Strategy Mechanism model with SSA is lower than Chaotic.

3.3 Variants of SSA

3.3.1 Binary

A Discrete SSA (DSSA) [121] with a global perturbation technique has been developed to solve the TSP. The roulette-wheel selection generates the population's first solution. The order-based decoding approach is then added to finish the sparrow position update. The global perturbation technique is used with Gaussian mutation and swap operator to balance exploration and exploitation capacity. Finally, the 2-opt local search enhances the solution's quality. These tactics improve the quality of the solution and speed up the convergence process. Experiments were conducted using 34 TSP benchmark datasets.

Furthermore, statistical tests confirm the significant differences between the DSSA and other current approaches. According to the results, the suggested strategy is more competitive and resilient in solving the TSP. A novel DSSA algorithm has been augmented with the genetic operator and local search to the robot route. Comparing the DSSA to other approaches (Hybrid FA, PSO, Adaptive ABC, etc.) revealed that the enhanced algorithm outperformed the others in the examples examined.

3.3.2 Multi-objective Optimization

Single or many designs are commonly involved in engineering optimization problems. Multi-objective optimization, as opposed to single-objective optimization, which tries to discover the best solution to a given issue using an objective function, includes optimizing two or multi-objective functions and offering optimum solutions.

To the dynamic reconfiguration integrated optimization model of an active distribution network, a novel solution technique based on a multi-objective SSA (MOSSA) [122] has been developed (ADN). Distributed generation and time-varying loads can aid in sustainable development and energy conservation. As a result, this study investigates the ADN integrated optimization problem while considering distributed generation and time-varying demand to improve ADN power quality, economics, and energy savings. The supremacy of the proposed MOOSSA for the multi-objective, multi-constraint, non-linear, high-dimensional ADN integrated optimization problem is first proven. Second, the ADN mathematical model for integrated optimization is created. The MOOSSA reduced power loss and node voltage fluctuation by 75.76% and 70.06%.

MOSSA is used to efficiently manage the functioning of a microgrid (MG) [123]. This paper presents two optimization problems. The first is a single-objective issue that tries to reduce the overall operating cost or the total emission from the system. The second issue is a multi-objective problem that simultaneously includes total operational costs and emissions. There is a new version of SSA available. To manage the energy of the MG optimally, photovoltaic modules (PV), wind turbines (WT), fuel cells (FC), micro-turbines (MT), batteries (BSS), and the grid are all integrated into the MG. The suggested method is statistically tested using Friedman and Kruskal–Wallis ANOVA tests in non-parametric analysis. In addressing the single objective issue, the recommended SSA achieved cost and emission depreciation of 1.44% and 54.76%, respectively, compared to Krill Herd (KH). In the multi-objective problem, the proposed MOSSA saved 42.78% operating expenses and 0.118% emissions compared to ALO. The critical findings indicated SSA's resiliency in regulating the created MG's functioning.

A MOSSA-based wireless sensor clustering and routing protocol model (MUSHROOM) has been presented [124]. A fitness function based on maximum neighbour node distance, the average distance to BS, and energy ratio are shown to conduct clustering. With the excess energy of the next-hop node, sink distance, and node degree, MUSHROOM applied the fitness function to the routing process. The suggested model has undergone extensive testing to guarantee that it has achieved maximum energy competence and network longevity when compared to other techniques with varied numbers of nodes.

MOSSA [125] is a suggested multi-objective variation of the SSA. MO-SSA performed well compared to other well-known optimization methods in tests (NSGA-II, NSGA-III, and MO-ALO). The MOSSA outperformed most baseline algorithms on numerous performance parameters.

3.4 Optimization Problems

The term "optimization" refers to selecting the best option from a set of alternatives. Engineers search for ideal

Table 3 Combination of SSA with ANNs

Refs	Models	Objective	Advantages	Disadvantages
[84]	SSA-RBF ISSA-RBF	Predicting the temperature of the sensors	Find the optimal value for RBF parameters	Non-optimal updates of individual
			Reduce data training time	Achieve a solution in the final iterations
			Increase detection accuracy	
			Error reduction	
[85]	SSA-ELM	The SSA-ELM model predicts the uniaxial compressive strength (UCS) of the cemented paste backfill (CPB) under different conditions	Increase forecast accuracy	Non-optimal updates of individual
			Discover the optimal value for ELM parameters	High execution time
			Settings for the number of layers and the number of nodes	
[86]	Firefly Algorithm SSA (FASSA-GRNN)	Prediction of industrial and laboratory materials	Enhance SSA search capability using FA	Slow convergence rate
			Determining the optimal weight for GRNN	
			Reduce the amount of output error	
[87]	SSA-ENN	The SSA-ENN strategy can improve road capacity and traffic stability	Reduce data training time	Achieve a solution in the final iterations
			Increase detection accuracy	
			Error reduction	
[88]	SSA-BP	The proposed SSA-BP algorithm can characterize the critical deformation dimensions (height, length, tilt angle) within the mean relative error of 10%	Find the optimal value for RBF parameters*	Slow convergence rate
			Reduce data training time	
			Increase detection accuracy	
			Error reduction	
[89]	FA-SSA-BPNN	Optimization of sensor features and model parameters	Reduce data training time	Achieve a solution in the final iterations
			Improve accuracy in data training	
[90]	ICEEMD-SSA-BPNN	Predicting the price of carbon and industrial materials	Settings for the number of layers and the number of nodes	High execution time
			Improve the internal structure of the network	
			Increase detection accuracy	
			Improve accuracy in data training	
[91]	WMF-SSA-MLELM	Short-term multistep wind speed forecasting	Reduce data training time	Achieve a solution in the final iterations
			Improve accuracy in data training	

Table 3 (continued)

Refs	Models	Objective	Advantages	Disadvantages
			Find the optimal value for network parameters	
[92]	SSA-BP	predicting possible threats based on commander mood (PTP-CE)	Improve the internal structure of the network	High execution time
			Improve accuracy in data training	
			Reduce data training time	
[93]	CMSSA-Elman	Short-term PV Power Forecasting Based on Time-Phased and Error Correction	Settings for the number of layers and the number of nodes	Achieve a solution in the final iterations
			Error reduction	
[94]	SSA-BP	Optimization of the BP Neural Network Algorithm with SSA for the Processing of Coal Mine Water Source Data	Settings for the number of layers and the number of nodes	Slow convergence rate
			Reduce data training time	
			Find the optimal value for network parameters	
[95]	SSA-ELM	Predicting air pollution	Increase detection accuracy	Non-optimal updates of individual
			Improve the internal structure of the network	
			Find the optimal value for network parameters	
[96]	SSA-BP	Based on the SSA-BP Neural Network, an assessment algorithm for network security is developed	Reduce data training time	High execution time
			Improve accuracy in data training	
[97]	Tent Cauchy SSA (TCSSA-BP)	Regression prediction of material grinding particle size	Settings for the number of layers and the number of nodes	Achieve a solution in the final iterations
			Reduce data training time	
[98]	SSA-KELM	Intelligent Fault Diagnosis	Error reduction	High execution time
			Improve accuracy in data training	
[99]	SSA-DBN	Predictability and accuracy of diagnosis	Find the optimal value for network parameters	Slow convergence rate
			Settings for the number of layers and the number of nodes	
			Error reduction	
			Improve accuracy in data training	
[100]	SSA-BP	Forecasting hydropower generation	Improve accuracy in data training	Slow convergence rate
			Improve the internal structure of the network	
			Error reduction	
[101]	SSA-KELM	From water quality assessment to environmental water quality management	Settings for the number of layers and the number of nodes	High iterations
			Improve the internal structure of the network	
[102]	SSA-BP neural network	Prediction of industrial and laboratory materials	Increase detection accuracy	Non-optimal updates of individual

Table 3 (continued)

Refs	Models	Objective	Advantages	Disadvantages
			Improve accuracy in data training Find the optimal value for network parameters Error reduction	
[103]	SSA-BP	Wind and solar power forecasting	Find the optimal value for network parameters Error reduction Improve accuracy in data training	High iterations
[104]	SSA-BP	Predicting the boiling point temperature of working fluid	Reduce data training time Error reduction Increase detection accuracy	Non-optimal updates of individual
[105]	SSA-KELM	Blood glucose prediction	Reduce data training time Improve accuracy in data training	Slow convergence rate
[106]	ISSA-FSCN(Fast stochastic configuration network)	Fire flame recognition	Good optimization ability Classification of flame images	Slow convergence rate

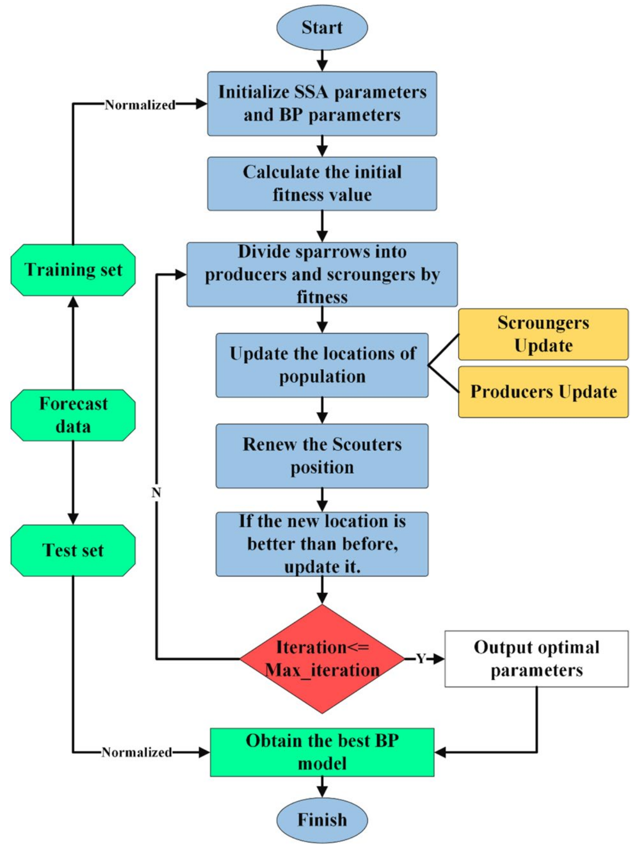

Fig. 10 SSA-BP combination flowchart [90]

parameters to save time or expense while improving their designs' operational efficiency, effectiveness, excellence, or lifespan. Traditional approaches such as regular linear programming are acceptable for fundamental optimization problems, and some employ gradient information to identify the best solution. Still, real-world engineering optimization problems are often nonlinear, indistinguishable, complex, and multifaceted. Solving these problems using classical optimization methods is relatively difficult. Hence, meta-heuristic algorithms that do not require gradient information are needed to solve them. The optimization section uses the SSA algorithm to solve forecasting, error detection, energy management, complex optimization, clustering, scheduling, and object detection in engineering disciplines. The algorithm has proven its effectiveness in most issues. Table 5 provides an overview of SSA in optimization.

Figure 12 shows the percentage of SSA application in different areas of optimization. As shown in Fig. 12, the highest rate of SSA utilization in Complex Optimization belongs to optimization in continuous and discrete problems. Fault Diagnosis is equal to 15%, which belongs to industrial and advanced issues. Clustering and Object Recognition are equal to 8%. The lowest percentage belongs to Location Optimization, and 5% is obtained.

Table 4 Hybridization of SSA with deep learning algorithms

Refs	Models	Objective	Advantages	Disadvantages
[107]	SSA-BI-GRU	Bidirectional GRU (Bi-GRU) and time-series production forecasting approach based on the integration of (SSA)	Improve accuracy in data training	High iterations
			Reduce data training time	
			Error reduction	
[108]	LSTM-SSA	Short-term wind speed forecasting	Find the optimal value for network parameters	Problem of Overfitting with an increasing number of iterations
			Increase detection accuracy	
			Improve accuracy in data training	
			Increase detection accuracy	
[109]	SCGRU-HSSA	Recognition of a linear source contamination	Improve accuracy in data training	Reduction of performance of middle neurons by increasing repetitions
			Settings for the number of layers and the number of nodes	
[110]	SSA-CNN	COVID-19 diagnosis and categorization based on chest CT scans	Error reduction	Non-optimal updates of individual
				High execution time
[111]	VMD-ISSA-GRU	Short-Term Photovoltaic Power Forecasting	Increase detection accuracy	Reduction of performance of middle neurons by increasing repetitions
			Find the optimal value for network parameters	
			Error reduction	
			Improve the internal structure of the network	
[112]	CEEMDAN-SSA-GRU	Wind power prediction	Find the optimal value for network parameters	Problem of Overfitting with an increasing number of iterations
			Reduce data training time	
			Error reduction	
[113]	BSSA-CNN	Optimal brain tumour diagnosis based on deep learning	Improve the internal structure of the network	High iterations
			Reduce data training time	
[114]	IMEFD-ODCNN-SSA	Design fall detection systems for smart homecare	Error reduction	Reduce network speed in detecting samples
			Improve the internal structure of the network	
[115]	TA-SSALSTM	Electric vehicle load forecast	Improve accuracy in data training	Reduce network speed in detecting samples
			Settings for the number of layers and the number of nodes	
[116]	ESSA-CNN	Optimal brain tumour detection	Find the optimal value for network parameters	Reduction of performance of middle neurons by increasing repetitions
			Reduce data training time	
			Error reduction	
[117]	SWT-ISSA-LSTM	Water quality prediction	Error reduction	High execution time
			Improve the internal structure of the network	
[118]	LSTM-SSSA	Accurate ultra-short-term wind speed prediction	Increase detection accuracy	Reduce network speed in detecting samples
			Find the optimal value for network parameters	
			Error reduction	
			Improve the internal structure of the network	

Table 4 (continued)

Refs	Models	Objective	Advantages	Disadvantages
[119]	SSA-LSTM	Residential high-power load prediction	Find the optimal value for network parameters Reduce data training time Error reduction	High execution time
[120]	ISSA-DELM	Accurate damage degree prediction	Find the optimal value for network parameters Error reduction	High iterations

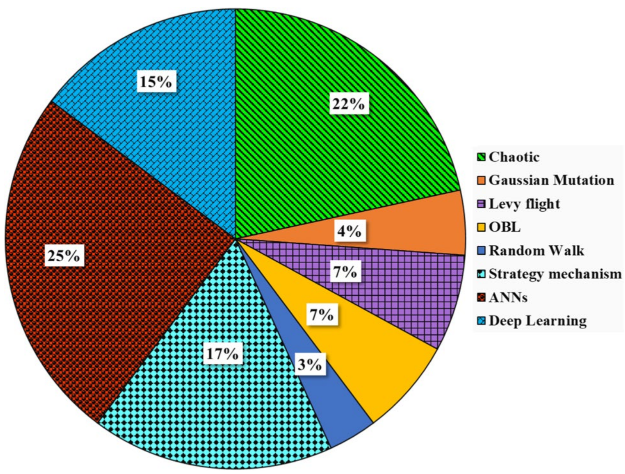

Fig. 11 Percentage diagram of improved SSA based on different methods

4 Discussion

Global exploration and local exploitation are critical components of the SSA algorithm's search process. An equal balance of exploration and exploitation must be struck to obtain a beneficial performance. In the early phases of the search process, search agents should always be deployed across the search space. They must, however, converge on the best candidate in the following stages of the search process. Agent During the global search phase, it changes its location by learning from the best international agent to expedite convergence and increase exploitation ability. On the other hand, the individual at the local stage renews his position by concurrently learning from present and random elements to promote population variety. Studies have shown that exchanging the global search section and the local search process uses a random distribution, sometimes losing the best agent in the search space.

Random search makes it possible to explore more significant parts of the search space than the local approximations created in gradient-based optimization. However, random search often leads to a large number of analyzes, which leads to minor improvements in modelling. Studies have shown that the search process is better with methods such as Chaotic and OBL.

The explorers update manufacturers' search positions to direct the next search. In each iteration, the solutions produced in previous generations can be used as a historical experience to guide explorers' investigations. The historical background of the manufacturers not only shows the explorers to the optimal points but also prevents the algorithm from being placed in the local optimal. Better use of manufacturers' experience leads to increased performance in convergence and optimization. In addition, since the Crawler Update Strategy may not apply to a variety of problems, Vanguard agents improve the effect of the current strategy, which is used as feedback information to set optimization strategies. Figure 13 shows the percentage of SSA methods based on four different areas.

Table 6 shows the general advantages and disadvantages of the SSA algorithm. The SSA algorithm also suffers from the problem of operational incompatibility in complex issues, and sometimes the accuracy of the solution is often unsatisfactory at the specified time required.

Various meta-heuristic algorithms have been successfully developed in recent decades to solve optimization problems. The SSA algorithm uses a variety of strategies to balance global exploration and local exploitation. In particular, the opposite learning strategy increases the search scope in the decision space. The gaussian approach is used to improve the performance of elite solutions. At the same time, random search is used to diversify people in the community. Studies have shown that improved SSA has a more vital ability to find better solutions than SSA. Hence, it is an effective evolutionary optimizer with a robust search capability and convergence rate for global optimization problems. The SSA algorithm has been improved by including hybrid factors to update positions to increase the utilization rate. In addition, SSA uses algorithms such as PSO and DE to increase the ability to exploit and explore the approach.

The main disadvantage of SSA is the fast or sometimes slow coverage of the problem search space, and a proper balance between the search steps is not established. This requires modified methods by creating an appropriate

Table 5 An overview of SSA in the field of optimization

Refs	Models	Application	Advantages	Disadvantages
[126]	SSA-DBN	Prediction	Strong global searchability	Non-optimal updates of individual
			Update the situation without getting lost	Slow convergence rate
[127]	Multipoint optimal minimum entropy deconvolution adjusted (MOMEDA-SSA)	Fault Diagnosis	Prevent useless search	Achieve a solution in the final iterations
			Better solution than other existing techniques	High iterations
[128]	SSA	Prediction	Update the situation without getting lost	Non-optimal updates of individual
			Good convergence	
			Short running time	
			Update the situation without getting lost	
[129]	SSA	Energy management system	Group and intelligent search towards the optimal solution	Achieve a solution in the final iterations
			Balance between exploration and exploitation	High iterations
			Better solution than other existing techniques	
[130]	SSA	Complex optimization	Strong global searchability	High execution time
			Update the situation without getting lost	Achieve a solution in the final iterations
[131]	SSA	Optimal scheduling	Prevent useless search	Non-optimal updates of individual
			Better solution than other existing techniques	
[132]	SSA	Object recognition	Balance between exploration and exploitation	Non-optimal updates of individual
			Update the situation without getting lost	Slow convergence rate
			Population diversity	
[133]	SSA	Complex optimization	Global optimization capability	Achieve a solution in the final iterations
			Balance between exploration and exploitation	High iterations
			High quality of solution and computation efficiency	
[134]	ISSACPM (control parameterization method (CPM))	Complex optimization	Group and smart search towards the optimal solution	Slow convergence rate
			Balance between exploration and exploitation	
			Better solution than other existing techniques	
[135]	IVMD-MSE-SSA-ELM	Prediction	Prevent useless search	Non-optimal updates of individual
			Better solution than other existing techniques	
[136]	SSA	Energy management system	Balance between exploration and exploitation	Non-optimal updates of individual
			Update the situation without getting lost	Slow convergence rate
			Population diversity	
[137]	SSA	Complex optimization	Global optimization capability	Achieve a solution in the final iterations

Table 5 (continued)

Refs	Models	Application	Advantages	Disadvantages
			Balance between exploration and exploitation	High iterations
			High quality of solution and computation efficiency	
[138]	SSA	Object recognition	Prevent useless search	Non-optimal updates of individual
			Better solution than other existing techniques	
[139]	ISSA	Energy management system	Faster convergence	Non-optimal updates of individual
			Global optimization capability	Slow convergence rate
[140]	SSA	Energy management system	Strong global searchability	High execution time
			Update the situation without getting lost	Achieve a solution in the final iterations
[141]	ISSA	Complex optimization	Prevent useless search	Non-optimal updates of individual
			Better solution than other existing techniques	
[142]	SSA	Clustering	Group and intelligent search towards the optimal solution	Achieve a solution in the final iterations
			Balance between exploration and exploitation	High iterations
			Better solution than other existing techniques	
[143]	ISSA	Object recognition	Group and intelligent search towards the optimal solution	Non-optimal updates of individual
			Balance between exploration and exploitation	
			Better solution than other existing techniques	
[144]	ISSA	Location optimization	Prevent useless search	Non-optimal updates of individual
			Better solution than other existing techniques	Slow convergence rate
[145]	LEACH-Wireless Gateway Rotation (WGR)-SSA	Clustering	Global optimization capability	High execution time
			Balance between exploration and exploitation	
			High quality of solution and computation efficiency	
[146]	SSA-based Resource Management (SSARM)	Optimal scheduling	Strong global searchability	Slow convergence rate
			Update the situation without getting lost	
[147]	ISSA	Complex optimization	Group and intelligent search towards the optimal solution	Achieve a solution in the final iterations
			Balance between exploration and exploitation	High iterations
			Better solution than other existing techniques	
[148]	Active Disturbance Rejection Control (LADRC-SSA)	Complex optimization	Prevent useless search	Slow convergence rate
			Better solution than other existing techniques	
[149]	SSA	Prediction	Faster convergence	Non-optimal updates of individual
			Global optimization capability	
[150]	SSA-PID	Complex optimization	Balance between exploration and exploitation	Achieve a solution in the final iterations

Table 5 (continued)

Refs	Models	Application	Advantages	Disadvantages
			Update the situation without getting lost	High iterations
			Population diversity	
[151]	SSA-XG-Boost	Prediction	Global optimization capability	Non-optimal updates of individual
			Balance between exploration and exploitation	
			High quality of solution and computation efficiency	
[152]	ISSA	Fault diagnosis	Balance between exploration and exploitation	Achieve a solution in the final iterations
			Update the situation without getting lost	High iterations
			Population diversity	
[153]	SSA	Optimal scheduling	Prevent useless search	Non-optimal updates of individual
			Better solution than other existing techniques	
[154]	SSA-SVM	Fault diagnosis	Update the situation without getting lost	High execution time
			Good convergence	
			Short running time	
			Update the situation without getting lost	
[155]	SSA	Fault diagnosis	Group and intelligent search towards the optimal solution	Achieve a solution in the final iterations
			Balance between exploration and exploitation	High iterations
			Better solution than other existing techniques	
[156]	SSA	Optimal scheduling	Prevent useless search	High execution time
			Better solution than other existing techniques	
[157]	SSA	Fault diagnosis	Balance between exploration and exploitation	Non-optimal updates of individual
			Update the situation without getting lost	
			Population diversity	
[158]	SSA	Optimal scheduling	Group and intelligent search towards the optimal solution	High execution time
			Balance between exploration and exploitation	
			Better solution than other existing techniques	
[159]	SSA	Clustering	Faster convergence	Non-optimal updates of individual
			Global optimization capability	
[160]	SSA	Complex optimization	Prevent useless search	Slow convergence rate
			Better solution than other existing techniques	
[161]	SSA-LA (SSA Based on Localization Algorithm)	Location optimization	Strong global searchability	Slow convergence rate
			Update the situation without getting lost	
[162]	SSA	Energy management system	Faster convergence	Non-optimal updates of individual
			Global optimization capability	

Table 5 (continued)

Refs	Models	Application	Advantages	Disadvantages
[163]	SSAE-SSA-SVM	Fault diagnosis	Update the situation without getting lost	High execution time
			Good convergence	
			Short running time	
			Update the situation without getting lost	
[164]	SSA	Complex optimization	Faster convergence	Non-optimal updates of individual
			Global optimization capability	
[165]	SSA	Threshold image segmentation	Prevent useless search	High execution time
			Better solution than other existing techniques	
[166]	SSA	Wireless sensor network coverage optimization	Nationwide coverage of the network	Non-optimal updates of individual
			Good convergence	

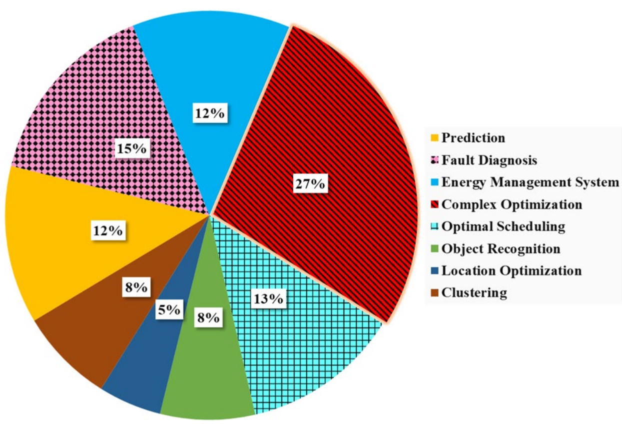

Fig. 12 Percentage of SSA application in different areas of optimization

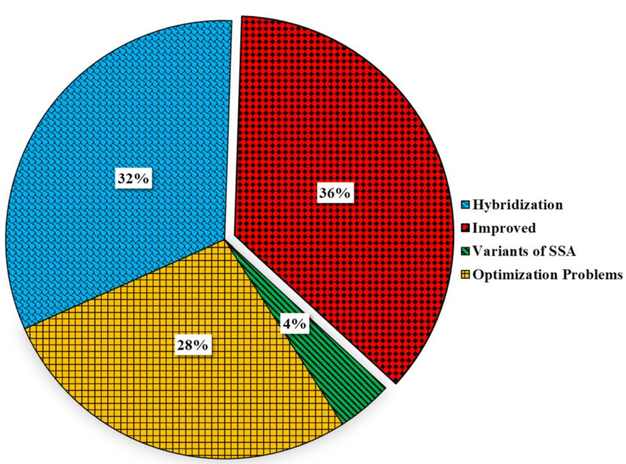

Fig. 13 Percentage of SSA methods based on four different areas

operator for the SSA equations. OBL is one of the suitable methods for the weaknesses of SSA. OBL-SSA aims to deal with the drawbacks such as local search area confinement, premature convergence, and balancing of the search process. There are two main reasons for the weakness of SSA in high-dimensional spaces. The first is the poor convergence rate. The ability to search the high-dimensional target space is insufficient. The second is diversity preservation because preserving diversity in a high-dimensional target space with a vast search space is challenging. Hence, effective maintenance of diversity in SSA is necessary to deal with multi-objective problems.

5 Conclusions and Future Works

Optimization problems have attracted the scientific community to various meta-heuristic algorithms. As the complexity of the problems increases, the need for new metaheuristic algorithms has become very acute. Optimization aims to find the best solution to a problem of all possible values to maximize or minimize output. Many researchers use practical meta-heuristic algorithms to find the optimal solution to obtain the global optimal. Because the search space grows exponentially in real optimization problems and the problem perspective becomes multidimensional, meta-heuristic algorithms are viable for generating optimal solutions. This paper examines the SSA algorithm from hybridization, Improved, Variants, and Optimization aspects. The SSA algorithm can run on most optimization problems due to its ease of implementation and rapid increase in the spread of agents in the problem space. Studies have shown that SSA uses the scout search concept, making it possible to track population characteristics in the optimization process.

Table 6 Advantages and disadvantages of the SSA algorithm

	Factors
Advantages	✓ A few parameters and simple implementation
	✓ Excellent performance for optimization problems
	✓ High-quality of solutions
	✓ Good convergence properties and low generation costs
	✓ The principle of balance between exploitation and exploration
	✓ Short computational time
	✓ Prevent the premature convergence
	✓ Getting quality results effectively in less computational time
	✓ Diversity of the population
	✓ The balance between local seek and global seek
	✓ SSA is highly competitive in finding optimal values
Disadvantages	✓ Incomplete exploitation in the solution of complex problems
	✓ Incoherence in the local and global seek
	✓ Increase of iterations with increasing the size of the issues

WOA, FA, SCA, and DE may suffer from premature convergence, stagnation, and sensitivity to the formulation. In addition, WOA and FA contain more internal parameters than SSA, which, if not adjusted correctly, can reduce the efficiency of the exploratory value in the optimization process. The results showed that the domain of Improved had the best performance. Chaotic, Gaussian Mutation, Levy flight, OBL, Random Walk, and Strategy mechanism methods have improved SSA. Orienting future work to complex and improved algorithms to solve the optimization problem will be complicated.

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