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Salp Swarm Optimization: A Comprehensive Review of Recent Advances, Variants, Applications, and Future Research Directions

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Abstract. One natural metaheuristic optimization technique is the Salp Swarm Algorithm (SSA), which takes its behavior from the swarming and feeding habits of salps in the ocean. With its straightforward structure, few parameters need, efficient exploration/exploitation balance, and adaptability to many optimization domains, SSA has garnered a lot of interest since its introduction. This paper provides a comprehensive review of SSA, highlighting its key advantages and applicability across a wide search space. The study includes its limitations, including sensitivity to problem types and reliance on the No Free Lunch theorem. This review analyzes different adaptations of SSA, such as binary versions, hybrid models, multi-objective extensions, and parameterless approaches, with the goal of enhancing performance and overcoming the limitations of the original algorithm. This paper analyzes the diverse applications of SSA in several domains, such as machine learning (including feature selection and neural network training), engineering optimization (covering scheduling, power systems, and renewable energy), image processing, localization, and additional practical areas. This study evaluates SSA through an analysis of its strengths, weaknesses, and potential areas for improvement. The study demonstrates that SSA is a promising and versatile optimization technique; however, it requires ongoing refinement to effectively address complex, dynamic, and multi-objective problems in future research.

2020 Mathematics Subject Classifications: 90C59, 68T20, 68W50

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1. Introduction

Some optimization problems have recently found solutions with the help of the salp swarm algorithm (SSA) [1]. It is a mathematical model for optimum solution discovery

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that mimics the swarming movement of sea salps. Salp swarm equations alter a previously created set of solutions by moving them either within or outside the solution space, producing new solutions. This process is called SSA. SSA's strong convergence acceleration makes it an excellent fit for a wide variety of optimization problems across many domains.

Numerous domains have made use of meta-heuristic approaches, including data mining, engineering, energy, networks, economics, and medicine. Typically, it's used to identify a number of best decisions or values in order to come up with potential solutions to problems. In most cases, algorithms are often tailored to solve optimization issues by taking into account the minimization or maximizing of a probable decision. Finding the best possible value among several options is the fundamental goal of decision making. Optimization procedures ultimately lead to picking the greatest value or conclusion out of all the available alternatives. When we talk about the best answer to an optimization issue, what we really mean is that it's a satisfactory solution. It is possible to estimate a satisfying solution as the better attainable solution across a sequence of procedures [2].

All sorts of problems, including those in the business world, the mathematical realm, the real world, and others, fall into the category of hard optimization problems known as NP-hard in nature [3]. Despite this, researchers in the optimization fields have remained active and produced encouraging results in recent years. Finding the best judgments, or solutions to problems, is typically the primary goal of optimization approaches, which try to optimize an objective function or fitness function.

Various optimization methods that draw inspiration from nature have been put out there to solve different kinds of optimization issues in the last several decades. These algorithms' strong and comprehensive search capabilities, as well as their techniques for effectively handling high-dimensional issues, make them marketable for problem solving. Typically, optimization algorithms are created by analyzing real-life occurrences, such as species or creatures attempting to improve their living conditions.

The primary objective of this paper is to undertake an exhaustive examination of all SSA viewpoints in various optimization issues across several domains, including machine learning, engineering design, wireless networking, image processing, and power energy, among others. Furthermore, the paper emphasizes and draws attention to the SSA's resilience as well as the changes proposed in the literature to overcome the algorithm's shortcomings. Figure 1 shows the number of publications per year, whereas Figure 2 shows the articles linked to SSA by subject area [4].

2. Salp Swarm Algorithm

This section presents the Salp Swarm Algorithm (SSA), outlining its biological inspiration and fundamental components. Emphasis is placed on the algorithm's modeling of convergence, exploitation, and exploration, which are essential in metaheuristic optimization.

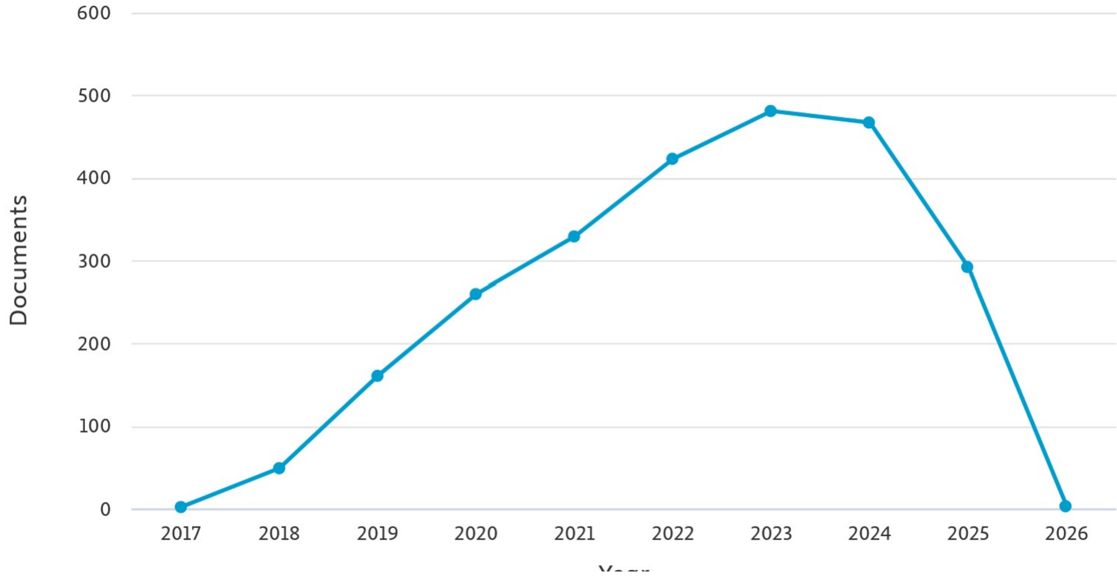

Figure 1: Number of publications of SSA per year.

2.1. Inspiration for Salp Swarm Algorithm

Marine ecosystems exhibit significant diversity, encompassing over 1.2 million species of marine organisms documented in centralized databases [5]. Many of these organisms, despite their diversity, exhibit comparable behavioral traits, including communication strategies, locomotion mechanisms, and foraging behaviors. Salps, classified under the family Salpidae, are marine organisms that have influenced the creation of optimization algorithms.

Salps are pelagic tunicates distinguished by their transparent, barrel-shaped morphology. Their morphology is akin to that of jellyfish, especially regarding gelatinous tissues and modes of locomotion. Movement is accomplished via rhythmic body contractions that expel water through their semi-transparent structures, enabling efficient propulsion in a jet-like manner.

Salps exhibit a significant behavioral characteristic in their propensity to aggregate into groups or swarms, frequently organizing into elongated structures referred to as salp chains. This collective arrangement enhances survival while improving mobility and foraging efficiency. Coordinated swarming's exact biological foundation is still a mystery, but scientists think it might be an evolutionary mechanism to improve movement and feeding efficiency through cooperative behaviors and synchronized movements. Salps' swarming behavior is similar to that of other marine species that demonstrate collective behavior. Similar to how birds flock together to ward off predators, schools of fish do the same [6]. Similarly, as seen in Figures 3.a and 3b, salps can create chains that exhibit coordinated, flexible, and adaptable group dynamics. The Salp Swarm Algorithm follows the underlying principles of collective movement, adaptation, and environmental reaction observed in nature.

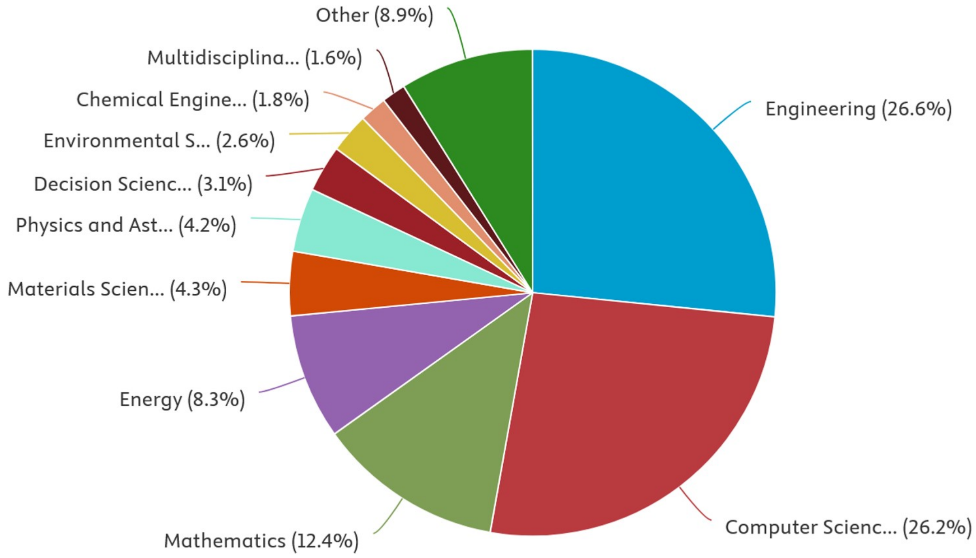

Figure 2: Publications by subject area.

2.2. The Procedure of Basic Salp Swarm Algorithm

In 2017, Mirjalili proposed the Salp Swarm Algorithm (SSA), a meta-heuristic method for optimization [1]. The algorithm's design is based on the swarming nature of ocean salps, which organize into chains to find food more effectively. In the SSA, the salp population is categorized into two main roles: leaders and followers. The leader occupies the foremost position in the chain, directing the swarm's movement, while the followers modify their positions in response to the preceding salp's actions, resulting in a dynamic and adaptive formation.

Figure 4 illustrates the primary operational steps of the SSA, presenting the overall flowchart of the algorithm [7]. In this framework, the location of each salp is illustrated in an m-dimensional search space, where n is the number of optimization problem variables. In a two-dimensional matrix X, where each row represents a salp and each column a problem variable, the population's locations are organized.

The swarm's primary objective is to find the best possible answer, or food source F, in the search space. To guide the swarm to its destination, the leader plays a crucial role. The swarm can efficiently search the solution space and avoid local optima because the leader's position is updated repeatedly according to a mathematical model that balances exploration and exploitation. The leader's update typically includes an element that encourages diversity in the search process and an element that leads the swarm toward favorable places within the issue space.

The followers then reposition themselves according to where the salps in the chain before them are located. This update can be articulated through principles of Newtonian mechanics, including the equations of velocity and position, which support the integrity of the chain's structure while enabling adaptive movement toward the food source. The salp

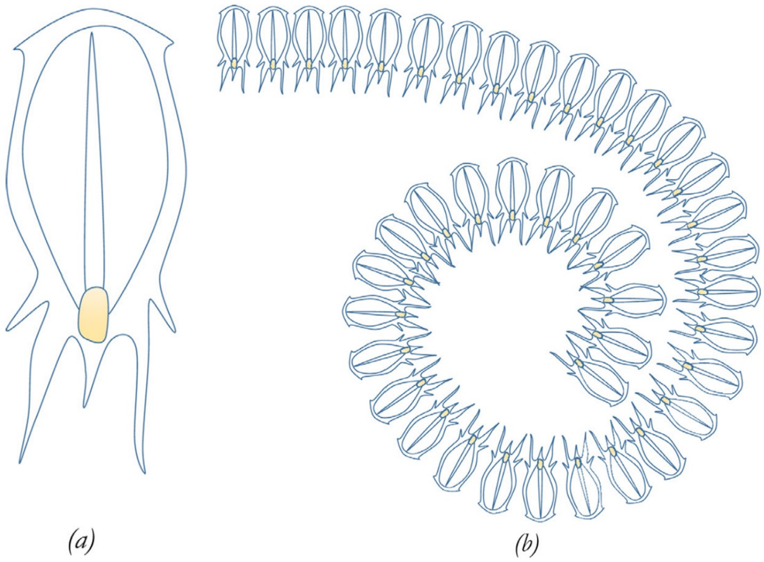

Figure 3: a) Individual salp, b) swarm of salps (salp chain).

swarm converges to the optimal solution through iterative updates between leaders and followers, thereby addressing complex multi-dimensional optimization problems effectively.

$$x_i^j = \begin{cases} F_i + k_1\big((ub_i - lb_i)k_2 + lb_i\big), & \text{if } k_3 \geq 0.5, \\ F_i - k_1\big((ub_i - lb_i)k_2 + lb_i\big), & \text{if } k_3 < 0.5. \end{cases} \tag{1}$$

where $j = 1$, $x_i^j\, \forall\, i = 1, 2, \ldots, n$ refers to the position of the first salp (leader) in the i^{th} dimension, lb_i is the lower limit at i^{th} dimension, ub_i is the upper limit at i^{th} dimension, F_i is the position of the food source in i^{th} dimension and k_2 and k_3 are values in range $[0, 1]$, which are generated randomly. In SSA, coefficient k_1 is the most important factor, as it decreases as the number of iterations increases, resulting in high exploration in the early phases of the optimization and high exploitation in the later stages, resulting in a balanced optimization. It is defined as follows:

$$k_1 = 2\, e^{-\left(\frac{t}{T_{\max}}\right)}, \tag{2}$$

where t is the present iteration, T is the maximum number of iterations and k_3 is in charge of determining whether the following position should be toward $-\infty$ or $+\infty$, as well as the step size. Newton's law of motion is used to adjust the location of the followers, as seen in the equation below:

$$x_i^j = 0.5at^2 + v_0 t \tag{3}$$

where $j \geq 2$, x_i^j $\forall i = 1, 2, \ldots, m$ indicates the position of the j^{th} follower salp in the i^{th} dimension, v_0 is the start speed;

$$a = \frac{v_{\text{final}}}{t}, \quad v_{\text{final}} = \frac{x - x_0}{t},$$

v_{final} is the final speed motion of the salp, and t is time. The time in the optimization process is the current iteration; the iteration discrepancy is equivalent to one. Assuming that $v_0 = 0$, we can define this equation as follows:

$$x_i^{(j,t+1)} = 0.5\left(x_i^{(j-1,t+1)} + x_i^{(j,t)}\right) \quad (4)$$

The salp chains can be modeled using Equations (1) and (4). Figure 5 shows the pseudo code of SSA.

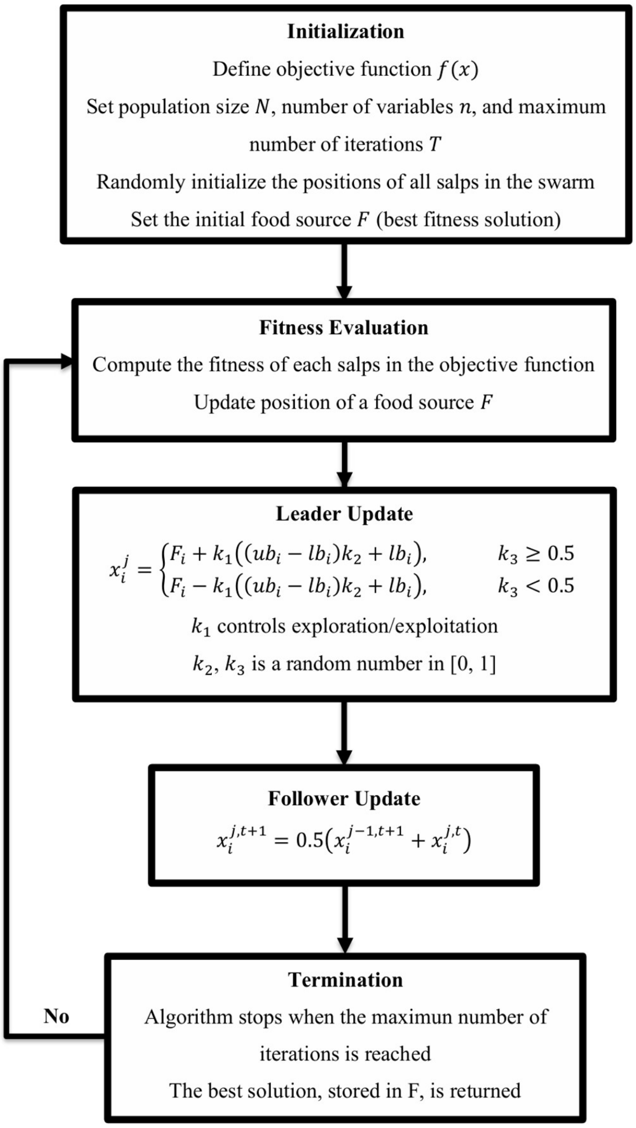

Figure 4: Flowchart of the salp swarm algorithm .

Initialize lb, ub, T
Initialize a population $x_i \forall i = 1,2, \dots, n$ initialized randomly.
While $t \leq T$
  Calculate the fitness of each search agent (salp)
  Determine the best search agent F
  Update k_1 using Eq. (2)
    For each salp (x_i)
      If ($i == 1$) then
        Genertae k_2 , k_3 randomly in rang [0,1]
        Update the position of the leader salp salp using Eq. (1)
      Else
        Update the position of follower salp using Eq. (4)
      End
    End
  $\boldsymbol{t = t + 1}$
End
Return F.

Figure 5: Pseudo code of the salp swarm algorithm (SSA).

2.3. Exploration and Exploitation in Salp Swarm Algorithm

Certain pairs of terms, including exploration and exploitation, global search and local search, as well as diversification and intensification, are prevalent in optimization algorithms, with all algorithms incorporating at least one of these pairs [8, 9]. The exploration seeks to identify promising regions within the search landscape, avoid stagnation in local optima, and enhance the likelihood of finding the global optimum. Exploitation seeks to enhance existing solutions by exploring the vicinity of each solution. In SSA, the parameter responsible for balancing exploration and exploitation is referred to as coefficient k_1, which is determined using equation (2). Nevertheless, SSA experiences an exploitation issue that results in a slow convergence rate [10].

2.4. Advantages and Disadvantages of Salp Swarm Algorithm

Like other optimization techniques, SSA presents several advantages and a few disadvantages. Despite the lack of conclusive evidence for this optimizer, the final features are summarized in this review to validate the competitiveness of SSA compared to other optimization algorithms concerning the stimulated convergence rate.

Advantages of salp swarm algorithm

- Possibility of hybridization: May be efficiently mixed with other algorithms to get frequently superior results.
- The optimization process is accelerated toward high-quality solutions with fast convergence.
- Skillful global search: Able to traverse large search areas while evading local optima.
- Flexibility: Works well with both continuous and discrete optimization problems as well as those with constraints.
- Investigating the neighborhood: Demonstrates excellent skills in doing local searches to enhance solutions.
- Robustness and adaptability: Scalably handles dynamic and complicated optimization challenges.
- Competence in handling a high dimensional problem: adept at handling several choice factors.
- Possibility of finding global optima: Higher likelihood of finding global optima than other heuristics.
- Very robust to beginning solutions: maintains respectable performance over a range of initial values.
- Compared to other metaheuristics, it is simple, meaning it is easy to grasp and use.
- Fair computing cost: calls for a modest amount of time and less computing resources to execute.
- Practical application is made easier by the fact that just a small number of parameters require tweaking.

Disadvantages of salp swarm algorithm

- Initial scope was narrow: it was suggested for use in engineering design challenges; therefore, it might not be directly applicable to other fields.
- The problem of premature convergence arises when the system converges to less-than-ideal solutions too soon.
- There is no formal evidence that guarantees convergence to the global optimum, which means there is no theoretical convergence guarantee.
- Predicting the algorithm's performance is difficult because of its dynamic probability distribution, which allows its behavior to fluctuate across generations.

3. Variants of Salp Swarm Algorithm

The SSA proposed in 2017 is a recent optimization algorithm in comparison with the Krill herd algorithm, firefly algorithm, harmony search algorithm, particle swarm optimization algorithm, and ant colony algorithm introduced in 2012, 2008, 2001, 1995, and 1992, respectively. But, the SSA has been renewed for various modifications developed by researchers to face and solve wide range optimization problems. Most of these modifications will be extensively but not exhaustively illustrated. The Main Variants of SSA are in the following:

(i) The Binary Salp Swarm Algorithm (BSSA) [11]: BSSA Designed for optimization problems with discrete or binary variables; apply it to feature selection and combinatorial optimization.

(ii) Improved Salp Swarm Algorithm (ISSA) [12]: To increase exploration and convergence, the ISSA introduces Gaussian perturbation, extremely disruptive polynomial mutation, and Laplace crossover as enhancements.

(iii) The Multi-objective Salp Swarm Algorithm (MSSA) [13]: SSA was modified to handle optimization issues with multiple objectives, ensuring that trade-offs are balanced between competing goals.

(iv) The Chaotic Salp Swarm Algorithm (CSSA) [14]: To increase variety and prevent local optima, it uses chaotic maps for both initialization and updates.

(v) Quantum-inspired Salp Swarm Algorithm (QSSA) [15]: QSSA enhances global search capabilities by integrating concepts of quantum computing.

(vi) Adaptive Salp Swarm Algorithm (ASSA) [16]: ASSA iteratively modifies control parameters to provide better resilience and avoid early convergence.

3.1. Binary Salp Swarm Algorithm

A binary search space is recognized as a hypercube. The solutions of a binary optimization algorithm force to only transfer to nearer and more distant corners of the hypercube by flipping several numbers of bits. Consequently, for producing a binary version of SSA, some essential concepts such as position updating rule should be changed. In the basic SSA, solutions could run around the current search space due to having vectors of positions with a continuous real region. Hence, the notion of position updating can be easily performed for solutions adding velocities to positions using binary transfer equation. However, the purpose of updating positions is changed in a binary space. In binary space, because of initializing with only two numbers (“0” and “1”), the position updating procedure cannot be done using the main equation of the positions updating in the basic SSA. Accordingly, there is a method can be used like sigma function to change solutions’ positions from “0” to “1” or vice versa [17].

In [18], this work proposed a new version of SSA (binary) called BSSA based on modifying arctangent transformation to transform the continuous space into binary space. The proposed work has two characteristics concerning the transfer function and mobility. The authors worked to improve the exploration and exploitation capabilities of the SSA. The suggested approach tackles the optimization problems by comparing BSSA with other four variants of transfer functions; in addition, a comparative study with a different binary algorithm and twenty-four benchmark issues is conducted. The results show a superior performance of the modified BSSA variant compared with other variants.

In [19], the authors proposed two wrapper feature selection methods that used the SSA as a binary search strategy. In the first method, eight command functions are used to transform the continuous version of SSA to the binary version. In the second method, the crossover procedures are employed to replace the average operator to improve the investigation behavior of the algorithm.

3.2. Modifications of Salp Swarm Algorithm

Meta-heuristic optimization algorithms have been utilized widely to address different problems. However, for complex problems, the largest part of the optimization techniques still yields some problems like trapped in local search and be unsuccessful to achieve the near-global solution. This is the purpose of the week of diversification (global search) part in the used technique. Several diversification search strategies are employed by modifying the basic version of SSA to enhance its effectiveness and to assist in preventing the drawbacks. These optimization methods are modifying, hybridization and elitism: the existence of elite as a dominating element in a system [20].

An enhanced salp swarm algorithm is proposed in [21] based on the simplex method named as simplex method based salp swarm algorithm (SMSSA). This simplex method is a random variant strategy, which extends a variety of populations and improves the local search ability of the algorithm. This method helps to attain a fitter balancing between the exploration and exploitation search ability of the SSA; in addition, it makes SSA stronger and faster. The proposed method is analyzed and compared with other meta-inspired optimization methods using 4 benchmark functions. SMSSA algorithm is also utilized to one real-life constrained engineering problem. The results confirmed that the proposed method performed significantly better than the other comparative meta-inspired optimization algorithms.

A new proposal in [22] called improved salp swarm algorithm (ISSA) based on inertia weight as a control parameter. The proposed algorithm (ISSA) is merged with the K-nearest neighbor approach for solving the feature selection problem. Twenty-three UCI benchmark datasets are employed to assess the performance of the ISSA. The ISSA is analyzed and confirmed with the basic SSA and other four optimization methods. The results showed that the introduced approach provided better outcomes than the other comparative algorithms in terms of accuracy value and reduction ratio.

A new proposed method utilized the pure SSA in [23] for solving dimension, reducing and removing noise from a huge dataset; this can be done through picking the best subset attributes on the source of particular criterion and improving the fitness of classification efficiency. Other work hybridized SSA with simulated annealing (SA) technique called SSA-SA. In this proposal, SSA is applied as an inner function to develop the exploitation search capability that is utilized to take a defective quality solution than the current solution. The effectiveness of the proposed approach is evaluated on 16 datasets including two groups of high-dimensional data from the UCI repository and compared with the pure (SSA) and other methods. The results showed that the proposed method gave better results. SSA-SA gave a better performance as a multi-objective where produced two different objects, maximal accuracy of classification with a minimal size of features on all datasets.

3.3. Hybridizations of Salp Swarm Algorithm

A hybrid algorithm is proposed in [24]; it combines the SSA with sine–cosine algorithm (called HSSASCA) to improve the convergence effectiveness with the global search and local search being better to other comparative test algorithms. This approach uses the space equations of sine–cosine to modernize the position of SSA in the search space; hence, the feasible optimal solutions are accomplished based on the sine–cosine algorithm. Within this procedure, each salp utilizes the information of sine–cosine algorithm to enhance their global and local search capability. To enhance the basic strategy, to avert premature convergence, and to better control the search toward the feasible search space, a combined version is incorporated in SSA. The proposed algorithm is proved on twenty-two standard functions and three applications, the 3-bar truss, cantilever beam design problems, and tension/compression spring. The results showed that the proposed algorithm (HSSASCA) performed better regarding the runtime in opposition to the other algorithms.

The efficient load forecasting for power system outlining and operational decisions are presented in [25]. Forecasting accuracy through impacts the safety and economy of the power system are studied. Obtaining the requested point forecasting precision has been perceived as a challenge because of the natural complexity and change of the power load. To overcome the challenges of critical point forecasting, the period prediction is fitted to allow extended problem and provide more information for efficient operation judgments. A hybrid system is proposed in [25] for short-term load forecasting (STLF) by combining a multi objective optimization algorithm, data preprocessing steps, and an interval prediction method. In this proposal, the training method is achieved by maximizing the coverage chance and by minimizing the forecasting period width at the same time. Furthermore, a hybrid lower upper bound evaluation (LUBE) based on multiple objectives is proposed. Furthermore, a hybrid model including data preprocessing, Elman NN, multiple objectives, and SSA. In this way, such a hybrid design can reduce the influence of noise in a dataset and the parameter optimization rule is more rich and effective in Elman NN. To confirm the effectiveness of the proposed approach, half-hourly load data are produced as sample problems and two experiments are conducted in four groups. The simulation results revealed the superiority of the proposed system, and the impacts of the sub-modules were measured by examining the results with those of benchmarks.

A hybrid optimization method is proposed in [24] for solving the feature selection problem. This proposed method forms a hybrid of the SSA and the PSO algorithm. The hybridization process is performed between the mentioned two algorithms (SSA and PSO) to design a new version, namely SSAPSO, in which the ability of the exploration and the exploitation search strategies is developed. The proposed approach is examined in two experimental groups. The first group compared the proposed approach using several benchmark functions of similar methods. In the second group, the proposed hybrid approach is utilized to achieve the optimal collection of features using different datasets, where the irrelevant features are excluded from the original dataset while maintaining the performance value or increase. The results confirmed the improvement in the SSAPSO regarding the performance and the accuracy without affecting the computational effort.

3.4. Salp Swarm Algorithm and Multi-objective Optimization

Multi-objective optimization is a branch of multiple-criteria decision making that deals with mathematical optimization problems that require more than one objective function to be determined at the same time. Multi-objective optimization has been used in many fields of science, such as engineering, cloud computing, and economics, where optimal judgments are required to be used in the presence of trade-offs among two or more conflicting objective functions. Minimizing the number of selected features while maximizing the performance of the underlying feature selection algorithm for finding the optimal features. In real-life problems, there can be more than two objectives [26].

The SSA is applied along with several recent optimization techniques in [27]. The proposed algorithms run over four different objective functions (e.g., mean square error, integral of squared error, integral of absolute, and time absolute errors). The study aims (1) to examine the most suitable optimization methods in terms of parameter extraction of three fractional-order chaotic systems and (2) to investigate the most appropriate objective purpose that encourages the algorithms to obtain more precise and consistent decisions. Experiment-based approach is carried out for the purpose of determining a new fitness combination (algorithm and objective function) that offer more accurate result in such complex systems. To achieve this, the experimental results of the algorithms and objective functions are tabled and compared. According to a comparative analysis, the salp swarm algorithm is the second-best algorithm for selecting the parameters of the three chaotic modes in the presence of judgment noise using couple objective functions. In addition, the comparison shows that SSA has the lowest values of relative error curves above the number of samples compared with the other comparative methods.

A new approach is introduced in [28] to decrease the dynamic equivalence order of surface electrical systems. This approach started by performing a revolution in the internal operation, followed by designating the system acknowledgments (e.g., energies, electrical controls, and angular velocities), and lastly estimating the parameters of the ES based on reported signals. However, to select the best parameters of the equivalent generator that preserves power circles at tie lines and electrical control of associated dynamos in the maintained system, the multi-objective SSA is utilized. The experiment was conducted to validate the nature of the proposed approach to control the dynamics of the original scheme. The results showed that the multi-objective SSA has a precision ability to show the aim of the new system.

A composite forecasting framework is developed for the reported power forecast based on the reported power features. The proposed framework is based on a novel multi objective method that aims to determine the upper and lower limit lines of the future reported speed concurrently [29]. The multi-objective SSA is utilized to find the balancing in between tuning the key parameters of the machine learning approach to invent the forecasting engine. The forecasting effectiveness of the proposed framework is validated using a case study approach with three real datasets. The analysis result of the case study revealed that the integrated of multi-objective SSA with the proposed method achieved better wind speed interval prediction than the single-objective algorithms.

3.5. The Chaotic Salp Swarm Algorithm:

The Chaotic Salp Swarm Algorithm (CSSA) is an enhanced version of the regular Salp Swarm Algorithm (SSA) that incorporates chaotic maps to boost its exploration capabilities and convergence efficiency. In CSSA, chaotic sequences—generated by logistic, tent, sine, or Chebyshev maps—are utilised in both the population initialisation and position-updating phases to substitute or enhance the random coefficients employed in the original SSA [30].

These chaotic maps provide deterministic but pseudo-random behaviour, exhibiting significant sensitivity to initial conditions, hence providing enhanced diversity and uniform coverage of the search space. The initialisation step prevents the clustering of salps in confined areas, whereas the update phase ensures dynamic, non-repetitive movements that enhance search diversity. This erratic behaviour facilitates the equilibrium between exploration and exploitation during the Optimization process.

Utilising chaos-driven control parameters, CSSA alleviates premature convergence and diminishes the probability of stagnation in local optima. The enhanced population variety and refined parameter tuning result in expedited convergence to the global optimum and increased solution accuracy. Numerous studies indicate that CSSA surpasses traditional SSA and other swarm-based algorithms in addressing difficult and multimodal Optimization challenges, such as engineering design, feature selection, image segmentation, and parameter estimation tasks [31].

3.6. Quantum-Inspired Salp Swarm Algorithm:

The Quantum-Inspired Salp Swarm Algorithm (QSSA) is a sophisticated enhancement of the traditional Salp Swarm Algorithm (SSA) that incorporates essential concepts from quantum computing to augment its exploration and convergence capabilities. In QSSA, the location and motion of salps are shown by quantum bits (qubits) and probability amplitudes instead of set deterministic placements inside the search space. This model permits each salp to remain in a superposition state, facilitating the algorithm's exploration of numerous potential solutions concurrently [32].

The quantum behaviour adds a probabilistic search method that enhances diversity and mitigates premature convergence. Furthermore, the quantum-based updating mechanisms offer nonlinear regulation of the equilibrium between exploration and exploitation, resulting in a more effective global search and expedited convergence to the optimal solution. The approach utilises a quantum rotation gate or quantum delta potential well to adaptively direct the evolution of solutions during the search phase.

QSSA demonstrates significant robustness in addressing high-dimensional, nonlinear, and multimodal Optimization challenges by integrating the swarm intelligence of SSA with quantum-inspired operators. Empirical research indicates that QSSA surpasses conventional SSA and several other metaheuristics for accuracy, convergence rate, and stability, especially in engineering design, feature selection, and machine-learning parameter Optimization tasks [33].

3.7. Adaptive Salp Swarm Algorithm (ASSA):

The Adaptive Salp Swarm Algorithm (ASSA) is an improved version of the standard Salp Swarm Algorithm (SSA) aimed at enhancing the algorithm's adaptability and convergence performance in intricate Optimization challenges. In ASSA, the principal control parameters—namely, step size, inertia weight, and leader-following coefficient—are not static but are constantly modified during the Optimization process in response to feedback from the current population's performance [34].

This adaptive approach allows the program to more efficiently balance exploration and exploitation. In the initial phases, settings are adjusted to promote extensive exploration, enabling the salps to traverse the solution space broadly and prevent premature convergence to local optima. During Optimization, control parameters are incrementally modified to concentrate on local exploitation in promising areas, hence improving convergence precision and stability.

The iterative adjustment of parameters enhances resistance to diverse problem landscapes and dimensionalities, rendering ASSA effective in addressing nonlinear, multimodal, and high-dimensional Optimization challenges. Research indicates that ASSA routinely surpasses traditional SSA and numerous other swarm intelligence algorithms regarding convergence time, solution quality, and dependability across various engineering and computational Optimization challenges [35].

4. Salp Swarm Algorithm and Parameters

An evaluation model is implemented in [36] to estimate the parameter of photovoltaic cells system. They employed the SSA in order to extract the parameters of the electrical similar path of the photovoltaic cell double-diode pattern. The experimental approach is used to measure the effectiveness and to examine the effectiveness of SSA. For example, to measure the effectiveness of SSA the experimental results are analyzed with other competitive methods. The comparative results showed that SSA is offered the best result over these algorithms in terms of convergence speed and nature of photovoltaic cell parameter extraction. To test the performance of SSA, several evaluation measures are utilized. However, the results indicated the better efficiency of the SSA-based optimizer as opposed to all other published methods.

The SSA is employed in the field of gene selection and cancer classification [37]. SSA is used to enhance the effectiveness of kernel extreme learning machine KELM algorithm. This is done by addressing the problem of selecting the optimal kernel and control parameters of KELM from huge search space efficiently. In addition, it used to choose the optimal value of the gene subset. The proposed model is confirmed in terms of ranking accuracy and efficiency. To validate the classification precision, several evaluation measures are utilized such F-measure. The experimental results of the introduced model are analyzed with pure SSA, PSO, and GA algorithms after they incorporated in KELM. However, the comparison result indicates that the proposed model yields into more accurate classification result than other models.

SSA applied in [38] to solve the electrical engineering problem. In the proposal, a model-based SSA is performed to determine the best value of foreign parameters of polymer exchange membrane fuel cells. Enhancing the polymer transfer membrane fuel cell modeling implies a complex model due to the level of nonlinearity and multiple variables. Therefore, the SSA is applied over other conventional approaches due to its efficiency to deal with such a complex problem. To prove the effectiveness of the proposed model, two test instances of typical commercial PEMFC stacks are used. In the first test case, the simulation results of the SSA in comparison with grasshopper optimizer and genetic algorithms along with the corresponding squared deviations reveal that SSA produced the minimum squared deviations over other algorithms which indicate very fast convergence characteristic, while in the second test case, the simulation results of the SSA in comparison with gray wolf optimizer and dynamic electrochemical produced the minimum squared deviations which indicate very fast convergence characteristic.

5. Applications of Salp Swarm Algorithm

Many applications of SSA have been reported from various fields. For instance, SSA has been employed to solve benchmark optimization and real-world problems. More details of the SSA applications are illustrated below. A brief summary of the main applications of SSA is shown in Table 1, while Figure 6 is a graphical presentation of details in Table 2. The main applications of SSA are in the following:

(i) **Optimization of Engineering Design** [1]: Resolving intricate engineering design challenges with several restrictions, such as structural optimization, mechanical design, and truss structure optimization.

(ii) **Power and Energy Systems** [39]: Improving power generation, distribution, and energy efficiency, including economic load dispatch, solar power plant optimization, and microgrid energy management.

Table 1: A brief summary of the main applications of SSA.

Application Area	Problem Type / Task	Example	SSA Variant Used
Engineering Design Optimization	Continuous, constrained optimization	Structural design, truss optimization, mechanical component design	Standard SSA / Improved SSA (ISSA)
Power and Energy Systems	Energy management, load dispatch	Economic load dispatch, PV system optimization, microgrid scheduling	ISSA / Adaptive SSA (ASSA)
Image and Signal Processing	Feature selection, clustering, denoising	Image segmentation, medical image classification, signal denoising	Chaotic SSA (CSSA) / ISSA
Machine Learning & Data Mining	Feature selection, hyperparameter optimization	Neural network optimization, high-dimensional dataset feature selection	Binary SSA (BSSA) / ISSA
Wireless & Communication Networks	Network optimization, routing	Wireless sensor network routing, IoT resource allocation	ISSA / Adaptive SSA (ASSA)
Environmental & Water Resources	Resource allocation, reservoir operation	Reservoir management, water allocation, pollution control	Standard SSA / Chaotic SSA (CSSA)
Combinatorial & Scheduling	Discrete optimization, scheduling	Job-shop scheduling, task assignment, logistics optimization	Binary SSA (BSSA) / Hybrid SSA

(iii) **Image and Signal Processing** [40]: Improving feature selection, grouping, and signal denoising, such as image segmentation, medical image classification, and signal denoising in communication systems.

(iv) **Machine Learning and Data Mining** [41]: Feature selection, parameter optimization, and classification challenges such as refining neural network weights, choosing features for classification, and adjusting hyperparameters.

(v) **Wireless and Communication Networks** [42]: Enhancing network characteristics and routing methods such as routing in wireless sensor networks, resource allocation in IoT, and optimization of mobile edge computing.

(vi) **Management of Environmental and Water Resources** [43]: Optimization in ecological, hydrological, and environmental systems, including reservoir operations, water resource distribution, and environmental pollutant control.

(vii) **Combinatorial and Scheduling Challenges** [44]: Resolving discrete, combinatorial, and schedule optimization issues, including job-shop scheduling, task allocation, and logistics optimization.

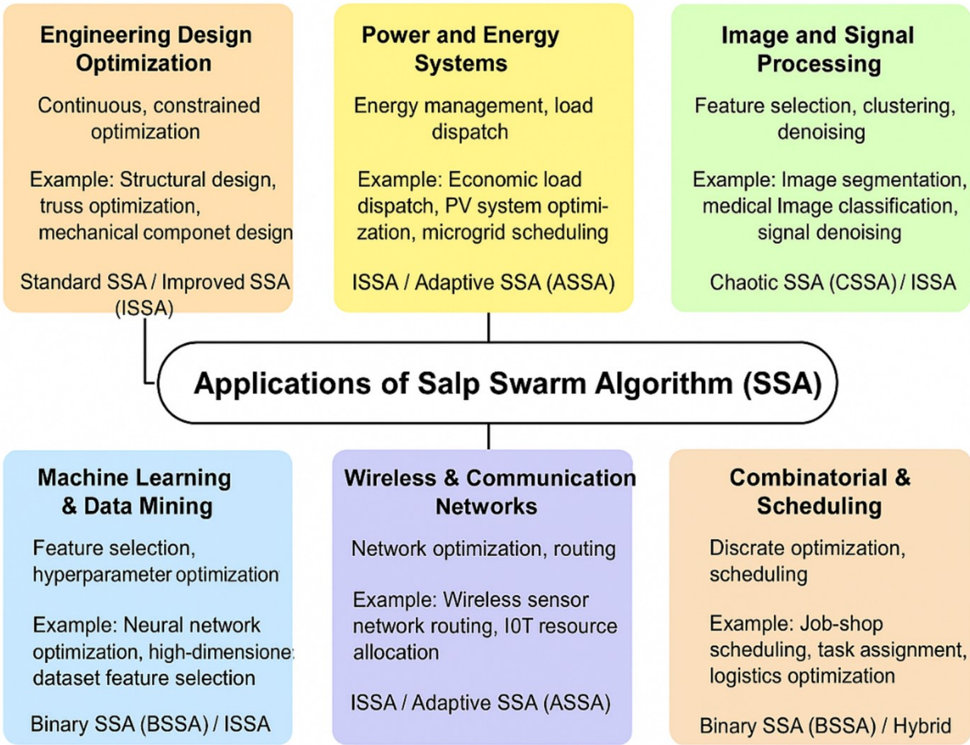

Figure 6: Graphical presentation of Table 1.

5.1. Machine Larning Applications

5.1.1. Feature Selection

Biologically inspired meta-heuristic strategies have been widely employed to tackle various challenges related to optimization, including feature selection, which is a crucial preprocessing step that affects the efficacy of data mining techniques [45]. Identifying an optimal subset of features from a comprehensive dataset presents a complex challenge, particularly in the context of large datasets.

In [46], the authors presented a novel leadership composition that incorporates a binary SSA and controls that are updated asynchronously. The objective of this work is to produce optimal leadership structures; multiple comprehensive simulations are conducted to identify the most effective leaders within the search space of the artificial salp series. The behavior of a termite colony motivated the division into four classes, leading to the segmentation of the salp series into multiple sub-chains. Consequently, each sub-series of salps can adjust their locations by employing a specific strategy. The authors employed three distinct updating strategies. Twenty prominent datasets from the UC Irvine machine learning repository are analyzed and validated by SSA. The experimental results and analyses confirm that utilizing a portion of the salps as leaders in the series can effectively improve the execution of SSA regarding accurate measurement. The single parameter of SSA is dynamically adjusted to enhance its efficiency in exploring the search area for different datasets in feature selection.

Ibrahim employed SSA to address the feature selection issue, referred to as SSA-FS [47]. The performance of SSA-FS was evaluated using the PSO algorithm and DE based on two primary criteria: accuracy and runtime. Real datasets of bladder and colon cancers were collected from Iraqi hospitals, alongside synthetic datasets for the validation of SSA-FS results. Compared to other established algorithms in the literature for both real and synthetic datasets, SSA-FS demonstrated the highest accuracy values with reduced runtime.

5.1.2. Training Neural Networks

This section emphasizes the use of SSA in conjunction with an artificial neural network (ANN), which is a type of analytical sample that relies on computer intelligence [45]. Artificial neural networks (ANNs) are able to mimic biological neural networks; in other words, they are able to reflect the connection that exists between a collection of biological neurons. An artificial neural network (ANN) is a collection of artificial neurons that are linked to one another and use artificial intelligence (AI) computation techniques in a similar manner. Artificial neural networks (ANNs) are effectively employed to carry out classification, pattern recognition, and a variety of other machine learning approaches.

Artificial neural networks (ANN) have a variety of methods of operation, but pattern categorization is the most commonly used and effective approach. There are a few drawbacks to using conventional training methods. For example, becoming stuck in local minima and the sluggish rate of convergence As a result, a number of optimization strategies, including SSA, are utilized in order to resolve these issues. In [10], the Salp Swarm Algorithm (SSA) is implemented in order to identify the ideal coefficients for neural networks, which results in the improvement of pattern classification. The suggested technique is proven to be advantageous through the use of a collection of frequently occurring categorization difficulties. The findings that were collected demonstrate that the classification accuracy measure and the sum of squared errors are two factors on which the suggested strategy performs better than other comparison techniques.

5.2. Engineering Applications

The SSA was utilized for the purpose of solving a variety of optimization issues, the majority of which were situated in engineering applications, including scheduling, power system control, and renewable energy systems. The efficacy of SSA in engineering applications is demonstrated by the parts that follow.

5.2.1. Scheduling

Scheduling is crucial for managing, organizing, and enhancing job efficiency. Consequently, scheduling offers several advantages, including enhanced efficiency and the conservation of time, costs, and effort. Consequently, many study methodologies employed scheduling to address these issues. Sun et al. proposed SSA based on blocks on the critical route (SSA-BCP) to mitigate reentrant job shop scheduling issues (RJSSP) [48].

5.2.2. Control of Power Systems

In the power and energy sector, an appropriate control system is essential for ensuring safe and rapid power generation, while also guaranteeing an enhanced quality of energy service for consumers. The primary idea in power system control, known as automated generation control (AGC), encompasses several components that govern numerous parameters, such as voltage, frequency, and interline power exchange [49].

Mohapatra and Sahu employed SSA to determine the fractional order parameters and optimal gains, namely the differentiator order (l) and integrator order (k), of the constructed fractional order proportional–integral–derivative (FOPID) controller [50]. The authors created FOPID to address the control challenges associated with the load between two interconnected regions: battery storage and a multi-source power system. The results indicated that the performance of SSA yields superior dynamic optimization of the FOPID controller by attaining low settling time in comparison to other controllers.

In [51], El-Fergany and Hasanien aimed to address the optimal power flow (OPF) problem by employing SSA to optimize four fitness functions: (1) stability of the static voltage (VS) in electric power systems, (2) total real power losses in the network, (3) overall fuel consumption costs, and (4) cumulative voltage variation across load buses. The VS has been emphasized through a modal analysis that regarded it as an objective function. The robust VS correlates with the magnitude of eigenvalues, whereby their relationship is positive; specifically, an increase in the size of eigenvalues results in a stronger VS. The simulation results demonstrated that the SSA validated its efficacy and resilience in comparison to other algorithms under same situations.

5.2.3. Renewable Energy System

Solar photovoltaic (PV) is a significant and efficient source of renewable energy due to its accessibility and environmentally beneficial characteristics. Consequently, solar photovoltaic energy systems have garnered focus in current research. Barik and Das employed SSA to enhance load frequency management for regulating the effective power of a decentralized renewable microgrid, which generates energy from rooftop solar arrays, fuel cells, biomass-fired combined heat and power systems, and aqua-electrolyzers [52]. This effort aims to manage electricity and waste by producing energy from solar irradiance, sewage, and urban solid waste. Therefore, this endeavor ensures the continuation of power even in the event of climate alterations.

5.3. Image Processing

Image processing extracts valuable information from an image to enhance its appearance by converting it into a digital format and subsequently applying various processes.

Nonetheless, several challenges exist regarding efficient search that must be conducted inside a complicated search area to identify an ideal solution [53]. Fish image segmentation is the fundamental stage in fish recognition. Furthermore, it may be utilized in the domains of aquatic product processing, ichthyology, and fish identification and classification. The segmentation of fish images encounters problems, including diverse species, varying illuminations, different locations, rotations, and the backgrounds included in the photographs. Ibrahim et al. suggested a novel segmentation approach utilizing SSA for fish images [54]. The authors utilized the SSA to refine the initial parameters for the simple linear iterative clustering (SLIC) approach, which was deployed to generate compact and almost uniform superpixels. Subsequently, they employed Otsu's approach for thresholding to identify optimal solutions for the extracted fish from the original Images.

5.4. Additional Applications of the Salp Swarm Algorithm

The Salp Swarm Algorithm (SSA) has gained prominence in addressing complex nonlinear optimization problems across diverse fields. A significant application is in time difference of arrival (TDOA) passive target localization, as proposed in [55]. This study presented a novel target localization scheme utilizing SSA to tackle the associated challenges. This approach included several significant innovations:

(i) A novel mechanism for updating the salp population has been introduced to optimize the balance between exploration and exploitation in the iterative search process. This mechanism facilitates a thorough exploration of the solution space, preserves diversity among individuals, and mitigates the risk of the algorithm becoming ensnared in local optima, a common limitation of conventional optimization algorithms.

(ii) The SSA method necessitates a limited number of tunable parameters, thereby streamlining implementation and minimizing computational overhead. This feature, along with the algorithm's inherent structure, facilitates a notable enhancement in computational speed relative to alternative methods.

(iii) Stable convergence and high accuracy are observed, indicating that the convergence behavior of SSA is both consistent and robust. In TDOA passive localization, SSA exhibited superior accuracy in position estimation and achieved faster convergence to the optimal solution relative to other published algorithms. The simulation results demonstrated that the proposed SSA-based approach effectively and reliably identifies the target with enhanced precision.

Another application area involves the assessment of nature-inspired optimization algorithms for general nonlinear problems, as explored in [56]. This study analyzed the effectiveness of various established metaheuristic algorithms through a series of benchmark test problems, which included two unimodal functions, two multimodal functions, and four nonlinear equation systems. The results indicated that:

- No single algorithm consistently outperformed the others in all test cases, suggesting that the selection of an algorithm may depend on the specific characteristics of the problem at hand.

- All tested algorithms, including SSA, demonstrated strong performance in addressing complex nonlinear equation systems, underscoring their utility as effective tools for solving challenging optimization problems.

Finally, SSA has demonstrated effectiveness as a robust and adaptable optimization method. The method's high accuracy, stable convergence, computational efficiency, and minimal parameter dependency render it particularly effective for a variety of problems, including target localization in sensor networks and general nonlinear optimization tasks.

6. Comparison of the Salp Swarm Algorithm with Other Metaheuristic Algorithms

Metaheuristic optimization algorithms exhibit common characteristics, including stochastic search, a balance between exploration and exploitation, and problem independence; yet, they vary in their inspiration, structure, performance, and adaptability. The following is a comparison of SSA with several commonly utilised metaheuristics:

- SSA versus Particle Swarm Optimization (PSO) [57, 58]

Similarity: Both are swarm-based and derive inspiration from collective behaviour observed in nature. Positions are updated according to leader-follower dynamics.

Difference:

- PSO necessitates a greater number of control parameters (inertia weight, cognitive and social coefficients), while SSA involves significantly fewer parameters.

- SSA maintains an inherent equilibrium between exploration and exploitation via leader-follower chains, whereas PSO occasionally experiences premature convergence.

Performance: SSA often has superior exploration capabilities, whereas PSO can achieve rapid convergence but is susceptible to entrapment in local optima.

- SSA versus Genetic Algorithm (GA) [59, 60]

Similarity: Both are stochastic optimisers based on population dynamics.

Difference:

- GA employs operators such as crossover and mutation; SSA utilises chain-based position updates.

- Genetic Algorithms exhibit greater parameter complexity, including population size, crossover probability, and mutation probability. SSA is more straightforward to execute.

Performance: Genetic Algorithms (GA) provide flexibility and extensive research applicability for discrete and combinatorial issues, whereas SSA demonstrates superior efficacy in continuous Optimization with a reduced number of parameters.

- SSA versus Grey Wolf Optimiser (GWO) [61, 62]

Similarity: Both are swarm-inspired algorithms employing hierarchy-based search methodologies (leader vs. followers).

Difference:

- GWO emulates wolf pack hunting characterised by an alpha–beta–delta hierarchy, whereas SSA replicates linear salp chains.
- GWO excels in exploitation, while SSA is superior in exploration.

Performance: GWO may attain expedited convergence on unimodal functions, whereas SSA frequently ensures superior diversity preservation and mitigates premature convergence.

- SSA versus Differential Evolution (DE) [63, 64]

Similarity: Both are proficient at addressing nonlinear and continuous Optimization challenges.

Difference:

- DE relies on the mutation and crossover of candidate solutions; SSA is contingent upon chain dynamics.
- DE necessitates the adjustment of the scaling factor and crossover rate, whereas SSA has a reduced number of control factors.

Performance: Differential Evolution excels in fine-tuning solutions (local search), but SSA is more proficient in global exploration.

- SSA versus Ant Colony Optimization (ACO) [65, 66]

Similarity: Both are nature-inspired, population-based Optimization techniques.

Difference:

- ACO is discrete and graph-oriented (using pheromone trails), whereas SSA is continuous and based on population chains.
- ACO is more appropriate for combinatorial tasks such as the Traveling Salesman Problem and routing, whereas SSA is designed for continuous optimization.

Performance: SSA demonstrates superior speed and simplicity for continuous issues, whereas ACO is more effective in discrete search spaces.
Table 2 shows a comparison between SSA and these metaheuristic algorithms.

7. Evaluation and Analysis of the Salp Swarm Algorithm

The Salp Swarm Algorithm (SSA) has been widely adopted for addressing various optimization problems since its inception, as previously discussed. Its success can be attributed to several key features [67]:

Table 2: Comparison of SSA with other metaheuristic algorithms.

Algorithm	Inspiration	Parameters	Strengths	Weaknesses	Best Suited Problems
SSA	Swarming of salps	Very few	Strong exploration, simple, stable convergence	Needs modifications for discrete/multi-objective problems	Continuous, nonlinear problems
PSO	Bird flocking	Several	Fast convergence, well-studied	Premature convergence	Continuous, engineering problems
GA	Natural evolution	Many (crossover, mutation, selection)	Flexible, handles discrete problems	Parameter tuning, slower	Discrete & combinatorial optimization
GWO	Grey wolf hunting	Few	Good exploitation, fast convergence	May lose diversity	Benchmark & engineering optimization
DE	Evolution-ary mutation	Several	Strong local search, global optimization	Sensitive to parameters	Continuous, multimodal optimization
ACO	Ant foraging	Many	Excellent for discrete search	Slow, pheromone update overhead	Combinatorial (TSP, routing)

- **Biological inspiration:** SSA is based on the swarming behavior of salps in the ocean, offering an intuitive and straightforward framework for implementation.
- **Minimal parameter requirements:** In contrast to numerous metaheuristic algorithms, SSA necessitates only a limited number of controlling parameters, thereby simplifying the tuning and implementation process.
- **Adaptive exploration and exploitation:** SSA effectively balances global search (exploration) and local search (exploitation), facilitating efficient convergence to optimal or near-optimal solutions.

While SSA offers several advantages, it exhibits similarities with other stochastic optimization algorithms and is not without its limitations. Comprehending these limitations is essential for effective application and subsequent enhancement. The primary constraints of SSA are as follows [68]:

(i) **Implications of the No Free Lunch (NFL) theorem:** A fundamental limitation of SSA is derived from the No Free Lunch theorem in optimization. The NFL theorem posits that no optimization algorithm can consistently outperform all others across all conceivable problems. The performance of any algorithm, including SSA, is standardized when averaged across a sufficiently large and diverse set of benchmark functions. This indicates that SSA may necessitate adaptation, hybridization, or parameter tuning when utilized for particular real-world optimization problems, particularly those characterized by unique constraints or highly irregular search spaces.

(ii) **Limitations of the objective function:** SSA is inherently structured for single-objective optimization problems, and its conventional formulation does not accommodate multi-objective optimization directly. Extending SSA to multi-objective problems necessitates modifications, including the integration of Pareto dominance, crowding distance, or other specialized operators. Solving problems involving binary, discrete, continuous, dynamic, or constrained variables may necessitate additional modifications to the algorithm to effectively address these problem domains.

(iii) **Problem-specific adaptability:** SSA exhibits strong performance across various continuous optimization problems; however, its efficiency may diminish in complex or noisy environments. The algorithm may necessitate hybridization with additional strategies, including chaotic maps, mutation operators, or local search techniques, to enhance convergence speed and solution quality in complex problem domains.

Finally, SSA is an effective and adaptable metaheuristic optimization algorithm characterized by robust exploratory and exploitative abilities. Nonetheless, similar to all optimization algorithms, its efficacy is contingent upon the specific problem at hand. Modification, hybridization, or operator design is often essential for extending SSA to multi-objective, discrete, dynamic, or other specialized optimization problems. Identifying these limitations enables researchers and practitioners to implement SSA.

8. Conclusion

This paper provides a thorough review of the Salp Swarm Algorithm (SSA), emphasizing its advantages, limitations, variants, and applications. A comprehensive collection of research articles was gathered and analyzed to offer a complete overview for researchers focused on metaheuristic optimization methods.

The findings indicate that the effectiveness of SSA is primarily due to its simplicity, adaptability, and minimal parameter requirements, contributing to its efficiency and ease of implementation. Several studies have introduced improved versions of SSA, including binary adaptations, hybrid models, multi-objective extensions, and parameter-free variants, to address the limitations of the original algorithm and expand its applicability to more complex and diverse problem domains.

Additionally, SSA has exhibited exceptional performance in numerous application domains, including:

- **Machine learning:** Tasks like feature selection and neural network training, wherein SSA enhances accuracy and minimizes computational expenses.
- **Engineering optimization:** Issues such as task scheduling, power system control, and renewable energy management, wherein SSA provides effective and reliable solutions.
- **Image processing:** Applications such as segmentation, enhancement, and pattern recognition.

- **Additional areas:** Optimization in wireless sensor networks, localization, and nonlinear system modeling.

Notwithstanding these strengths, SSA has limitations. Similar to other metaheuristic approaches, it is subject to the No Free Lunch theorem, which indicates that no algorithm can be deemed universally superior across all optimization problems. The original SSA is primarily intended for single-objective optimization and necessitates modification or hybridization to effectively address multi-objective, discrete, dynamic, or constrained problems.

In conclusion, SSA remains a promising and evolving optimization algorithm, demonstrating significant potential for further advancement.

8.1. Future Research Directions

While various Salp Swarm Algorithm (SSA) variants, including Chaotic SSA (CSSA), Quantum-inspired SSA (QSSA), and Adaptive SSA (ASSA), have demonstrated significant improvements, multiple opportunities remain for further research and development:

- **Hybridisation with Other Metaheuristics:** Integrating SSA variants with complementary Optimization methods, such as Differential Evolution, Particle Swarm Optimization, or Genetic Algorithms, has the potential to enhance convergence speed and solution quality, particularly in high-dimensional and multimodal contexts. Hybrid approaches can leverage the strengths of each algorithm to overcome their respective limitations.

- **Dynamic and Real-Time Optimization:** Most current SSA variants are designed for static Optimization problems. Future research could focus on developing dynamic SSA frameworks capable of adapting to evolving environments, time-varying constraints, or online data streams. This is especially relevant for real-time applications in engineering, robotics, and control systems.

- **Parameter-Free or Self-Adaptive Strategies:** Although ASSA incorporates adaptive parameters, opportunities remain for creating fully self-tuning or parameter-free SSA variants. Such algorithms would autonomously adjust control parameters based on problem complexity or population behaviour, eliminating manual tuning and improving robustness and usability.

- **Integration with Machine Learning Models:** SSA variants could be combined with machine learning tasks, including feature selection, hyperparameter optimization, and neural network training. Quantum-inspired or chaotic-enhanced SSA variants may be particularly effective for high-dimensional data-driven problems, offering superior global search capabilities.

- **Rigorous Benchmarking and Comparative Analysis:** Future studies should prioritise systematic benchmarking of SSA variants against classical metaheuristics and emerging algorithms using standard datasets and real-world problems. Statistical analysis of results will provide insights into the strengths and weaknesses of each variant.

- **Multi-Objective and Constrained Optimization:** Extending SSA variants to handle multi-objective and heavily constrained problems presents a valuable research opportunity. This may involve hybrid methodologies or the integration of Pareto-based mechanisms, advanced constraint-handling techniques, and diversity preservation strategies for real-world engineering and industrial applications.
- **Theoretical Analysis and Convergence Proofs:** While SSA and its variants show strong empirical performance, formal theoretical studies of convergence properties, stability, and computational complexity are limited. Future research could focus on developing mathematical guarantees to strengthen the scientific foundation of these algorithms.

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