Archives of Computational Methods in Engineering (2023) 30:2683–2723
https://doi.org/10.1007/s11831-023-09883-3

SURVEY ARTICLE

Slime Mould Algorithm: A Comprehensive Survey of Its Variants and Applications

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Received: 5 September 2022 / Accepted: 5 January 2023 / Published online: 12 January 2023

Abstract

Meta-heuristic algorithms have a high position among academic researchers in various fields, such as science and engineering, in solving optimization problems. These algorithms can provide the most optimal solutions for optimization problems. This paper investigates a new meta-heuristic algorithm called Slime Mould algorithm (SMA) from different optimization aspects. The SMA algorithm was invented due to the fluctuating behavior of slime mold in nature. It has several new features with a unique mathematical model that uses adaptive weights to simulate the biological wave. It provides an optimal pathway for connecting food with high exploration and exploitation ability. As of 2020, many types of research based on SMA have been published in various scientific databases, including IEEE, Elsevier, Springer, Wiley, Tandfonline, MDPI, etc. In this paper, based on SMA, four areas of hybridization, progress, changes, and optimization are covered. The rate of using SMA in the mentioned areas is 15, 36, 7, and 42%, respectively. According to the findings, it can be claimed that SMA has been repeatedly used in solving optimization problems. As a result, it is anticipated that this paper will be beneficial for engineers, professionals, and academic scientists.

1 Introduction

Meta-heuristic algorithms (Mas) have been brought to light in the scientific community owing to their applicability in a wide range of disciplines, including but not limited to mechanical, electrical, civil, mathematics, physics, control, finance, economics, etc. [1, 2]. As real-world optimization problems have grown in complexity and difficulty over the last several decades, the need for optimization methods has become more apparent. The performance of multi-modal, non-continuous, and non-differentiable issues is well-served by the meta-heuristic algorithm family of stochastic search approaches [3]. Two primary categories may be used to classify optimization approaches: gradient-based techniques and Mas [4]. Gradient-based methods require knowledge of the gradient of the fitness function to direct the search effectively. Although gradient-based methods are mathematically fascinating, they frequently suffer from three serious flaws: the potential for getting stuck in an optimal local solution, a slow rate of convergence, and a strong dependence on the starting point [5].

In contrast to gradient-based techniques, MAs do not require gradient information throughout the search process. The approaches may quickly and effectively identify optimum or near-optimal solutions to optimization problems that are discrete, non-convex, or discontinuous within an acceptable amount of time. Consequently, MAs are essential for various engineering applications [6]. The MAs are defined by four features: low complexity, high adaptability, lack of a need for mathematical derivation, and the ability to avoid local optimums [7]. The idea behind and implementation of a meta-heuristic algorithm is straightforward since it is often based on observations of natural phenomena, evolutionary processes, and the actions of animals and people. Due to the absence of a clear-cut solution for each given objective problem, MAs are adaptable to a wide variety of optimization issues [8].

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Non-embedded analysis paired with commercial finite element software is more accessible because most MAs do not need derivative information during the optimization phase. It is beneficial for issues where the gradient information is unknown. Last but not least, the meta-heuristic method is well-suited to address complex optimization problems, including those with many local optima [9]. Even though many MAs have specific distinguishing characteristics, the search gradation always consists of two steps that are the same for all: exploration and exploitation [10]. Exploring the solution space in as broad, unpredictable, and comprehensive a manner as is humanly feasible is referred to as the exploration phase. The algorithm's ability to search more precisely in the region gained by the exploration phase is referred to as its "exploitation phase," during this phase, the algorithm's level of randomness diminishes. Its level of accuracy improves [11]. When the exploration capacity of the algorithm is prioritized, which enables it to converge rapidly, the algorithm may search the solution space in a more random manner and yield solution sets with a greater diversity of elements. The algorithm searches for solutions in a more localized area to increase the quality and accuracy of the solution sets when the potential for exploiting a scenario is at its most significant [12]. Nevertheless, exploitation capacity will suffer if the exploration capacity is improved, and vice versa. These effects will be reciprocal. Another difficulty stems from the optimal combination of these two skills is not always the same for each issue. As a consequence of this, achieving an acceptable balance between the two stages that are effective for all optimization issues might be considered to be a somewhat tricky task [13].

The swarm-intelligence (SI) optimization algorithm is a highly developed subset of nature-inspired MAs that draw inspiration from the intelligent actions of animals, plants, and other species [14]. The social activities of predation, reproduction, and hunting are ubiquitous. With a set of randomly apparent results in the search space, SI builds numerous heuristic approaches to simulate such social behaviors, optimizing the algorithm globally and locally via iterative processes. Cooperation between humans may lead to sophisticated and organized swarm intelligence activity among a group of search agents. In this category, several suggestions for well-known algorithms have been published. Even though many different algorithms have been presented, they all have one key feature. There are two phases to optimization: exploration and exploitation. Algorithms seem to conduct a worldwide and exhaustive search for better solutions distant from the present peak in the search space during the exploration phase. In the exploitation phases, algorithms often explore the solution's neighborhood to improve upon the best solution identified so far; this search seems local and intense. When working together to solve an issue, exploitation and exploration always clash. Exploration often dominates the first half of each iteration to explore the whole variable space and skip forward to local optimums. The second part of the iteration process is dominated by exploitation, which searches the neighborhood of the best solution thus far. A proper balance between an algorithm's exploitation and exploration phases may reduce excessive local stagnation and immature convergence.

Natural systems are often used as models for the optimization techniques that have been developed. Of these methods, SMA was introduced by Li et al. [15]. From the acronym's name, one may probably guess the phrase that SMA uses a mathematical model of the foraging behavior of a eukaryotic organism called *Physarum* polycephalum to find optimal solutions to issues. There are two main phases: "approach food" and "wrap food," respectively. This paper aims to cover broader scopes of SMA methods to develop optimization techniques in different fields. The following are this paper's main contributions:

- Hybridization, improved variants on SMA, and optimization difficulties are all explored with SMA techniques.
- The SMA is analyzed by pseudo-code and schematic.
- It improved SMA analysis by different methods. The SMA includes its explanation, construct, merit, demerit and applications.
- An analysis of SMA's effectiveness in resolving various issues, considering convergence rate, exploration, and exploitation aspects.

This paper's general structure is as follows: In Sect. 2, the SMA algorithm and its operators will be described. SMA methods will be broken down into four areas in Sect. 3: optimization problems, improvement, hybridization, and SMA variants. In Sect. 4, we'll address discussions and comparisons. In Sect. 5. conclusions and future work are introduced.

2 Slime Mould Algorithm

The SMA is a population-based meta-heuristic algorithm recently introduced by Li et al. [17]. The SMA takes on the shape of the acellular Slime Mould Physarum polycephalum while actively searching for a source of nutrition. What follows, *Physarum polycephalum* will be referred to as "Slime Mould". It is a complex amoeboid structure of interconnected tubes that carry cytoplasm throughout the organism. Slime Mould can do this because of its unusual anatomy, which allows it to construct complex networks of veins between its many food sources, allowing it to feed on all of them at once. After locating a food supply, Slime Moulds' biochemical oscillator sends contraction waves across the venous system, resulting in tubular veins flowing with the cytoplasm. The velocity of cytoplasmic streaming is related to the vein's wall thickness. Therefore, as the rate of cytoplasmic streaming increases, the vein thickens; when it decreases, the vein thins. The Slime Mould relies on positive and negative input to find its way to food sources. Detailed explanations of the suggested mathematical model and procedure will be provided in this section.

2.1 Approach Food

Slime Mould can approach food based on the odor it gives out. The following mathematical formulae have been offered to reproduce the contraction mode to use mathematical formulas to understand its approaching behavior. Equation (1) is a formula for approaching food [15].

$$\vec{X}(t+1) = \begin{cases} \vec{X}_b(t) + \vec{vb} \times \left(\vec{W} \times \vec{X}_A(t) - \vec{X}_B(t)\right) & r < p \\ \vec{vc} \times \vec{X}(t) & r \geq p \end{cases} \quad (1)$$

In Eq. (1), $\vec{vb}$ is a parameter whose values may fall between a negative (-1) value and a positive $(+1)$ value. In contrast, $\vec{vc}$ falls linearly from 1 to 0, $\vec{W}$ is the weight of the Slime Mould. t is the current iteration, $\vec{X}_A$ and $\vec{X}_B$ are two people that were randomly picked from the Slime Mould, $\vec{X}$ is the location of the Slime Mould, and $\vec{X}_b$ is the individual location with the most incredible smell concentration presently found. The equation of p is defined by Eq. (2).

$$p = \tanh |S(i) - DF| \quad (2)$$

In Eq. (2), DF represents the highest level of fitness achieved throughout all iterations., $i \in 1.2. \ldots .n$, S(i) shows the fitness of $\vec{X}$. The equation of $\vec{vb}$ is defined according to Eq. (3) [15].

$$vb = [-a \cdot a] \quad (3)$$

$$a = \operatorname{arctanh}\left(-\left(\frac{t}{max\_t}\right) + 1\right) \quad (4)$$

The equation of $\vec{W}$ is shown according to Eq. (5).

$$\vec{W}(SmellIndex(i)) = \begin{cases} 1 + r \cdot log\left(\frac{bF - S(i)}{bF - \omega F} + 1\right) & condition \\ 1 - r \cdot log\left(\frac{bF - S(i)}{bF - \omega F} + 1\right) & others \end{cases} \quad (5)$$

$$SmellIndex = Sort(S) \quad (6)$$

where *SmellIndex* represents the sequence of fitness values sorted in ascending order, F represents the worst fitness value obtained in the iterative process currently, bF indicates the optimal fitness value obtained in the current iterative process, r denotes a random value in the interval [0,1], the condition shows that $S(i)$ ranks in the top half of the population, and max_t shows the maximum number of iterations.

The results of Eq. (3) are seen in Fig. 3. The position of the person being searched for $\vec{X}$ maybe altered by fine-tuning the parameters $\vec{vb}$, $\vec{vc}$, $\vec{W}$, and the location of the individual being searched for can be updated to reflect the best location $\vec{X}_b$, that has just been acquired. Figure 1 also depicts how the seeking individual's location changes during the search in a three-dimensional space. The arctan$h$ formula can have the power to make people construct search vectors at any angle,

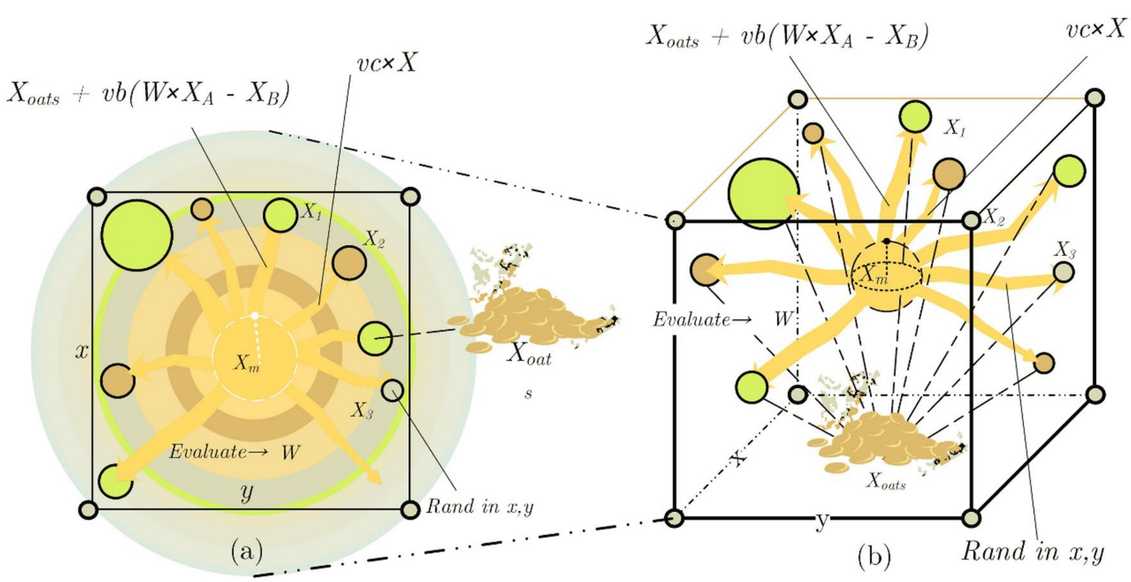


Fig. 1 Possible locations in 2-dimensional and 3-dimensional [15]

i.e., explore the solution space in any direction, allowing the algorithm to find the optimal solution and potentially find the optimal solution. Because of this, Eq. (1) provides folks interested in investigating in all directions nearby with the appropriate alternative to imitate the circular sector structure that Slime Mould uses while it is approaching food. Utilizing this concept to produce hyper-dimensional space is also a viable option.

2.2 Wrap Food

This component models Slime Mould's venous tissue contraction mechanism when seeking. When more food is consumed, the bio-oscillator generates a more substantial wave, the cytoplasm moves quicker, and the vein becomes more visible. Equation (5) was used to model and simulate the positive and negative feedback loops between the slime mould's vein diameter and the food content under investigation. In Eq. (5), the variable r represents a simulation of the unpredictability of the mechanism of venous contraction. A log is used to delay the rate of change of the numerical value to guarantee that the value of the contraction frequency does not vary dramatically. The Slime Mould is simulated by condition to change its foraging strategies in response to the food's quality. When there is enough food nearby, the weight in the area is more significant; when there is not enough food nearby, the region's significance is reduced, which prompts the creature to turn its focus to other places to examine. The procedure for determining the Slime Mould's fitness values is shown in Fig. 2.

Based on the theory presented earlier, the formula for the mathematical approach used to update the position of slime mold is specified as Eq. (7) [15].

$$X^* = \begin{cases} rand.(UB - LB) + LB \;\; rand < z \\ \vec{X}_b(t) + \vec{vb} \times \left(\vec{W} \times \vec{X}_A(t) - \vec{X}_B(t) \right) \;\; r < p \\ \vec{vc} \cdot \vec{X}(t) \;\; r \geq p \end{cases} \tag{7}$$

The bottom and upper bounds of the search range are represented by the symbols LB and UB in Eq. (7), respectively. In addition, rand and r stand for the value chosen randomly from the range [0,1]. During the phase of the experiment devoted to modifying the parameters, we will have a conversation about the significance of the value z.

2.3 Oscillation

To change the cytoplasmic flow in veins, the Slime Mould essentially uses the propagation wave produced by the biological oscillator. In terms of food concentration, it makes the Slime Mould more favorable. It is utilized $\vec{W}$, $\vec{vb}$, and $\vec{vc}$ to represent the changes in venous width to simulate the variations that occur in Slime Mould. The goal is to manufacture the Slime Mould. To enable slime mould to move more swiftly toward food when they locate high-quality food, $\vec{W}$ models mathematically the oscillation frequency of slime mould close to one at various food concentrations in Eq. (7). When there is a lesser concentration of food in a given place, the rate at which food is brought in is slower. It improves Slime Mould's ability to choose the best available food source.

As the number of iterations rises, the value of $\vec{vb}$, which fluctuates at random between $[-a \cdot a]$, approaches zero. The value of $\vec{vc}$ vacillates between [− 1,1] and finally approaches 0 after all of its gyrations. Figure 3 illustrates the trend that can be seen between the two numbers. The preferential

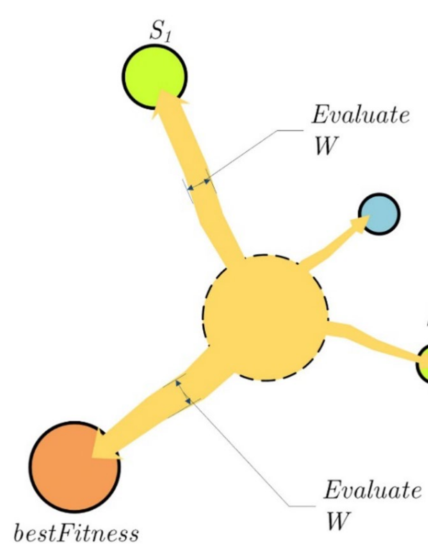


Fig. 2 Assessment of fitness [15]

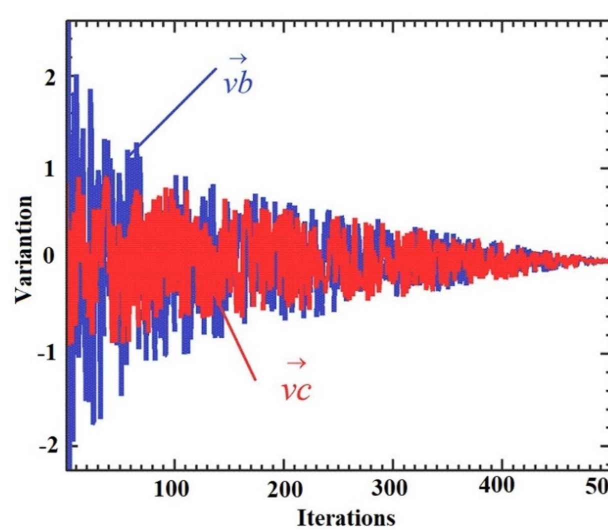


Fig. 3 Trends of *vb* and *vc* [15]

activity of Slime Mould may be imitated by the synergistic interaction between $\overrightarrow{vb}$ and $\overrightarrow{vc}$. Slime Mould will continue to separate organic materials to look for a higher-quality food source, even if it has found a good one. It is done to increase Slime Mould's chances of finding a supply of food of a better caliber.

The oscillation mechanism of vb duplicates Slime Mould when considering whether to approach the food source or look for alternatives. On the other hand, exploring food is a difficult task. Several elements, including a dry and light atmosphere, may prevent Slime Mould formation. On the other side, this helps Slime Mould avoid becoming caught in an ideal local condition and boosts their chances of finding higher-quality food. In Algorithm 1, the SMA's pseudo-code is displayed.

Algorithm 1 The pseudo-code of the SMA [15]

Input n, dim, *MaxFEs*;
Initialize the locations of slime mould $X_i(i = 1.2. \cdots .n)$;
While ($FEs \leq MaxFEs$)
Calculate the fitness of all slime *moulds*;
Upgrade the best fitness, X_b;
Compute the W by Eq. (5);
For each search portion
IF rand < z
Upgrade locations by Eq. (7);
Else
Update p, *vb*, *vc*;
IF r < p
Upgrade locations by Eq. (7);
Else
Upgrade locations by Eq. (7);
End IF
End IF
End For
$FEs = FEs + n$;
t = t + 1;
End While
Output *bestFitness*, X_b;

Figure 4 shows the clear and thorough SMA procedure. Figure 5 also depicts the SMA's general logic.

Numerous other processes may be included in the algorithm, and the life cycle of Slime Mould can be simulated in greater detail. To make the method more generalizable, however, they strip out unnecessary steps and operators in favor of a more streamlined procedure.

2.4 Computational Complexity Analysis

Initialization, fitness assessment, sorting, weight update, and location update are the primary components of SAM [15]. Other features include location updates and weight updates. The number of cells that Slime Mould has is denoted by the letter N, the letter T indicates the maximum number of iterations the letter T, and the dimension of functions is represented by the letter D. The complexity of computation for initialization is O(D), the complexity of calculation for fitness evaluation and sorting is $O(N + NlogN)$, the computational complexity of updating the weight is $O(N \times D)$. The complexity of updating location is $O(N \times D)$. As a colusion, the $O(D + TN(1 + logN + D))$ represents the entire complexity of SMA.

In 2020, researchers explored many approaches to using SMA to address optimization issues. The complete collection of SMA articles was downloaded. A category was made using the proportion of documents in various publications and the volume of SMA papers published each year to establish the overall number of SMA papers. Figure 6 shows that SMA has published articles in various journals. Journals published by ScienceDirect (28%), IEEE (26%), Springer (20%), MDPI (9%), Wiley (7%) *Tandfonline* (5%) and Others (3%) accounted for the majority of publications. Figure 6 demonstrates that ScienceDirect had the largest share of total papers after publication.

Several types of research published in SMA per year (in a graphical form) are presented in Fig. 7. In 2020, there were 18 papers on SMA published. Figure 7 shows that the percentage of schools using SMA has grown over time.

The papers are collected based on the title, keywords, and abstract. The research of the articles has been done very carefully. All reliable and global databases have been checked. Each paper has been thoroughly reviewed in terms of text and type of algorithm. Duplicate papers were removed in the screening phase. Finally, the papers belonging to the SMA algorithm were grouped. Figure 8 shows the search steps and the number of articles in different steps.

3 Methods of SMA

Figure 9 presents a classification of the many SMA approaches. The kind is built on optimization problems, hybridization, improvement, and SMA variants. There are MAs involved in the hybridization process. In the section "Improved," multiple sub-categories have been consulted to produce better answers. The usage of binary and multi-objective approaches can be found in SMA variants. SMA is applied to resolve various optimization problems in determining which option provides the optimal answer.

3.1 Hybridization with Other Meta-heuristics

In this section, the hybridization of SMA with other algorithms is examined. To address the issue of becoming trapped in the local optimum, SMA uses MAs. SMA used SOA, WOA, TLBO, DE, SA, ABC, SCA, PS, EO, AOA, ACO, MPA, FA, and PSO algorithms.

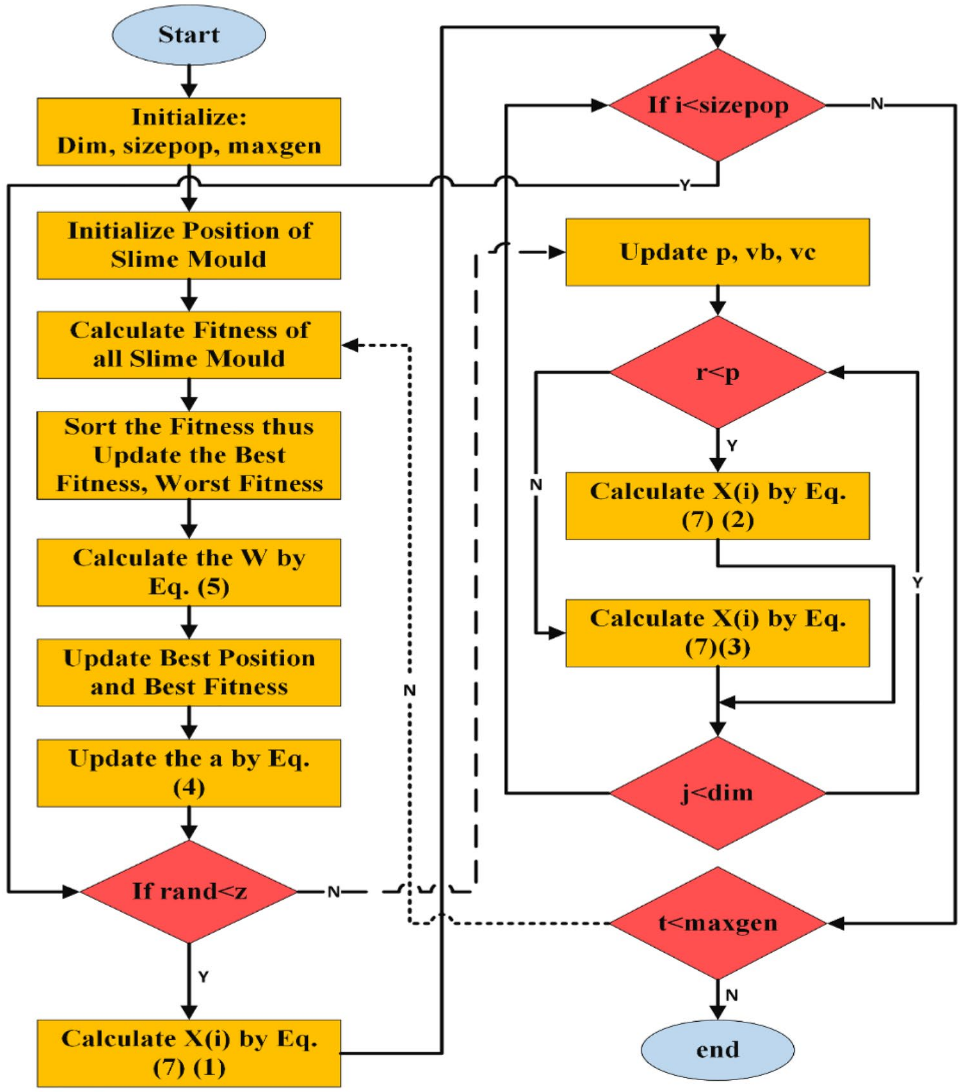


Fig. 4 Flowchart of SMA [15]

3.1.1 SMA- Seagull Optimization Algorithm (SOA)

Based on the SMA and the SOA, a brand-new structured approach for function optimization research has been presented [16]. The use of SOA allows for an even more significant rise in exploration. A comprehensive evaluation is validated using 23 different benchmark functions.

3.1.2 SMA- Whale Optimization Algorithm (WOA)

The best placement of hybrid power flow controllers (HPFC) has been accomplished with hybrid SMA-WOA [17]. Integrated SMA, which has been offered as a method, will be put into practice (ISMA). How the WOA behaves when it updates its position is beneficial to the searching behavior of the SMA. The ISMA technique optimizes the line with the most significant power loss (UPFC) to choose the best placement for the unified power flow controller. The ideal placement parameters and dynamic stability limits have been reinstated with the typical constraints, and the UPFC's optimal capacity has been modified to save cost using the ISMA approach.

A unique hybrid strategy is offered to overcome the ISP for COVID-19 chest X-ray pictures by hybrid an SMA with the WOA to increase entropy [18]. They have compared the efficacy of integrated SMA to that of WOA, FA, HHO, SSA, and the baseline SMA on 12 chest X-rays with thresholds as high as 30. While the standard SMA might surpass the other algorithms in the comparison under all metrics, the testing findings showed that the suggested approach outperformed SMA under entropy.

3.1.3 SMA- Teaching–Learning-Based Optimization (TLBO)

TLSMA proposes a hybrid SMA using TLBO to address global and reliability-based design optimization (RBDO)

Fig. 5 The steps of SMA [15]

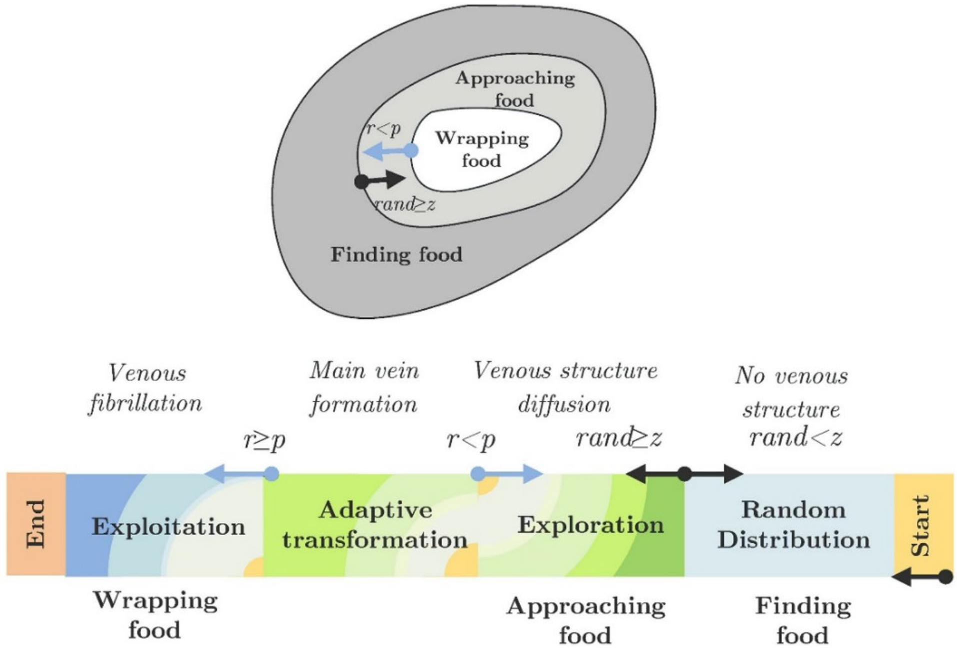
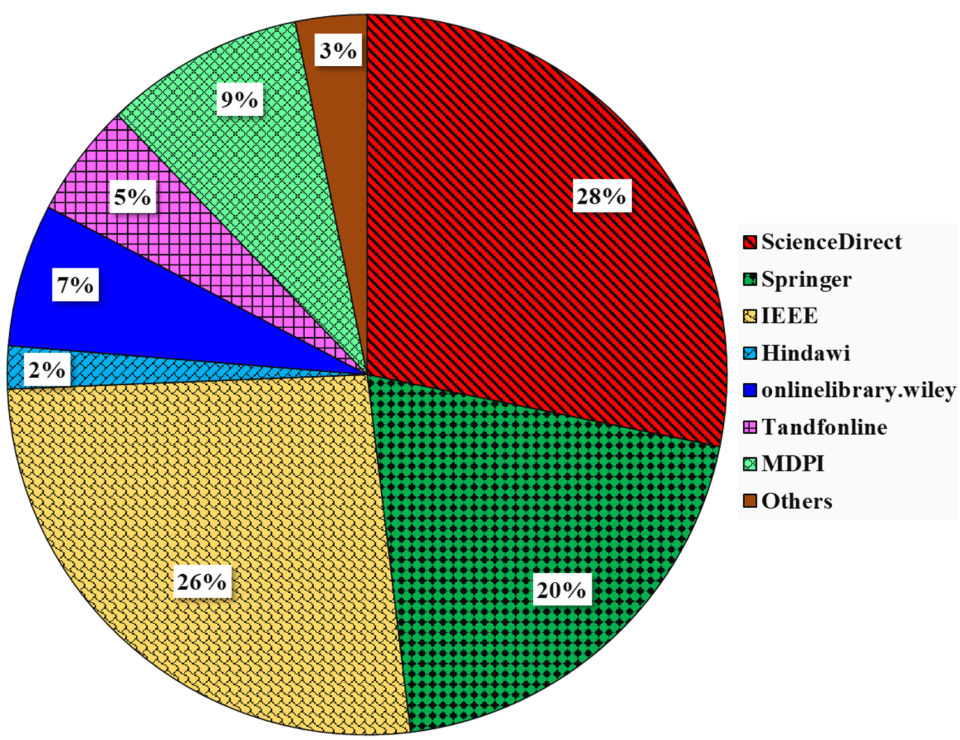


Fig. 6 Percentage of papers published with SMA in different publications



issues [19]. The main idea of TLSMA is to merge the exploitation and exploration capabilities of SMA with TLBO to improve SMA's convergence capability. Further, the adaptive chaos management approach is applied to the TLSMA to allow for its use in resolving RBDO issues with probabilistic constraints. Two-part experiments are used to evaluate the suggested method. Before being compared to other MAs that are considered state-of-the-art, TLSMA is first validated on 24 industry-standard benchmark optimization problems. These issues include both unimodal and multi-modal functions. TLSMA outperforms BBO, SMA, GWO, TLBO, WOA, PSO, and SSA in several benchmark optimization problems. The TLSMA-RBDO system is then put through its paces with five RBDO tasks, of which one is numerical

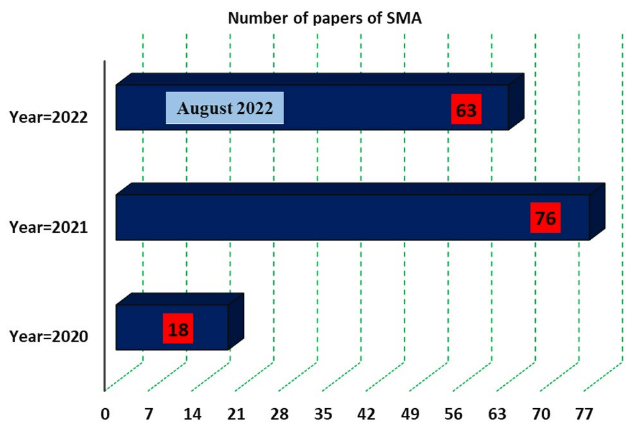
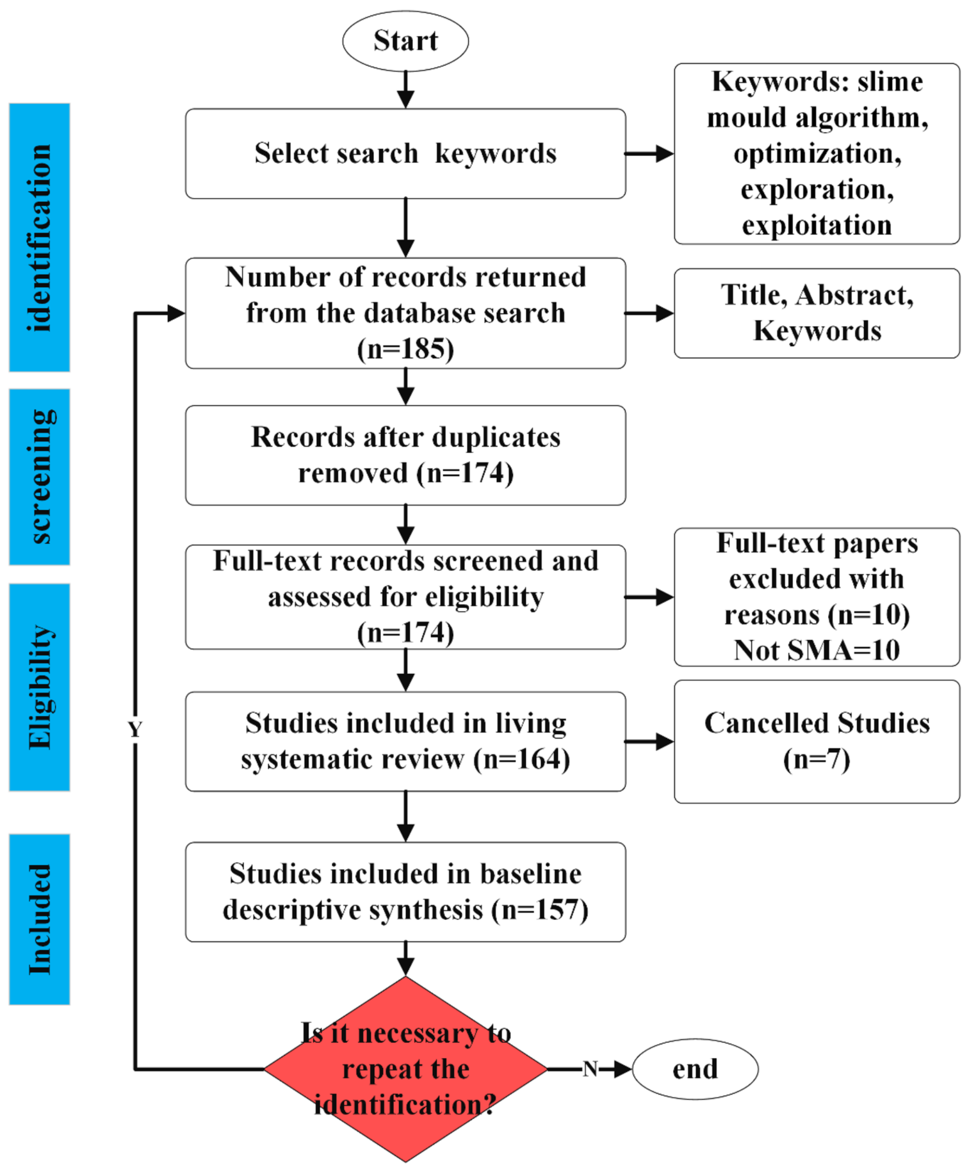


Fig. 7 Total incidence of SMA Articles Published

and the remaining four are engineering difficulties. The results show that the suggested method performs better than the algorithms used in the RBDO problems. A novel LSMA-TLBO hybrid has been developed to circumvent the challenges presented by numerical and engineering design optimization [20]. It balances exploitation and exploration via SMA and TLBO properties. This research also offers a Levy flight-based mutation to enhance the exploratory capabilities of the system further. SMA has a few problems: a tendency to become stuck on local optimums, a poor convergence rate, and an imbalance between exploiting and exploring. In light of these drawbacks, they present the hybrid algorithm LSMA-TLBO, which combines the strengths of SMA and TLBO to achieve optimal exploration by using the former's global solid searchability and the latter's quick convergence. The proposed LSMA-TLBO is tested on unit-modal and

Fig. 8 Procedure for extracting papers belongs to the SMA algorithm



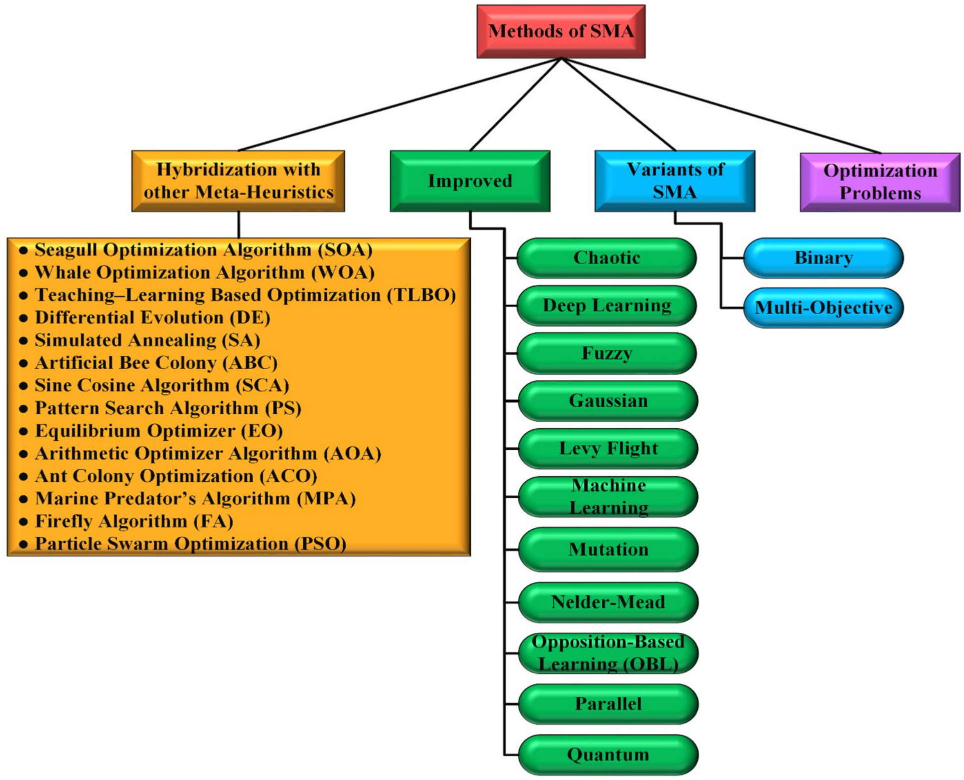


Fig. 9 Classification of SMA methods

multi-modal benchmark functions totaling twenty-three. Six engineering design concerns and the IEEE CEC-C06 2019 test suite are also taken into account to assess the method's feasibility. The simulation results show that the proposed approach is superior to several freshly presented state-of-the-art algorithms. In addition, the Wilcoxon rank-sum test is utilized to do a statistical analysis of the LSMA-TLBO. They conclude that the suggested LSMA-TLBO is ideal for solving complicated OPs in the real world.

3.1.4 SMA- Differential Evolution (DE)

SMA has demonstrated more excellent performance than other MHs approaches by successfully applying the method to various real-world problems and mathematical optimization [21]. SMA lacks the population's diversity and tends to converge towards a local minimum. Since the standard SMA has shortcomings, this study suggests a new SMA with the catchy acronym CHDISMA. The ergodic and random qualities of chaotic mapping approaches are employed to replace the original random initialization and increase the algorithm's variety, making it more suited for early-stage exploration of promising regions. Then, DE's crossover and selection operations were used to CHDISMA to prevent the algorithm from being trapped at a local maximum. They updated the position by combining the original SMA operator with DE's mutation strategy. The effectiveness of CHDISMA was evaluated using the CEC2017 and CEC2014 test suites in conjunction with four actual engineering issues. Modern algorithms and DE variations were compared to CHDISMA. The experiments and the statistical analyses show that CHDISMA can compete with the best algorithms available.

A modified differential evolution (MDE) algorithm with an SMA-inspired vision has been devised to assess the viability of the proposed strategy [22]. An experiment was carried out at IEEE CEC 2014 in which MDE was compared to other algorithms of a similar kind. An MDE-based multi-level image segmentation model was tested and validated using a reference photo collection. In conclusion, utilizing pictures of breast invasive ductal carcinoma, the MDE-based multi-level segmentation model was compared to its rivals. The created model is a top-notch segmentation technique that might offer helpful assistance for the following studies into pathological image processing for breast invasive ductal carcinoma. Additionally, several experimental findings have shown that MDE is a very accurate evolutionary algorithm capable of jumping out of the local optimum. It is now known to be an evolutionary algorithm due to this. Adaptive Guided DE Algorithm (AGDE) [23] is a mix of SMA and AGDE. The AGDE mutation strategy enhances population variety and local search performance and delays the early convergence of swarm agents. The SMA-AGDEs are assessed using the CEC'17 assessment package for three engineering design issues (tension/compression spring, rolling element bearing, and pressure vessel) and two combinatorial optimization tasks (quadratic assignment, bin packing). The SMA-AGDE is contrasted with (1) the well-researched MAs, such as TLBO, BBO, and GSA; (2) the newly developed MAs, such as MRFO, SMA, and HHO; and (3) the high-performance MAs, such as AGDE and CMA-ES. The simulation findings demonstrate that SMA-AGDE outperforms competing approaches over various functions. As a result, the suggested SMA-AGDE is a valuable optimization tool for global and combinatorial optimization and engineering issues.

3.1.5 SMA- Simulated Annealing (SA)

A new hybrid opposition-based learning (OBL), SMA, and Simulated Annealing (SA) algorithm has optimized the controller's settings [24]. The proposed method improves the exploitation and exploration capabilities of the original SMA by using OBL and simulated annealing. A time domain objective function was developed as a performance metric for designing automated voltage regulator (AVR) and direct current (DC) motor systems. The first performance assessment used benchmark functions that were both unimodal and multi-modal. The outcomes demonstrated that the created algorithm outperforms existing state-of-the-art optimization algorithms in exploration and exploitation. Analyses of the method's resilience and disturbance rejection, together with statistical tests, have been used to assess the performance of the proposed algorithm in the context of DC motor and AVR systems. The recommended strategy has proven to be more successful for the procedures compared to the current various optimization approaches.

3.1.6 SMA- Artificial Bee Colony (ABC)

A distributed foraging SMA (DFSMA) is suggested to improve the SMA and preserve population diversity [25]. The alphabetic basis principle (ABC) inspired the dispersed foraging approach. IEEE CEC2017 experiments based on several functions are complete. Eleven different MAs, ten more sophisticated algorithms, and three more recently suggested algorithms were compared to the DFSMA. The Wilcoxon signed-rank test was also employed to examine the experimental results for more thorough data analysis. In trials comparing the DFSMA to other optimizers, it was shown to have the fastest and most accurate convergence. They used the transform function to derive the binary DFSMA. Analysis of the results was done using 12 datasets from the UCI repository. The experimental findings show that the BDFSMA outperforms the traditional SMA and has the potential as an engineering tool for spatial search and feature selection because it improves classification accuracy while using fewer features. The right heart fails and eventually stops beating in patients with pulmonary hypertension (PH), making it an uncommon but ultimately deadly illness. Neither the causes nor treatments for PH are fully understood.

Animal models must be established and accurately assessed to further PH research. In [26], PH from arterial blood gas measurements is accurately analyzed using an evolutionary, extreme learning machine with several integrated SMA (MSSMA). To achieve a decent balance between depth and breadth, they add two effective bee-foraging learning operators to the basic SMA in MSSMA. The MSSMA is used to construct the arterial blood gas PH kernel extreme learning machine that is dependable for evaluating PH from arterial blood gas readings, with a sensitivity of 91%, a specificity of 90%, and a Matthews coefficient of 90%. Its approach might be a responsible way to judge mouse PH models. For better Lupus Nephritis (LN) diagnosis, a multilayer SMA-based LN image segmentation approach is developed. Finding the optimal threshold set is a crucial step in multi-level thresholding image segmentation, and it's also one of the most time-consuming (MLTIS). It is especially true when the entries are lower. However, swarm-based techniques often create segmentation thresholds of poor quality and get mired in local optima while attempting to segment. The actual implementation of the ASMA-based MLTIS strategy is the insertion of ABC's position update mechanism into the SMA. The ASMA strategy is a modified SMA (ASMA) version. Consequently, this technique shows much promise as an image segmentation method.

3.1.7 SMA- Sine Cosine Algorithm (SCA)

Convergence to optimality relies heavily on Slime Moulds updating their locations. In [27], the SCA's position updates are integrated with the SMA's. These revisions alter the Slime Mould oscillation processes and use various alterations to the previous sine–cosine algorithm. Instead of stacking two random Slime Moulds inside a predetermined interval, the arctanh function, which the SMA mathematical model uses, employs a modified sigmoid function. This paper presents the suggested procedure and its theoretical derivations using the Schwarz lemma. It has been demonstrated through the results of tests that the proposed algorithm has strong exploration and exploitation capabilities. The trigonometric functions sine and cosine were used in the investigation, resulting in an updated SMA placement. The provided approach has been tried on several real-world issues, including the construction of a cantilever beam, a 3-bar truss, a speed reducer, and a pressure vessel, with promising results. Due to this, the proposed hybrid algorithm outperforms the SCA and the SMA in terms of its capacity to escape local optima and achieve faster convergence.

The single- and multi-objective Economic and Emission Dispatch (EED) issues may be solved using an enhanced version of the SMA known as the ISMA, which also considers the impacts of valve points [37]. ISMA was designed to improve upon the performance of SMA. ISMA updates the solution locations until the optimal one is discovered using two equations derived from SCA. The author uses the Pareto dominance principle and fuzzy decision-making to build multi-objective ISMA (MOISMA) and multi-objective SMA (MOSMA). They are used in the multi-objective EED problem to cut emissions and fuel costs at the same valve point. Five test systems are used to validate the proposed single and bi-objective economic emission dispatch methods. They evaluate the suggested algorithm's performance by contrasting it with some of the most popular ones. The results demonstrate that the proposed algorithms are more stable than many widely used alternatives. With the tools at our disposal, they can devise practical options that adjust the generation schedule within legal parameters.

3.1.8 SMA- Pattern Search Algorithm (PSA)

Efforts are being made to devise more efficient methods of exploration via exploitation. The suggested hybrid SMA-PSA has been tested extensively and compared to proven and trustworthy meta-heuristics to determine its efficacy [28]. In addition, the algorithm's potential effectiveness in engineering-based optimization issues is estimated using nine traditional optimization problems using design as input. Experiments showed that this algorithm achieved impressive, often surprising, results in complex search environments.

3.1.9 SMA- Equilibrium Optimizer (EO)

EOSMA [29] is an EO-guided SMA that seeks to maximize efficiency by enhancing the search for SMAs. SMA has improved its exploitation and exploration skills to enable better exploitation during the maturation phase and better exploration during the commencement phase. In addition, the EO's search operator is used to direct SMAs' search spaces rather than the latter's anisotropic one (EOSMA). Afterward, population location updates are used to assist the SMA in avoiding being stuck in a rut. A stochastic difference mutation operator boosts population variety in the final iteration. When comparing Min metrics, EOSMA provides more outstanding performance than IMODE, LSHADE, and $LSHADE - cnEpSin$ for the most recent CEC2021 functions. EOSMA, in particular, beats the various comparison algorithms regarding solution robustness, speed, and accuracy and can identify viable solutions fulfilling all requirements for all nine engineering issues.

By using the Equilibrium Optimizer's (EO) equilibrium pool approach for updating slime-mold position updates, a novel Equilibrium SMA (ISMA) is presented for thresholding color images [30]. ISMA's performance is compared to optimization algorithms and ranked using Friedman's mean rank, utilizing a total of 53 test problems. Additionally, a multilayer color thresholding technique based on entropy reduction is developed using the ISMA to interpret breast thermograms. Both breast thermograms' grayscale and color channels are used in two studies. An examination of thermogram images shows promising findings. They discover even more surprising conclusions when they evaluate their method using many measurements, such as the feature similarity index, the structural similarity index, and the peak signal-to-noise ratio. The statistical evaluation showed that the method was adequate for analyzing breast thermograms. As a supplementary resource, the procedure may be helpful to doctors. The ISMA has the potential to aid in the resolution of a variety of engineering optimization issues.

3.1.10 SMA- Arithmetic Optimizer Algorithm (AOA)

HAOASMA [31] is a hybrid technique that combines SMA with an AOA to combat the problems of insufficient memory and delayed convergence at local minima. The convergence rate of the hybrid optimizer is increased by including a lens OBL technique in the algorithm. The search procedure of AOA is kicked off by the global best (*gbest*) and local best (*Pbest*) of SMA. Using the AOA-obtained *Pbest* as a new starting point, the SMA may explore the search space even further. The created hybrid algorithm uses the exploitative and exploratory potentials of SMA and AOA. Twenty-three benchmark functions in varying dimensions have been used to evaluate the created HAOASMA against the baseline SMA, AOA, and six well-known MAs. Engineering design issues from the past have also been tackled with the HAOASMA. Compared to standard SMA, AOA, and other MAs, HAOASMA has much more excellent performance.

3.1.11 SMA- Ant Colony Optimization (ACO)

The authors present a new SMA fractional-order ACO (SMFACO) approach for solving Traveling Salesman Problem (TSP) [32]. The newly created SMFACO method makes excellent use of the long-term memory properties of fractional calculus to strike a good compromise between the two. In addition, it considers the crucial path-preserving feature of the slime-mold model to prevent becoming stuck in a cycle of local optimization. The results show that the proposed algorithm is superior to its contemporaries regarding solution quality, search efficiency, and convergence time. It is simple for the ACO to become stuck in the local optimum, and the rate at which it converges on the optimal solution to the TSP is sluggish. As a result, they propose an algorithm called the Slime Mould-Ant Colony Fusion Algorithm (SMACFA) [33]. First, an optimized path for TSP is obtained using SMA. After that, the two endpoints of the high-quality pipelines are used as fixed-point pairs on the path generated using SMA. The fixed selection concept is applied to the fixed-point teams directly to the ACO. As a result, the SMACFA model is obtained together with a limited set of high-quality pipelines. The development of the route length was 15,381 by SMACFA when it was tested using the chn31 in the TSP Library (TSPLIB), and this result was improved by 1.42% compared to ACO. The algorithm time complexity and convergence speed experienced considerable drops, the former by 73.55 and the latter by 80.25%, respectively. It has been shown without a reasonable doubt that SMACFA performs significantly better than alternative TSP solution techniques.

3.1.12 SMA- Marine Predators Algorithm (MPA)

HMPA hybrids MPA and SMA to improve MPA exploitation while determining TDM parameters [34]. In addition to the fundamental iterations of MPA and SMA, the results of HMPA are contrasted with those obtained by more recent iterations of several algorithms. Various non-parametric tests and statistical analyses are conducted to compare objectively. The proposed technique's convergence property is assessed with the convergence curves' assistance, and their counterparts' properties are compared to the characteristics of the convergence curves. The HMPA demonstrates its ability to successfully manage the complex multi-modal and multi-dimensional optimization procedure required to determine the TDM parameters. It can choose the TDM parameters, which proves it. HMPA estimates the root-mean-square error (RMSE) and the lowest standard deviation, the least between the measured and estimated datasets. Both of these calculations are done by HMPA. The HMPA yields the minimum feasible difference between the estimated and actual datasets, preserving a high degree of consistency across several experiments carried out separately. Convergence curves of the recently proposed HMPA demonstrate that it is capable of lightning-fast response while also addressing the difficulty of TDM optimization. Some parameters have been determined to model the performance of PV modules under various light levels. It is essential to affect the performance of PV modules. Under partial shading, the recommended parameters for series string arrays and series–parallel arrays are also studied.

3.1.13 SMA-Firefly Algorithm (FA)

Feature selection approaches are needed to develop intelligent analytical tools for data preparation. These strategies are essential for advancing machine learning algorithms and improving their effectiveness. By using fewer features, feature selection seeks to achieve the maximum classification accuracy possible. A novel technique for feature selection is based on the FA and uses a modified SMA [35]. As a result of feature selection's superior capability to pinpoint the regions where an optimal solution may be found, it has been included in the created SMAFA to facilitate further investigation. It was done to make the most of the fact that FA is included in the SMAFA. It will increase convergence by improving the quality of the output as a whole. Twenty datasets are used to evaluate SMAFA, and the approach is compared in detail to some currently existing MH techniques. They employ two high-dimensional datasets associated with QSAR modeling to assess SMAFA's usefulness in further depth. The experimental results corroborated SMAFA's promising performance when measured across many metrics.

3.1.14 SMA- Particle Swarm Optimization (PSO)

The PSO and SMA have been hybridized to provide residents of the SMA access to their historically significant finest locations [36]. The enhanced hybridization would have the effect of reducing the impact of individuals' self-trajectories. As a result, the improvements may boost capacity, at least in terms of optimizing non-symmetric benchmark functions.

Figure 10 shows the advantages of combining SMA with other algorithms.

Figure 11 shows the disadvantages of combining SMA with other algorithms.

Table 1 shows the primary motivation of algorithms with SMA combination. Each algorithm has specific advantages, and they enhance SMA.

3.2 Improved SMA

In this section, the methods related to Improved are reviewed. These methods include Chaotic, Deep Learning, Fuzzy, Gaussian, Levy Flight, Machine Learning, Mutation, Nelder-Mead, OBL, Parallel, and Quantum. The goal of all these methods is to improve the SMA. Figure 12 shows the percentage of methods used for Improved SMA.

3.2.1 Chaotic

An intelligent approach for calculating the peak cutting force of conical picks is proposed [39], which is based on random forests (RF) and chaos-based support vector machines (CSVA) [39]. Chaos algorithms, ergodicity, and unpredictability are used to strategically establish the CSVM starting point. It allows for the formation of a CSVM. The RF hyperparameters are then modified using the SMA and CSVM, and the mean square error is selected as the fitness function. Ultimately, the CSVM is utilized to determine the best solution to the issue. Findings indicated that Sinusoidal map optimized SMA (SSMA), Logistic map optimized

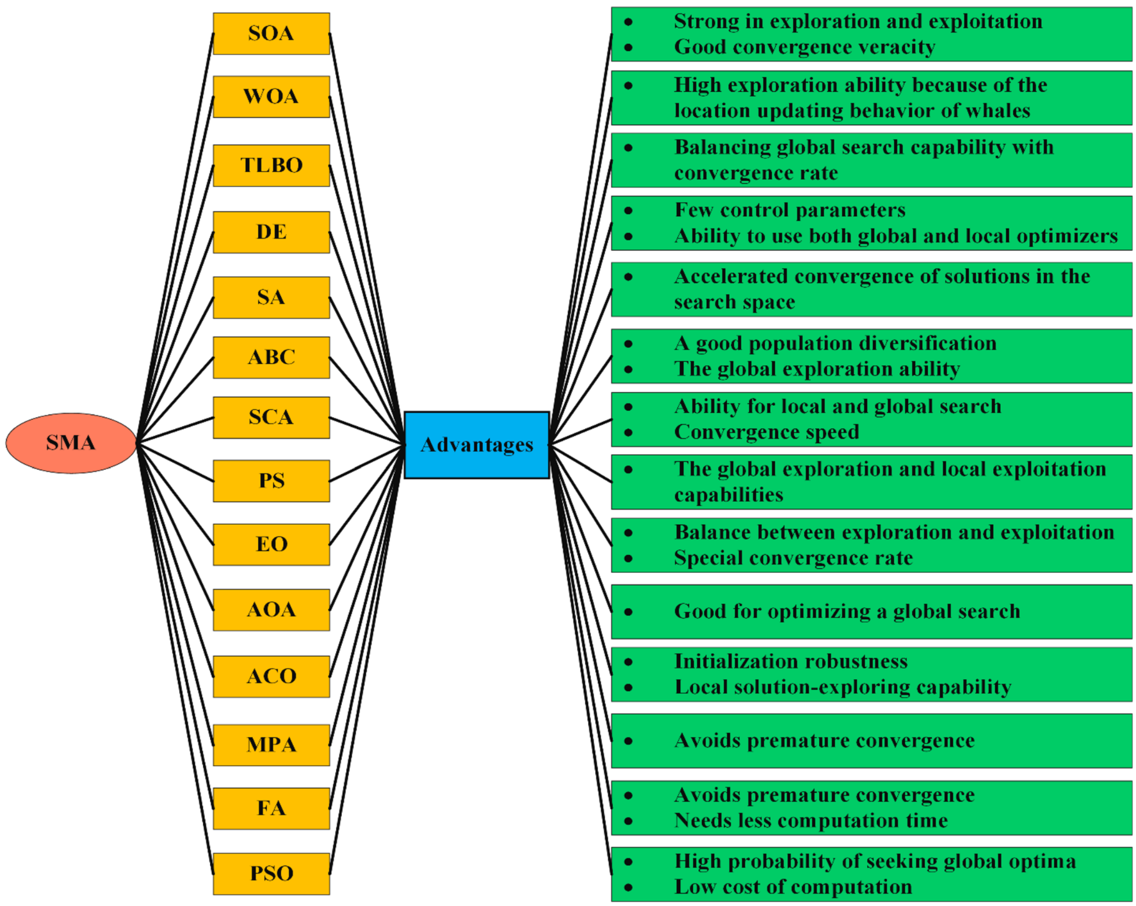


Fig. 10 Advantages of combining SMA with different algorithms

SMA (LSMA), and Sine map optimized SMA (SINSMA) had improved convergence ability and accuracy compared to the standard SMA. These results were found in contrast to the standard SMA. The PCF prediction performance of the three aproches is significantly enhanced compared to theoretical formulae and traditional machine methods.

An optimum load-shedding strategy that hybrids chaotic self-organizing map analysis (CSMA) with sinusoidal mapping has been presented to realize improved efficiency [40]. The assessment used a restricted function, a static voltage stability margin (VSM) index, and the total residual load after load shedding. In MATLAB, three islanding scenarios of IEEE 33 bus and IEEE 69 bus radial distribution systems were utilized to test the proposed load-shedding technique. The recently developed Backtrack Search Algorithm (BSA) outperformed SMA. CSMA outperforms SMA and BSA in every test system's residual load and voltage stability margin index values. For wind turbines situated in high-altitude settings, a chaos-opposition-SMA (CO-SMA) has been proposed to lower the cost of energy (COE) [41]. The coefficient of efficiency model is built using rotor radius, rated power, and hub height. An enhanced variation of SMA based on a crossover-opposition strategy (COS) and chaotic search strategy (CSS) is developed. This improved form of SMA, known as CO-SMA, is suggested as a remedy to address the shortcomings of traditional SMA when handling non-linear problems. To begin, the COS was developed to expand the variety of possible solutions and, therefore, to boost exploratory inclinations. CSS is added to the fundamental SMA to increase exploitative powers and prevent early convergence. The design of high-altitude wind turbines proves CO-SMA. The influence of the COE model's optimized parameters is shown using the Taguchi method. The effect of uncertainty based on the fuzziness scheme of wind resource data is also examined to create an appropriate solution for seasonal, meteorological, and topographic variations. The CO-SMA algorithm shows a higher rate of convergence in comparison to the other methods.

An adaptive SMA, or ASMA, has been created as a technique of optimization that is both resilient and exact [42]. In combination with the ASMA, the following five upgrades are recommended for use: (1) An appropriate method is implemented to allow for the selectively adapted selection of the SMA's control parameters. (2) Trigonometric

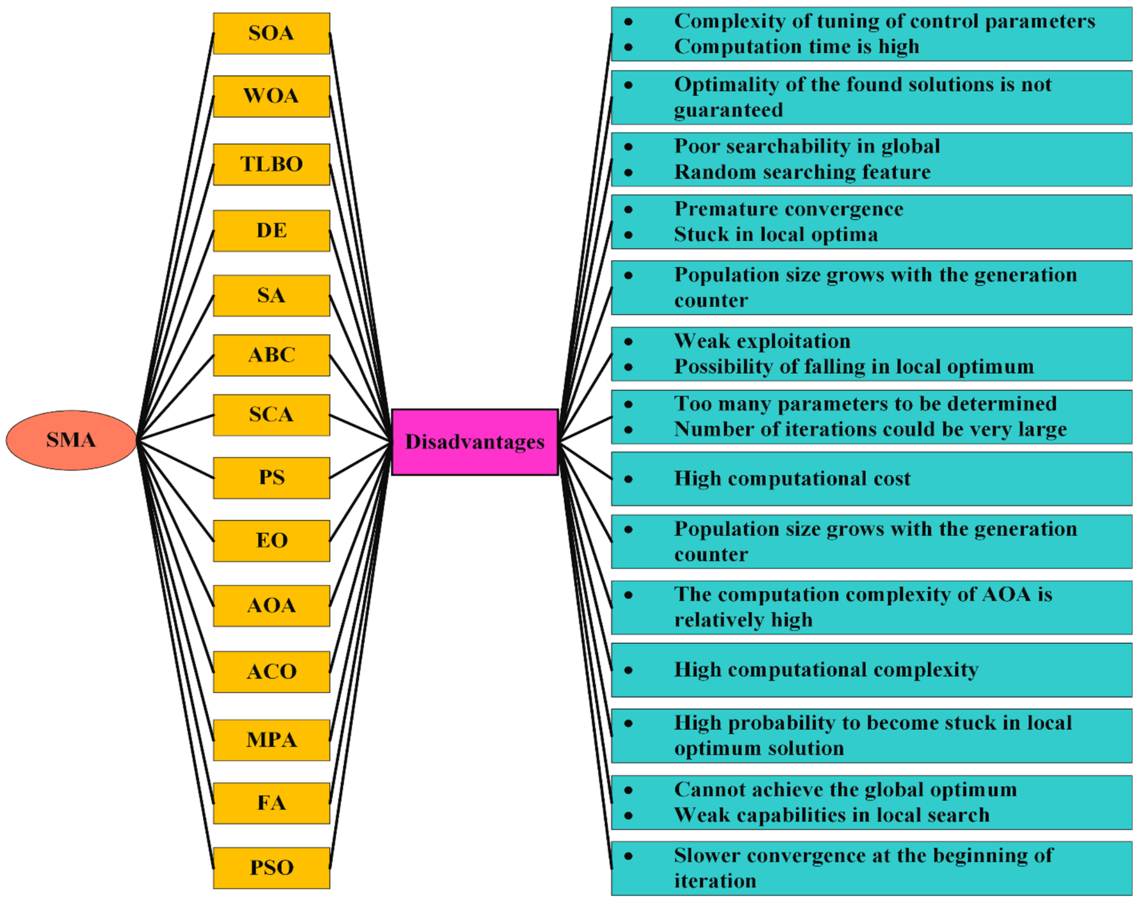


Fig. 11 Disadvantages of combining SMA with different algorithms

and double-based best mutations are introduced to improve global and local search. (3) An exit plan for the immediate area is presented. (4) The ideal solution has been improved using an OBL operator. (5) An exit plan for the immediate area is presented. ASMA identifies the optimal PV model parameters. After that, the models are put through a series of tests in which eight distinct optimization strategies are applied. The ASMA's competitiveness in accuracy and convergence speed is well-documented. The findings show that the ASMA performs exceptionally well in comparison to other systems in this regard. A multi-strategy enhanced SMA (MSMA) improves SMA's search stagnation, weak convergence speed, and poor transition ability from exploration to exploitation [43]. It is essential for optimization problems with a large dimension count and several potential optimal values at each location. The elite chaotic search strategy (ECSS), also known by its acronym, is used to improve an algorithm's skill of exploring in close vicinity to select people. This method is also known as ECSS. The SMA's z parameter is transformed into a chaotic non-linear convergence factor to improve the algorithm's capacity to transition between exploration and exploitation. It was done so that the algorithm could find more optimal solutions. A comparison is made between MSMA and nine other MAs, which may be classified as either classical or advanced, via the optimization of 12 benchmark functions. The comparison findings indicate that MSMA has higher performance in terms of the correctness of its solution, the speed at which it converges, and its durability.

As with other meta-heuristic optimization approaches, a significant issue in SMA is the slow convergence speed. Ten distinct chaotic maps have been implemented to make the SMA technique better. These chaotic maps provide chaotic values in place of random values, which SMA would otherwise produce. It is envisaged that employing chaotic maps would make it feasible to hasten the global convergence of SMA and keep it from becoming bogged down in its local solutions. This paper used 62 benchmark functions to apply the Chaotic SMA (CSMA). This approach has never before been proposed. These exam suites include the CEC2019 and CEC2017 and are unimodal, multi-modal, fixed dimension, etc. [44]. The application's outcomes have been compared to one another. Statistical analysis has been carried out using various meta-heuristic optimization techniques, such as PSO

Table 1 The primary motivation of algorithms with SMA combination

Refs.	Type of the problem	Hybrid	Motivation	Publisher	Year
[18]	Image segmentation	SMA-WOA	The WOA wants to strengthen and more evenly distribute the capacity of discovering and utilizing resources	ScienceDirect	2021
[19]	Optimization problems	SMA-TLBO	TLBO achieves a high convergence rate while maintaining an optimal balance between exploring and exploiting	Springer	2022
[20]	Numerical optimization and engineering design problems	SMA-TLBO	TLBO ultimately results in improved solutions and an investigation of the full scope of the issue	ScienceDirect	2022
[17]	Power flow controller	SMA-WOA	The WOA aims to strike a better balance between discovery and exploitation	Tandfonline	2022
[16]	Function Optimization	SMA-SOA	SOA maintains a quick convergence rate while striking the proper balance between discovery and exploitation	IEEE	2022
[21]	Global Optimization	SMA-DE	The DE algorithm uses an adaptive mutation technique to enhance convergence speed as rapidly as feasible	IEEE	2022
[22]	Image segmentation	SMA-DE	Increases convergence speed and searchability	ScienceDirect	2021
[23]	Global optimization problems	SMA-DE	DE ultimately results in improved solutions and an investigation of the full scope of the issue	ScienceDirect	2021
[24]	FOPID controller	SMA-SA	SA makes improvements to the proximity stage of the meal, leading to the discovery of the finest locations	Tandfonline	2022
[25]	Wrapper-based feature selection and global optimization	SMA-ABC	ABC is the path that leads to improving solutions and investigating the full scope of the issue	ScienceDirect	2022
[37]	Feature selection	SMA-ABC	ABC helps to increase the closeness stage of the meal, which results in the best spots being identified	ScienceDirect	2022
[26]	Image segmentation	SMA-ABC	In addition to having a high convergence rate, ABC maintains the optimal balance between exploring and exploiting the market	ScienceDirect	2022
[27]	Global optimization and real-world engineering problems	SMA-SCA	Increases both the capacity for seeking and the rate of convergence	ScienceDirect	2022
[38]	Optimal economic emission dispatch	SMA-SCA	The SCA process ultimately results in improved solutions and an investigation of the full scope of the issue	ScienceDirect	2021
[28]	Numerical and engineering design challenges	SMA-PS	ACO's sequential search decreases the efficiency of random point searches	Springer	2022
[29]	Engineering Design Problems	SMA-EO	Produces higher quality results in a shorter time and demonstrates rapid convergence	Springer	2022
[30]	Multi-level thresholding	SMA-EO	EO improves the proximity stage of the food, and the best points are found	ScienceDirect	2021
[31]	Global optimization and conventional design problem	SMA-AOA	AOA helps to increase the closeness stage of the meal, which leads to the discovery of the finest spots	Springer	2022
[32]	TSP	SMA-ACO	ACO sequentially explores the search space, which degrades the quality of the random search of points	Springer	2021
[33]	Solving Traveling SalISMAn Problem	SMA-ACO	ACO looks at the search space one step at a time, which makes the random search of points less effective	IEEE	2020
[34]	Photovoltaic system	SMA-MPA	Increases convergence speed and searchability	ScienceDirect	2021
[35]	Feature selection	SMA-FA	FA leads to strengthening solutions and exploring the entire problem space	Springer	2021
[36]	Function Optimization	SMA-PSO	PSO makes it easier to find the optimal places, enhancing the meal's proximity stage	IEEE	2020

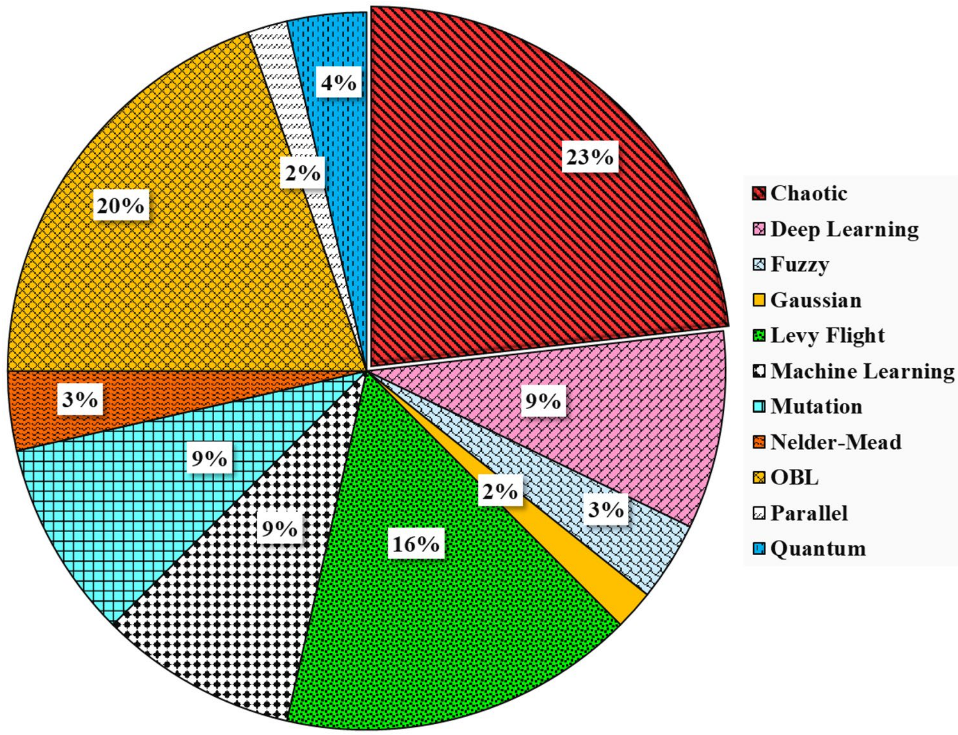


Fig. 12 Percentage of methods used for Improved SMA

and the differential evolution algorithm, GWO and WOA. In addition, statistical comparisons and analyses were carried out on the CSMA technique in the context of the CEC 2017 test suite. This approach contrasted with the SMA, the WOA, the GWO, the HHO, the Archimedes optimization, and the COOT algorithm. In addition, CSMA has been put through its paces in three specific real-world engineering problems. CSMA delivered more effective solutions than other classic SMA techniques in 62 benchmark functions and real-world engineering design issues. These findings are based on the results of the experiments that were conducted. Figure 13 presents an overview of the CSMA's flowchart.

Within a set of predefined parameters, the economic load dispatch (ELD) problem seeks to achieve an ideal allocation of the total power demand among the available power suppliers. The situation may be handled by scheduling the producing units of a power plant to serve the load demand at the lowest possible generation cost while meeting various equality and inequality criteria. Getting global optimum points is problematic since a non-linear objective function is involved, and there is a comprehensive search domain to review. The SMA is a relatively new idea recently introduced to handle complex challenges. The pace at which it converges and the capacity to identify optimum solutions on a global scale are both adequate. It is the first time that a chaotic number-based SMA (CSMA) has been proposed for ELD difficulties, which is recommended in this study [45]. To evaluate how well the suggested method performs compared to other methods such as SMA, SSA, MFO, GWO, biogeography-based optimizer (BBO), GOA, and MVO on ELD issues. Five test cases have been evaluated, each with distinct power demand. The findings of the experiments demonstrated that the suggested algorithm successfully lowered the overall generating cost. The results of all test scenarios that support the usefulness of chaotic sequences employed in the proposed study show that CSMA performed better than SMA. Three statistical tests have also been run to validate the suggested strategy's feasibility in the current market.

An improved version of SMA that was given the name CNMSMA [46] incorporated the Nelder-Mead simplex technique with the chaotic map. Chaotic maps are used instead of random numbers to enhance the exploration patterns. The Nelder-Mead simplex is also used to improve the algorithm's capacity for intensification. CSMA delivered more effective solutions than other classic SMA techniques in 62 benchmark functions and real-world engineering design issues. These models are ST40, SM55, and KC200GT, respectively. CSMA delivered more effective solutions than other classic SMA techniques in 62 benchmark functions and real-world engineering design issues. In addition, whether the circumstances include inadequate irradiance or excessive temperatures, CNMSMA continues to exhibit good strength and maintains its accuracy without fail.

As a consequence of this, the suggested method has the potential to serve as a dependable and well-developed instrument for the identification of critical photovoltaic models' unknown parameters. A multi-strategy upgraded variant of

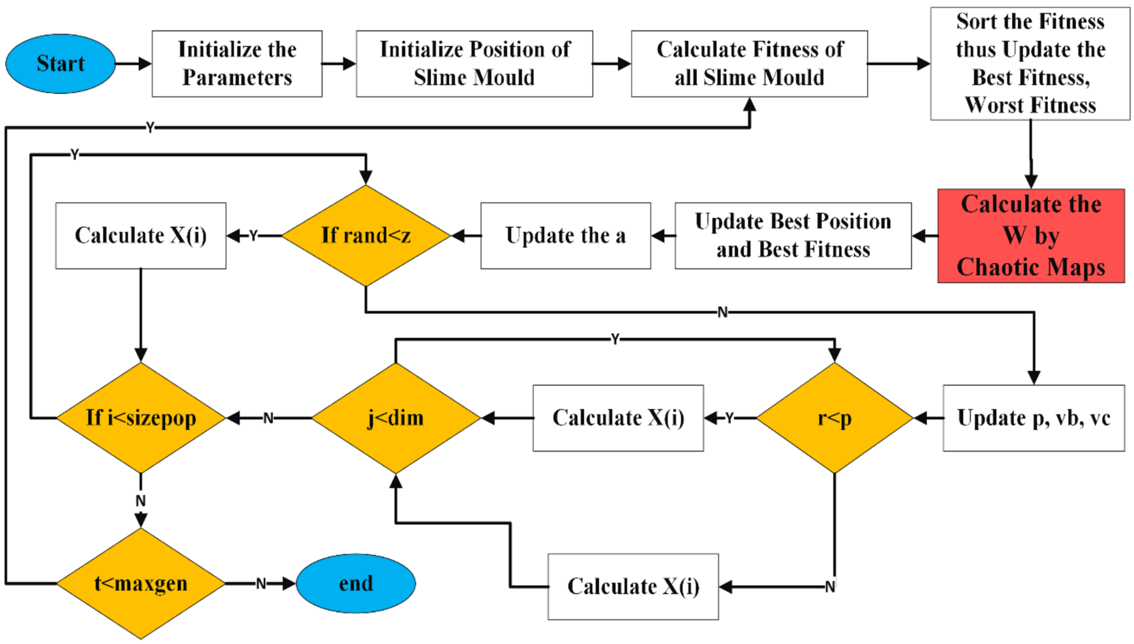


Fig. 13 Flowchart of the CSMA

SMA dubbed ISMA has been presented to solve the deficiencies of SMA [47]. The three enhanced techniques are the chaotic initialization strategy (CIS), the orthogonal learning strategy (OLS), and the boundary reset approach. In the early stages of ISMA, the CIS generates a demographically varied beginning population. It enhances the algorithm's output quality and the rate at which it converges. The OLS is then used to uncover vital details about the best answers and offer a likely search route. The CIS is used in the earliest stages of ISMA to create a diverse starting population. It enhances the algorithm's output quality and the rate at which it converges. The OLS is then used to uncover vital details about the best answers and offer a likely search route. It improves the capacity of the local search as well as the convergence rate. ISMA comprises three distinct approaches, each of which has contributed significantly to the overall improved performance of the core SMA.

There is a suggestion for an enhanced variation of SMA called MSMA [48]. A chaotic antagonistic learning approach is used to increase population diversity. Two adaptive parameter control algorithms are presented to strike a balance between exploitation and exploration. SMA uses a spiral search technique to avoid the disadvantages of having a local optimum. In addition to the ten fixed-dimensional test functions, 13 multi-dimensional test functions are used to demonstrate MSMA's superiority. The capability of MSMA to offer answers to actual optimization problems is also confirmed using two engineering optimization challenges. A brand-new chaotic algorithm that combines the fundamental SMA with a sinusoidal chaotic function has been developed and published in [49] to make the exploitation phase of the SMA even more effective. The produced chaotic SMA (CSMA) is used for ten transdisciplinary design problems and 23 standard test functions. The outcomes of various newly developed and well-known classical optimizers have been contrasted with those of CSMA. It was done to determine whether or not the suggested method is sound. According to the statistical analysis findings, a chaotic approach seems to make it easier for SMA to deliver superior performance in terms of solution correctness. The simulation demonstrated that the recently created chaotic algorithm surpasses all benchmark functions and engineering design challenges across many disciplines while obtaining great convergence.

It has been suggested that the SMA might be enhanced by using a piecewise map [50]. Three benchmark functions were used in simulation experiments, including multi-modal and unimodal benchmark functions with troughs in their three-dimensional profiles. The research findings suggested that the improved SMA with a piecewise map will function more effectively than the SMA. The proper chaos improvement is to map chaotic random numbers to the random numbers in the Gauss distribution. The K-means clustering method (KMCM) and chaotic SMA (CSMA) are used in a reported SVR-based prediction system [51]. Eight separate high and low-dimensional benchmark datasets are used to measure the forecast accuracy, stability performance, and processing complexity. This technique aims to obtain the correct critical parameters for KMCM and CSMA. The method that has been developed achieves the highest possible (joint best) prediction accuracy on six different datasets and generates the steadiest output on three of those datasets. The results showed that the SVR's parameters could be adjusted using the described approach. The integration of KMCM, CSMA, and SVR has been done with skill, and the outcomes have been promising. The suggested method displays excellent prediction accuracy and computing complexity, even though the stability performance is not very impressive. The CSMA provided evidence that the proposed method had enormous promise in prediction.

Figure 14 shows the most critical chaotic goals in SMA.

3.2.2 Deep Learning

Optical coherence tomography, often known as OCT, is a method of imaging that captures pictures of the retina in slices with a high resolution. The examination and interpretation of the OCT pictures by specialists take some time [52]. Experts must use the chances provided by technological advancement to improve this procedure's effectiveness and accuracy. This study made use of three datasets. Dataset #1 includes a variety of optical coherence tomography (OCT) image types, including images of drusen, normal eyes, diabetic macular edema (DME), and choroidal neovascularization (CNV) (UCSD dataset). Dataset2 (the Duke Dataset) and Dataset 3 comprise OCT images from patients with AMD, DME, and normal eyes. It has been suggested that a hybrid technique based on artificial intelligence may be used to detect retinal diseases.

The proposed ultra-short-term wind power forecast technique consists of PSO-variational mode decomposition (PVMD), deep extreme learning machine (DELM), and improved SMA (ISMA) for elite OBL strategy (EOBL) [53]. The first stage in developing the PVMD approach involves using the PSO to optimize the variational mode decomposition's (VMD) two fundamental parameters. The rolling time series is what researchers use to investigate the PVMD's stable sub-sequences, which are derived from the original wind power data. The DELM input weights and thresholds are then adjusted using the ISMA, followed by the construction of the DELM predictive model. The EOBL is then employed to boost the Slime Mould population's variety and quality of life, increasing the SMA's global optimization performance, convergence accuracy, and the DELM model's prediction precision. Finally, the prediction components are superimposed over one another using the DELM that has been improved using the elite OBL-SMI. This research illustrates the effectiveness of the suggested model blended forecasting model, which offers a distinctive approach to ultra-short-term wind power prediction, by analyzing the impacts of other forecasting models with the assessment of computation instances.

The primary o bjective is to identify AML early on using morphological pictures. The suggested method identifies AML by passing it through four significant steps [54]. During the pre-processing step, any necessary picture adjustments are made. The nucleus and the cell mask are broken into their respective components in the segmentation process. When a person is infected with AML, the middle will take on an asymmetrical form, and its texture will be different. The classifier takes as its input the features that were obtained via the process of feature extraction. A hybrid convolutional bidirectional long short-term memory (LSTM)-based recurrent neural network is used for the classification. Although numerous optimization algorithms have been proposed to solve various segmentation problems in the published research, the SMA is used because it can achieve a more optimal classified result. Even though the literature

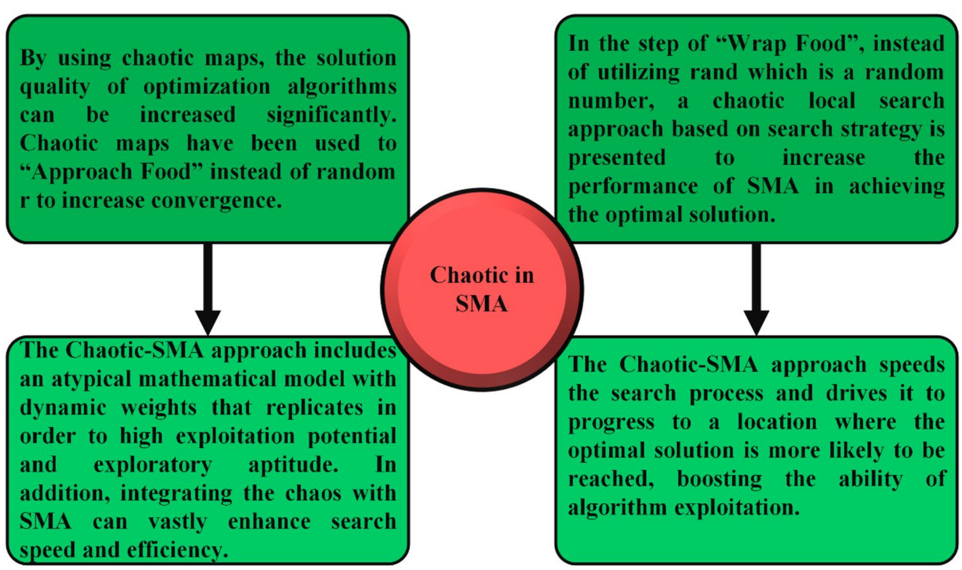


Fig. 14 The most critical chaotic goals in SMA

has presented several solutions to these problems [54], it is the case even though there are many different segmentation problems. The data sets from the Munich University Hospital were utilized to diagnose AML. It implies that the recommended method is superior to currently used optimization algorithms.

Fuzzy maps balance the relationship between the SMA's exploration and exploitation stages [55]. Twenty-three industry-standard mathematical optimization functions were utilized as benchmarks to determine how effective the built fuzzy SMA (FSMA) was. After that, they put the DCNN–ELM–FSMA algorithm through its paces using three different experimental sonar datasets to evaluate how well it deals with high-dimensional data. They compare the FSMA algorithm to the optimization algorithms regarding detection accuracy, entrapment in local minima, and convergence rate. It allows us to conduct a complete examination. The findings demonstrated that the recommended strategy outperformed the best benchmark model by an average of 2.11% in detecting underwater anomaly targets. The issue of low prediction accuracy and poor generalization capacity of the neural network in the prediction of the remaining usable life (RUL) of bearing was addressed through the presentation of a prediction method that resulted from the hybridization of SMA and Long Short-Term Memory (LSTM) [56]. It was done to resolve the problem. Through the use of the SMA's built-in capability for dynamic search, the LSTM's hyperparameters were automatically tuned. The SMA-LSTM model was used to calculate the bearing's RUL. SMA outperforms the genetic algorithm and the GWO in their respective optimization impacts. The SMA-LSTM model outperforms the SMA-SVR and SMA-BP models in bearing RUL prediction, proving the viability of the suggested approach.

3.2.3 Fuzzy

An enhanced and current version of the adaptive neuro-fuzzy inference system (ANFIS) was utilized in developing a time series forecasting model for oil production [57]. They used an optimization process known as the SMA that allows this model to be improved. The proposed model, known as ANFIS-SMAOLB, is assessed using various oil production data obtained from oilfields located in the *Masila* oilfield in Yemen and the *Tahe* oilfield in China. In addition, the assessment of this model is carried out by making thorough comparisons to several different methodologies and using several other evaluation metrics. The findings determined that the created ANFIS-SMAOLB had a high capability as an effective time series forecasting model demonstrating considerable performance. The SMA provides an overview of the optimum tuning of fuzzy controllers [58]. In the first section, they will talk about the architectures of low-cost proportional-integral (PI) and proportional-integral-derivative fuzzy controllers in their Mamdani and $Takagi - Sugeno$ forms. These are two variants of the same fuzzy controller. In the second half, the operating principles of current nature-inspired optimization algorithms, including GWO, WOA, SMA, hybrid PSO–gravitational search algorithm (PSOGSA), and hybrid Grey Wolf Optimizer–PSO (GWOPSO) algorithm, are discussed. These methods include: This section introduces the information feedback model F1 used in these algorithms. This model ultimately results in the GWOF1, WOAF1, SMAF1, PSOGSAF1, and GWOPSOF1 algorithms. In the third and final section, these algorithms inspired by nature are used for the optimum tuning of $Takagi - Sugeno$ PI-fuzzy controllers for nonlinear servo systems. The purpose is to minimize the fitness functions, which are the total absolute errors multiplied by times. When compared to GWO and WOA, SMA has shown superior performance.

3.2.4 Gaussian

The primary objective is to enhance the optimization capabilities of the SMA by combining the newly developed Gaussian kernel probability method for movement strategy [59]. These two steps lessen the likelihood that MGSMA will become trapped in a local optimum, and the rate of convergence will be slowed down due to the delay. Second, they construct a unique multi-level image segmentation (MLIS) model based on the proposed MGSMA by combining non-local mean, 2D entropy, and other methods. The purpose of this is to construct the model. To prove how well MGSMA works, they run a battery of tests against different algorithms based on the IEEE CEC2014. The MGSMA swarm intelligence approach may escape the local optimum, according to tests, and the convergence process does not purposefully diverge. They evaluate the MLIS technique based on the MGSMA and compare it to eight similar approaches at low and high thresholding levels, providing supporting experimental evidence where necessary. Using this comparison, they want to show that the MLIS technique based on the MGSMA may provide reliable segmentation results. Therefore, the MGSMA-based MLIS technique may result in high-quality segmentation results, and MGSMA is an optimization strategy based on swarm intelligence that offers excellent performance.

3.2.5 Levy Flight

The driving element of the optomechanically scanned system, the brushless direct current (BLDC) motor, whose positioning precision and speed stability are closely coupled, significantly contributes to the overall picture quality of the system. One of the control systems that see many usages is called active disturbance rejection control, or ADRC for short. It has powerful anti-interference capabilities, a quick reaction, and excellent resilience. The parameters of an upgraded ADRC are adjusted using an SMA based on a Levy flight operator (LF-SMA) [60]. The ADRC that has been proposed is stable, according to the Lyapunov stability theory. In the classic Slime Mold Analyzer (SMA), a Slime Mould propagation wave focused on a bio-oscillator is simulated by employing adaptive weights to offer both negative and positive feedback. The goal is to determine the most effective way to connect excellent exploration capacity and exploitation tendency with food. Despite this, SMA-like meta-heuristics often become stuck in local optima while attempting to solve many optimization issues. As a result, in the candidate selection phase, they used the Levy distribution instead of the more common uniform distribution to solve the challenge of finding the optimal local solution for the SMA algorithm. Using the advantages of the Lévy flight to overcome the challenge of locating the best local solution while enhancing the efficiency of the conventional SMA [61]. Twenty-three well-known benchmark test functions were utilized to gauge how well the proposed LSMA performed. The proposed LSMA's performance was contrasted with that of the traditional SMA. The "welded beam structure problem" is a well-known illustration of a classic engineering problem used to assess the success of the suggested LSMA approach. A technical issue involving the convergence curve and statistical performance evaluation has been researched.

A strategy for the distribution network that utilizes dynamic reconfiguration across many periods is proposed [62]. First, load monotonicity and amplitude change segment reconfiguration time. Reconfiguration time is determined using real load duration. The time-varying load distribution network is used to construct a multi-objective dynamic reconfiguration model. Active power loss, static voltage stability, and load balance are considered. The time-division strategy maximizes outcomes by dynamically adjusting the optimal period partition function. The optimum reactive power dispatch issue, often known as ORPD, is essential in determining a power system's economics and dependability. The approaches available for addressing the ORPD issue are inadequate regarding their accuracy and the amount of calculation time needed. The SMA's oscillation mode was inspired by how Slime Moulds seek food in the real world. However, there are situations where SMA fails to find the real solution and instead gets stuck at a sub-optimal solution. It results in early convergence and is detrimental to finding the global optimum solution. The ISMA, an improved variant of the SMA, has been proposed as a remedy for the ORPD problem [63]. It was shown that using this technology to solve a power system's ORPD problem is effective and reliable and offers benefits.

Image segmentation is a fundamental step in the pre-processing stage and a crucial part of image analysis. It suggests an improved SMA-based approach for image classification called entropy multi-threshold picture segmentation (DASMA). To improve the population's variety and provide variations a greater chance of avoiding slipping into local optima, the original SMA is given an injection of diffusion mechanism, often known as DM. After that, the LF is included to assist the algorithm in finding the best answer in a shorter time [64]. The efficacy of the new method is demonstrated by contrasting the suggested approach with several well-known methods using the Berkeley segmentation dataset and benchmark (BSD). The multi-level threshold segmentation approach based on DASMA has also successfully separated COPD-related segments from CT images (COPD). The tests' findings are examined using several picture quality criteria, demonstrating that the suggested approach works effectively. It indicates that it may aid medical experts in doing a qualitative and quantitative analysis of the lesion tissue, enhancing diagnostic accuracy and allowing for an effective treatment plan.

Because it has such a significant bearing on what comes after it in terms of image analysis, image segmentation is an elementary but necessary stage in the processing of images. Many studies have employed MAs to establish the threshold values since multi-level thresholding image segmentation is one of the most used strategies for segmenting images. An improved SMA version, ISMA, is presented for use in picture segmentation that incorporates global optimization and multilayer thresholding. The LF approach enhances the exploration capability shown by SMA [65]. Second, quasi-OBL, a type of learning, is used to improve exploitation skills and Maintain a balance between exploration and exploitation. After that, all 23 benchmark functions demonstrate the suggested work ISMA is much better. The least cross-entropy is employed as the fitness function, and the ISMA is used for multi-level thresholding picture segmentation. They compare them against established and cutting-edge computer vision methods utilizing the same eight black-and-white photographs as test benchmarks. The Wilcoxon rank-sum test is used to assess the effectiveness of the segmentation. The results of the experiments indicated that ISMA is superior to other algorithms and is capable of providing better levels of segmentation accuracy. In [66], the authors propose a unique method for choosing the unknowable components in proton exchange membrane fuel cells. By reaching the outstanding value of the model parameters, the main goal is to offer a workable method for decreasing the error between the empirical and estimated output voltages. It will be achieved by outlining the ideal model parameter valuation. The BSMA, often known as the balanced form of the SMA, is presented and verified. As a consequence, this demonstrates that the approach that was presented yields the best results compared to the others when it comes to model identification. In addition, to give a more in-depth study, the consistency of the approach that was recommended was tested under a variety of temperature and pressure circumstances. The results showed that the recommended strategy yields trustworthy outcomes regardless of the environment.

It is believed that a reliable model might be used to quickly diagnose COVID-19 by extracting high-level features from chest X-ray (CXR) images. This study intends explicitly to provide an optimization model for the diagnosis of COVID-19 based on adaptive Fuzzy C-means (AFCM), also known as AFCM-LSMA, and improved SMA based on the Lévy distribution. The best path for food connection has been proposed to be formed by the SMA optimizer adjusting weights while the algorithm is in oscillation mode and simulating the process of producing positive and negative feedback from the propagation wave. LSMA is a version of SMA that does a local search using LF as a permutation to provide various solutions that are different from the candidates currently running [67]. It paves the way for the technique to be used for CXR images to segment pulmonary regions. CXR images have been utilized in validating the outcomes of the AFCM-LSMA model compared to the impacts of other models. When solving global continuous optimization issues, SMA often becomes stuck in the optimal local state. A modified SMA version improves the strategy for the best overall result [68]. It is incorporated with LF direction to ensure that it takes the most effective routes possible when linking food sources with a high tendency for exploration. The results show that the proposed model obtains superior performance in 13 benchmark test functions and one examined engineering scenario regarding the computing cost and the solution.

3.2.6 Machine Learning

Having recurrent spontaneous abortions, also known as RSA, is a common atypical pregnancy that may have long-term psychological implications and can cause the entire family's tranquility to be disrupted. The occurrence of recurrent spontaneous abortion is another significant challenge that must be overcome to diagnose and treat RSA, which is made worse by thyroid disorders. The pathophysiology of RSA, as well as potential treatment strategies, are not yet fully understood. JASMA-SVM, also known as joint self-adaptive SMA and standard kernel learning support vector machine (SVM) with maximum-margin hyperplane theory, is an acronym for these two algorithms. This combination creates a framework that is detailed [69]. A supplementary management approach (MSMA) that considers several populations has been suggested. In addition, the authors of this study offer a prediction model known as MSMA-SVM [97], founded on the SVM and MSMA algorithm. The multi-population method is one such method. It enhances the system's precision while balancing the algorithm's exploration and exploitation capabilities. The proposed model further enhances the SVM's capacity for optimizing parameter tweaking and identifying compact feature subsets, allowing the acquisition of more optimal parameters and feature subsets. The next phase is putting the proposed MSMA through its paces with a battery of tests on the 30 benchmark functions created for the IEEE CEC 2017 conference. The experimental results demonstrated that the well-known MSMA outperforms the algorithms in most operations. The predictive power of the best SVM model was compared to that of several machine learning techniques. According to the results, the best SVM model outperformed the others regarding classification accuracy and performance consistency. Therefore, it is reasonable to assume that the best SVM model is a powerful tool that can produce reliable forecasts regarding the likelihood of a worker's continued employment. In clinical diagnosis, a practical, intelligent prediction model that can discriminate and classify COVID-19 infection severity has been described [70]. The system's backbone comprises an SVM model and a random forest optimized using an SMA. After using a random forest to determine which criteria were the most important, a support vector machine was trained with the help of support vector analysis (SMA). Experiments were conducted using COVID-19 data to compare RF-SMA-SVM to other popular machine-learning techniques. According to the findings of this investigation, the suggested RF-SMA-SVM enhances stability across four metrics and classification performance. It also eliminates the distinguishing characteristics that were once used to differentiate highly sick COVID-19 patients from those with less severe instances. Because of this, one may conclude that the RF-SMA-SVM model could provide a diagnostic strategy relevant to the clinical diagnosis of COVID-19 infection.

The regulation of speed is an essential function performed by BLDC motors. These motors find widespread use in high-end industrial applications such as robotics, aeronautics, disk drives, factory automation, consumer electronics, transportation, and military applications. To enable effective speed regulation of the BLDC motor while still satisfying the given parameters, a unique wavelet neural learning (WNL)-based type-2 fuzzy system controller has been constructed. This controller was developed. Simulation and analysis of the performance characteristics of a brushless direct current (BLDC) motor are carried out with the use of a wavelet neural learning-based type-2 fuzzy proportional–integral–derivative (PID) controller [71]. When the design features of the BLDC motor are taken into account, the simulation results demonstrate that the proposed speed controller is efficient and more effective than the contributions offered in the previous literature. It is difficult for water utilities to estimate urban water demand based on climatic indicators due to the uncertainty caused by unanticipated increases in water consumption due to stochastic climatic patterns. It was performed to prevent multicollinearity. Second, an artificial neural network (ANN) model was optimized with SMA (SMA-ANN) to forecast the stochastic signal of monthly urban water demand over the medium term [72]. It was used to make medium-term forecasts for the stochastic monthly sign of urban water demand. This approach yields believable findings in most instances. Local water management might benefit from a greater comprehension of operating the existing system and developing it to meet future demands.

3.2.7 Mutation Strategy

The high dimensionality and nonlinearity of the problem make it hard to locate a single answer that can be used everywhere; as a result, determining the appropriate policies for multiple hydropower reservoir systems may be difficult. Developing an optimization algorithm with high precision is necessary to optimize such a problematic solution correctly. A complex hydropower multiple reservoir prediction issue calls for a Multi-strategy SMA (MSMA), which will establish the appropriate operating rules for the system [73]. In conclusion, another beneficial outcome of this research was providing an instrument for optimizing numerous reservoir issues challenging hydropower. The use of technology for the parallel connection and operation of many stacks of solid-oxide fuel cells (SOFCs) A concept for a control system that would handle the process and sharing of parallel stacks in SOFCs is provided here. Realizing equal output voltages when each cell's current value varies is a technological problem related to a similar operation. It is one aspect of the whole challenge. To determine the operating characteristics of SOFC stacks that are run in parallel, an enhanced SMA known as an ISMA has been developed [74]. The effectiveness of the proposed system has been demonstrated through the use of digital simulations, which were run with the proper dynamic parameters under various operational conditions. The step-load adjustments (increase/decrease) under equal and unequal load sharing and emergent fault circumstances created by short-circuiting disruption and protection tripping are included in these potential outcomes. The simulated results revealed that the proposed approach and representation effectively enhance the system's dynamic performance that is being discussed, for instance, in a specific setting are effective.

Electrical models consisting of one, two, or three diodes may be used in the process of PV unit characterization. For the majority of simulation and analytical applications, including those that take place in steady-state and dynamic settings, a one-diode model (1-DM) is sufficient. This paradigm is applicable in both instances [75]. A new program employing the SMA and its enhanced version (IMSMA) is being considered. The performance of SMA/IMSMA is evaluated by demonstrating and analyzing two benchmarking test scenarios, which are common in the relevant research literature. This evaluation is followed by following debates and analyses. In addition, performance tests and comparisons with other competing algorithms are conducted to validate the cropped findings. It is done by demonstrating various scenarios under various settings using the model's optimal values for its parameters. It is possible to conclude that the validations, when taken along with the established results, demonstrate that the IMSMA can identify the unidentified 1-DM characteristics. The dimensionality reduction approach, also known as the FS, needs data processing since it is necessary to increase classification accuracy using the technique. It is possible to make the most of the SMA's potential by combining two different strategies: the restart strategy (RS) and the composite mutation strategy (CMS) [76]. Its acronym, CMSRSSMA, also refers to the enhanced SMA. This abbreviation stands for the CMS, RS, and improved SMA. CMS and RS are applied to prevent the population from exceeding their local maximum and improve the demographic makeup variety. This research evaluates the efficacy of the suggested CMSRSSMA using the CEC2017 benchmark function. The CMSRSSMA-SVM model is then provided as a solution for concurrently optimizing both the FS and the parameters. Fourteen different data sets taken from the data repository at UCI are used to evaluate how well the model performs. According to the findings of the tests, the suggested technique outperforms previous algorithms in terms of classification accuracy, the number of features, and the fitness value on the vast majority of the chosen datasets. It has been recommended that a brand new SMA application be developed to extract the optimal model parameters of solar PV panels [77]. Using the SMA yields exact and rapid ways of assessing the properties of solar cells. Utilizing adaptive weights allows for one-of-a-kind mathematical modeling of the optimization issue to be provided by the SMA stochastic optimization. In addition, the SMA effectively obtains the globally ideal values for the characteristics of the solar photovoltaic cell. It can handle the nonlinearity and multimodality that are characteristic of photovoltaic cells. The suggested procedure offers a standardized answer to the problem of accurately finding the parameters for various kinds of solar cell technology. This study extensively compares the proposed SMA and other approaches for extracting solar cell parameter sets already in use. The results indicate that the proposed SMA delivers more significant levels of performance and precision than the currently employed methods.

3.2.8 Nelder–Mead Simplex (NMS)

Since NMS [78] is an iterative method that possesses significant local search capabilities and provides a gradient-free optimization solution, it has found widespread application in the context of optimization challenges. NMS guarantees that each consecutive set of findings is better than the prior by utilizing an iterative procedure, which repeats the process. The objective is to build a simplex in a D-dimensional search field by choosing D + 1 vertices to generate a polyhedron. It will bring about the desired result. A simplex will arise as a consequence of this. After assigning a fitness value to each vertex of a simplex, the appropriate reflections, extensions, and contractions are carried out, which results in the formation of a new simplex polyhedron.

ISMA is an upgraded version of the SMA that has been offered as a technique to precisely and effectively extract the unknown features of the solar cell [79]. ISMA was developed as a direct successor to the SMA. The NMS mechanism ensures that the population will be dense and grow to bring it even closer to the sources of sustenance. It reduces the distance people need to travel to find food. ISMA exhibits exceptional strength in determining the unknown features of three commercial solar modules when those modules are subjected to various environmental circumstances. In conclusion, the Integrated System Modeling Approach (ISMA) that has been suggested is a method that is an approach that has the potential to be advantageous in the process of extracting the parameters of the photovoltaic models. The NMS search technique was used as a supporting framework to improve the SMA in the local search [80]. The SMA-NM is a newly developed hybrid approach that incorporates both the SMA and the NMS to achieve a higher level of diversification and intensification. Ultimately, this enhances the algorithm by adjusting the ratio of exploration to exploitation. It was tested against the test functions in several different ways, including exploitation, exploration, statistical significance, and ranking. These evaluations demonstrate that the suggested method is superior for tackling optimization issues.

3.2.9 OBL

To modify the parameters of a model referred to as proportional integral derivative plus second order derivative (PIDD2), a one-of-a-kind improved SMA that will hereafter be referred to as ISMA has been provided [81]. The proposed method employs a variant of OBL and Nelder-Mead simplex search to enhance the performance of standard SMA during exploration and exploitation. As a performance indicator, the DC motor system with a FOPID controller and the AVR system with a PIDD2 controller employs a time domain objective function. Specifications for the function's time response range from the time it takes to reach its steady state to the time it takes to exceed its target value and settle down. Simulations assess the unique methods proposed for usage with both systems in the time domain, the frequency domain, and statistical testing. The improved method has been shown to perform better in several tests. Also, additional tactics readily available and proven beneficial in the literature are contrasted with the proposed methods for both systems to determine which is more successful. After a comprehensive comparison, the recommended technique for managing the speed of DC motors and automated voltage regulator (AVR) systems was shown to be superior to the currently considered to be state-of-the-art. It is demonstrated by the fact that the advised technique yielded excellent outcomes.

An enhanced SMA known as ISMA has been suggested and used for the problem of optimizing the size of truss structures within the restrictions of their natural frequencies [82]. It has been discovered that traditional SMA suffers from delayed convergence and frequently converges to solutions that are not optimal, particularly for problems involving large-scale optimization. It is particularly problematic because large-scale optimization typically involves many variables. The proposed ISMA improves upon the standard SMA in two significant ways. During the ISMA's replacement phase, (1) an elitist strategy is adopted instead of the traditional SMA's generational replacement tactic. It happens because replacing workers based on their age is no longer practical. Faster convergence of the ISMA is the goal of the elite-favored strategy. (2) A traditional SMA's exploration phase is fine-tuned to ensure a comprehensive examination of the search space. An adjustment has been suggested for the ISMA to circumvent the conventional SMA issue, which is that it converges too rapidly. In conclusion, three large-scale, natural-frequency-restricted benchmark dome trusses demonstrate the efficacy and robustness of the ISMA. The numerical data showed that the ISMA outperformed the standard SMA and was on par with or better than the performance of other published methods. An evolutionary TS-AOSMA technique [83] is offered to reduce the computing cost of TS-based multi-class segmentation. An adaptive OBL-based SMA (AOSMA) optimizer is used in this research. The suggested method is tested using T2-weighted brain MR imaging slices taken from the entire brain atlas dataset maintained by the Harvard Medical School. The proposed system produced superior quantitative and qualitative results when contrasted with the most recent optimization algorithms based on shared entropy.

One of these issues is the difficulty in striking an appropriate balance between the exploration and exploitation stages, which may result in the algorithm becoming stuck in a state referred to as local optimality. This study presents a new SMA form, dubbed the MSMA. It is derived by hybridizing the SMA with a modified version of the OBL and Orthogonal learning (OL) strategies [84]. An intelligent defect detection method has been proposed using the extreme learning machine (ELM) model [85]. This method is intended to discover flaws in taper roller bearings. The optimum parameters of ELM are explored by comparing them to those of an adversarial slime SMA. Tuned ELM parameters are utilized to construct the classification model. The validity of the constructed ELM model is evaluated using the test data. The accuracy throughout training and testing is 100%, and the amount of time spent computing is only 0.0023 s. An upgraded quasi-reflection-based learning technique of SMA called QRSMA has been presented [86]. It is comprised of two significant subcomponents. The tent map has been established to extend the demographic reach of the population in the first phase. Second, to strengthen the exploitation capability, a method of learning based on quasi-reflection is described in this research. In the end, the performance of QRSMA is assessed using a variety of tests and compared to various optimization algorithms. Results demonstrated that the QRSMA performed much better than other algorithms regarding convergence quality and exploring capacity.

An enhanced version of the improved SMA with the OBL technique (ISMA) has been developed to overcome these limitations [87]. OBL maximizes our ability to explore the world while reducing the likelihood of accidental convergence. It has been suggested that an enhanced SMA, also known as an ISMA, be used to predict the water demand in Nanchang City between 2004 and 2019 [88]. The OBL strategy and the elite chaotic seeking technique are used in the beginning stages of elevating the SMA. The ISMA performed better on 23 benchmark test functions than any other intelligent optimization approach currently available, with advantages including fast convergence, high convergence accuracy, and increased durability. To do this, they compared our findings to those of the ISMA. Second, four distinct estimating models are created utilizing the information on past water use and the economic makeup of Nanchang. Examples of these models include linear, exponential, logarithmic, and mixed ones. First, the estimating models are optimized by defining their parameters using the ISMA, and then the models are put to the test. Simulation findings showed that all four models had room to increase their predictive precision. Prediction accuracy may exceed 97.705% if the proposed ISMA is used in the hybrid prediction model. In conclusion, a forecast of Nanchang's water use between 2020 and 2024 has been produced.

An enhanced version of SMA, known as OBLSMAL [89], is proposed as a solution to alleviate the conventional method's primary flaws. The traditional SMA has had two more search techniques added to it. To begin, OBL increases the speed of convergence achieved by the SMA. Second, low-frequency distribution (LFD) is used to optimize preliminary and final exploitation searches. In the second scenario, the OBL process will be executed if the rand is less than 0.5, and the LF process would be achieved otherwise. Either OBL or LF may be employed, depending on the specifics. The standard SMA's searchability and convergence behavior are vastly enhanced by combining two distinct search techniques. The results of the experiments show that significant improvements have been made, not only to the search methods but also to the convergence behavior of SMA. The results obtained using the suggested OBLSMAL optimization approach are encouraging, and its performance is superior to that obtained using other well-known optimization methods.

The flowcharts for OBL and LF in SMA are shown in Fig. 15.

The SMA picks the future displacement and direction of the best search agents based on a random drawing. It severely restricts both its exploitation and exploration capabilities. To find a solution to this issue, they are looking at an adaptive method for determining whether or not OBL will be implemented [90]. The OBL is used at times to boost further the exploration that is being done. In addition, it maximizes exploitation by replacing a random search agent with the most effective one in the position update. An adaptive opposition SMA is the name of the approach that has been proposed (AOSMA). AOSMA is analyzed qualitatively and quantitatively across 29 different checkpoints. The IEEE CEC 2014 test suite includes the test above functions, which span 23 more conventional test functions and six more contemporary composition functions. Modern optimization tactics and methods are used to examine the data. According to the results of this research, it is abundantly evident that AOSMA achieves superior performance compared to alternative optimization strategies. The Wilcoxon rank-sum test is utilized in the process of analyzing the AOSMA. The AOSMA approach would help optimize functions to answer practical engineering problems.

To improve the performance of the optimization algorithm, a new method of enhancing SMA, known as ISMA, has been proposed [91]. Modifying the weight coefficient and coordinating the use of the reverse learning approach in the expression of agents updating their positions are both required steps in this method. The performance of the proposed method is evaluated based on the results of many carefully selected benchmark functions and the effective utilization of cascade reservoirs. The findings of the suggested solution produced higher performance than the various competing algorithms when compared to the results produced by the proposed approach and the multiple algorithms applied to the case scenarios. Figure 16 shows the most critical positive goals by levy flight in SMA. LF leads to the amplification and discovery of the global optimum in SMA.

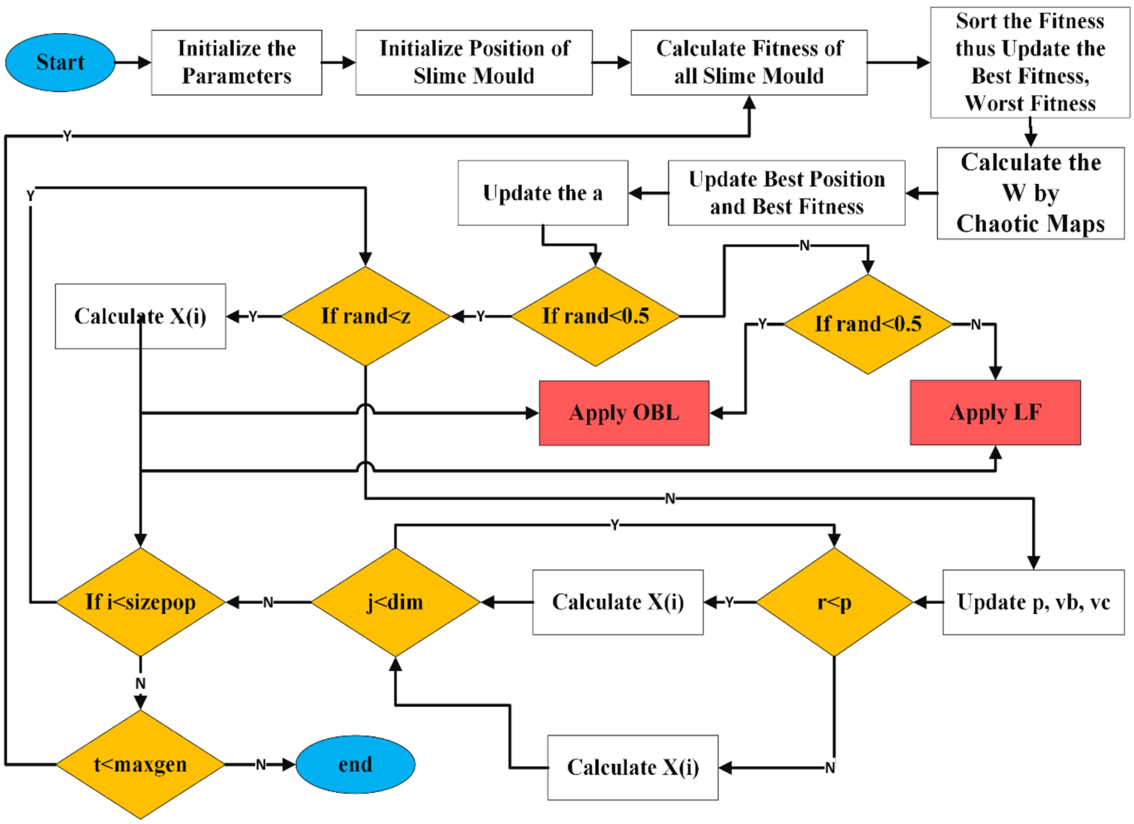


Fig. 15 Flowchart of OBL and LF in SMA [89]

3.2.10 Parallel

This research proposes a solution for the problem of distribution network reconfiguration (DNR) with distributed generation (DG) that is based on the parallel SMA (PSMA) [92]. The active power loss, voltage stability index, load balance degree, and switching operation durations are the four goals of optimization that are combined using the analytic hierarchy process(AHP). The DNR problem models come in a variety of forms. The next thing that has to be done is to propose the PSMA using the grouping communication approach and the inertia weight. It has been determined that a CEC2014 test suite was successful in validating the performance of PSMA. On the PSMA, tests have been done for the six various kinds of DG comprising the IEEE-33 bus distribution network functioning as the case study. These tests were run as part of the case study. The trials indicate that the PSMA is superior to the other three algorithms in terms of its ability to address the DNR issue with DG reasonably and accurately. The findings also suggest that the extent to which DG will affect the DNR issue will vary based on the kind of DG and the access location. It is shown by the fact that the degree to which DG will affect the DNR issue has been determined.

3.2.11 Quantum

A hybrid optimization has been devised based on the two independence requirements of Blind Source Separation (BSS) to create blind source separation that is both more effective and more resilient. Quantum SMA (QSMA) is suggested by the hybridization of quantum computing theory and SMA, and QSMA is utilized to solve the hybrid optimization algorithm function [93]. BSS based on QSMA is the name given to the strategy offered as an approach (QSMA-BSS). The simulation results show that QSMA-BSS is superior to the previously employed methods in the industry. QSMA-BSS boasts a more extensive application range, steady performance, and accuracy than the BSS techniques.

As the algorithm iterates, the problem's difficulty increases, and the solution may depart from the global optimum. The convergence rate will become more gradual. Given the term WQSMA, a superior SMA is presented as a solution to rectify the abovementioned flaws [94]. The quantum rotation gate and an operation based on the water cycle are utilized for the first time to reinforce the original SMA. Incorporating these processes has given the exploration and exploitation inclinations inside the algorithm equal weight. It also does a more in-depth analysis of the surrounding area

Fig. 16 The most critical positive goals by LF in SMA

as it expands the search field for each population. Due to the slight angle at which it rotates, the quantum rotation gate can effectively use the approach and conduct thorough searches inside the constrained space. The water cycle's mechanism might aid the algorithm in its quest to find the optimal solution among all the possibilities. The verification procedure is then used for three other engineering challenges to highlight the value of WQSMA in real-world settings. The experimental findings demonstrate the efficacy of WQSMA in resolving comparable real-world scenarios.

3.3 Variants of SMA

This section investigates the Variants of SMA using the Binary SMA and the Multi-Objective SMA methodologies. Figure 17 shows the percentage of Variants of SMA based on two approaches.

3.3.1 Binary

An improved binary SMA has been presented to resolve the 0–1 knapsack issue at various sizes [95]. Eight distinct transfer functions have been employed and analyzed in the binary SMA that is now being given. They use the Gaussian and Bitwise mutation operators to improve the suggested binary SMA's overall functionality. The results pointed to the validity of the proposed approaches being better.

A new binary variant of the SMA known as NBSMA has been developed [96] to overcome the spectrum allocation problem. The BSMA technique has been modified to include a transfer function in the comparison. The top two transfer functions, an S-shaped transfer function, and a V-shaped transfer function, are compared to the presented transfer function. The results of the experiments indicate that the newly integrated transfer function has a significantly more substantial influence than was previously thought. This research recommends a strategy for agents with poor search performance that involves adding new, unselected variables to existing solutions to improve them. If NBSMA is combined with this method, the resulting algorithm, called AUBSMA, may achieve even better performance than NBSMA alone. Compared to other optimization algorithms like BSMA, mutation and attacking-feeding strategy (FMB-SMA), BSMA with attacking-feeding approach (AFBSMA),

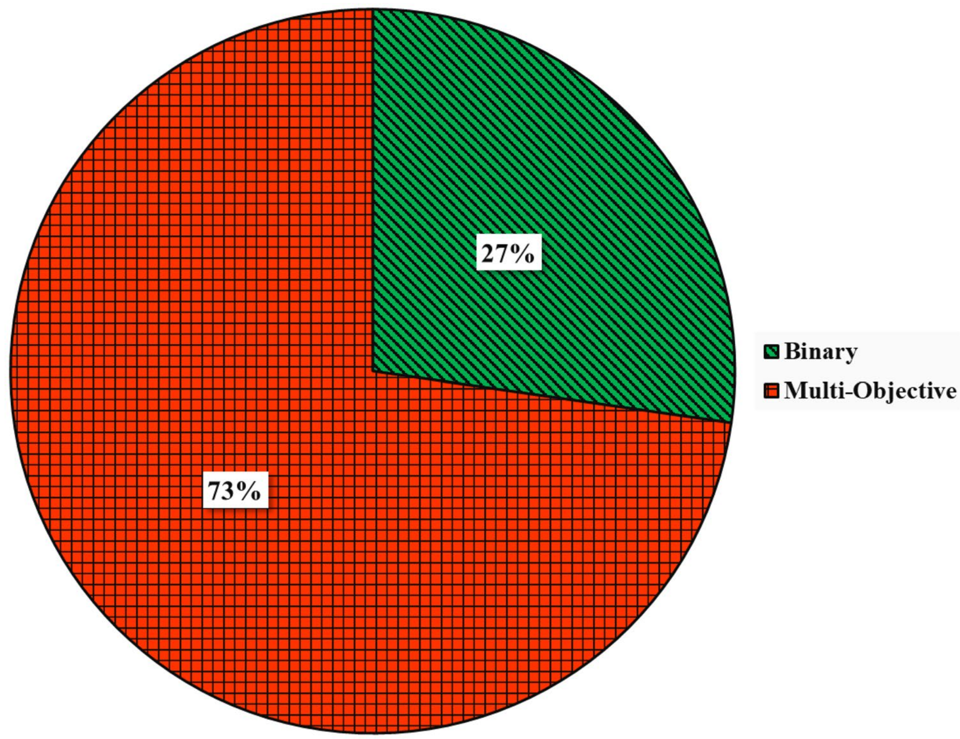


Fig. 17 Variants of SMA percentage chart based on two different methods

Table 2 Specifications regarding the transfer functions

Abbreviation	Transfer function
S1	$S1(x) = \frac{1}{1+e^{-2x}}$
S2	$S2(x) = \frac{1}{1+e^{-x}}$
S3	$S3(x) = \frac{1}{1+e^{\frac{-x}{2}}}$
S4	$S4(x) = \frac{1}{1+e^{\frac{-x}{3}}}$
V1	$V1(x) = \left\lvert erf\left(\frac{\sqrt{2}}{\pi}\right)\right\rvert$
V2	$V2(x) = \lvert\tanh(x)\rvert$
V3	$V3(x) = \left\lvert\frac{x}{\sqrt{1+x^2}}\right\rvert$
V4	$V4(x) = \left\lvert\frac{2}{\pi}\arctan\left(\frac{\pi}{2}x\right)\right\rvert$

PSO, QGA, GA, NBSMA, and AUBSMA proposed in this paper achieve MSR and MPF goals more effectively in the vast majority of network situations. The particulars of the transfer function are presented in Table 2. S-shaped transfer functions and V-shaped transfer functions are now the most common forms of transfer functions. In their study on binary PSO, Mirjalili et al. [97] compared the effectiveness of S-shaped functions to that of V-shaped functions. The S4 and V1 transfer functions, which can be found in Table 2, are the two functions that are the most useful for FS.

Four binary variants of the SMA have been suggested for FS. In each of these versions, the conventional SMA is hybrid, with the transfer function determined to be the most suitable out of S-Shaped and V-Shaped transfer functions. The first implementation generates a binary variant of the standard SMA known as the BSMA [98]. TMBSMA hybrids BSMA with two-phase mutation to find better solutions near the best-so-far. AFBSMA hybrids BSMA with an attacking-feeding approach that trades exploration for exploitation dependent on how much memory each particle saves. By hybridizing two-phase mutation (TM) and AF, FMBSMA is created. Classification precision of the selected attributes may be measured using this method. The performance of the four available versions of BSMA is assessed using a combined total of 28 established datasets. The results show that the AF method successfully achieves excellent results. Further, after comparing the four versions, it was concluded that the FMBSMA version was better than the other FS algorithms.

3.3.2 Multi-objective Optimization

A novel process parameter optimization method for laser cladding has been proposed using a multi-objective support vector algorithm (MOSVA) and support vector regression (SVR). This technique is intended to improve the quality of the cladding [99]. Specifically, SVR bridges the gap between goal and process parameters to enhance function relationship information. The modern meta-heuristic algorithm MOSVA has been developed to locate Pareto solution sets and fronts. Process parameters may be considered Pareto solution sets, and Pareto fronts are optimal objectives. Users may tailor the procedure to their needs by adjusting the available parameters. Topologically oriented principal component analysis (TOPSIS) evaluated the suggested method's efficacy using real-world laser cladding data. The findings demonstrated that by adhering to the approach that was given as a recommendation, the optimal process parameters could be acquired.

The Inverse Kinematics (IK) of complex manipulators are successfully solved using a hybrid equilibrium optimizer SMA (EOSMA) [100]. The EO's concentration update operator directs the SMA's anisotropic search, improving its efficacy. The greedy technique then updates the individual and global historical optimum to speed up algorithm convergence. In the last stage, EOSMA includes the random difference mutation operator to increase the chance of leaving the optimal local solution. Based on this, a MOEOSMA is recommended. EOSMA and MOEOSMA are applied to the 7-DOF manipulator's IK in two distinct conditions and compared with 15 single-objective and nine multi-objective algorithms. EOSMA is more accurate and faster to compute than prior studies. In [101], multi-objective SMA (MOSMA), an optimization technique that builds on SMA to address optimization problems with multiple objectives, is proposed. The SMA is then used to save the resultant Pareto-optimal solutions in a separate database. The Slime Mould was used as a social model to develop a multi-goal search engine for the archive. MOSMA's performance is validated using CEC'20 multi-objective benchmark tests. MOSMA was tested using eight confined and unconstrained test cases and four constrained engineering design issues. The price of crude oil is one of the most important energy sources in the world, and small shifts in that price may have a considerable influence on the financial markets, businesses, and governments. Therefore, it is essential to calculate crude oil futures prices (COFP) accurately. It includes chaotic time series, external neural networks, linear model prediction, and deep learning. In this step, the values that the sub-models have predicted are mixed with the ideal weight established by MOSMA [102]. By applying MOSMA to identify CIACs, the outcomes of IF were improved to have a smaller width and greater prediction accuracy. These improvements were achieved by introducing them.

SMA is a multi-objective water distribution model that integrates social, economic, and environmental aims. An accurate search solves the issue [103]. They collected water allocation designs for the area in 2025 and 2030. Then they conducted separate analyses of the distribution outcomes from the supply and demand sides. According to the findings, the total volume of water distribution in the years 2025 and 2030 is projected to be around 323 million m3 and 346 million m3, while the water deficit ratios are projected to be 2.90% and 6.95%, respectively. Many algorithms have been developed to handle the multi-objective optimum power flow (MOOPF) issue, but improved generation performance still needs novel approaches [104]. Recently, SMA was introduced as a meta-heuristic method that outperforms many others in solving many optimization problems, except the MOOPF issue. The effectiveness of the SMA in resolving MOOPF difficulties is studied by applying it to the IEEE 30-bus, 57-bus, and 118-bus systems. They evaluate SMA's output in objective values and compare them to those produced by other algorithms. The simulation results demonstrated that SMA offers definitive answers compared to many different algorithms.

The MOSMA approach calculates Pareto optimal solutions with elitist non-dominated sorting and convergence based on the same fundamental SMA principles [105]. The MOSMA keeps the multi-objective formulation as an a posteriori technique and uses a crowding distance operator to guarantee more optimum solutions are considered for each goal. Forty-one case studies are supposed to evaluate and validate MOSMA's performance. These case studies range from unconstrained to confined to real-world engineering design challenges. The simulation results demonstrated that the recommended method is superior at delivering answers to all multi-objective issues, including Pareto optimum fronts in linear, nonlinear, continuous, and discrete settings. These findings demonstrate that the suggested approach can effectively resolve multi-objective complex problems.

3.4 Optimization Problems

Optimization is finding the best possible combination of system maximize or minimize variables or parameters to a known function. The term "fitness function" is often used to refer to this metric. It is common practice to refer to the algorithm responsible for carrying out the optimization task as an optimizer. An optimization process is a maximization approach if the goal is to get the best possible outcome. It is a minimization approach if the goal is to achieve the least likely result. Materials, cost, time, and error are all examples of objective functions that may be reduced. However, productivity, earnings, and quality must be optimized. When it comes to optimization strategies, MAs are highly regarded. Their inherent attractive qualities—simple, adaptable, easy to learn and implement; led to their rapid rise to prominence. As a result, many academics focus on creating and using MAs to address massive, complex, and complicated issues across various disciplines. Traditional mathematical methods may not apply in other study areas, such as engineering, science, business, or finance. An overview of SMA in optimization is provided in Table 3.

Figure 18 presents a breakdown, based on SMA, of the number of publications published in each subfield of optimization. As shown in Fig. 18, it is abundantly evident that

Table 3 An overview of SMA in its application to optimization algorithms

Ref	Application	Advantages	Weaknesses	Publisher	Year
[106]	Wireless Sensor Network	Good convergence Maintain a balance between exploration and exploitation	Solve the last few iterations of the process	Tandfonline	2022
[107]	Prediction	Keep them up to date on the issue without confusing them Increase the efficiency of the fitness function	Solve the last few iterations of the process High iterations	Wiley	2022
[108]	Optimal Energy Management	A few perfect the parameters Maintain a balance between exploration and exploitation Strong global search ability	High iterations Non-optimal updates of individual	Tandfonline	2022
[109]	Engineering Optimization Problems	Less dependency on first random solutions Accelerated process of getting excellent solutions Prevent useless search	High execution time Non-optimal updates of individual	ScienceDirect	2022
[110]	Prediction	Short running time Keep them up to date on the issue without confusing them Population diversity	Slow convergence rate High iterations	IEEE	2022
[111]	Pid Controller	Keep them up to date on the issue without confusing them Increase the efficiency of the fitness function	Slow convergence rate High iterations	IEEE	2022
[112]	Multilevel Image Thresholding	Increase the efficiency of the fitness function Low likelihood of being mired in a local optimum	Slow convergence rate Solve the last few iterations of the process	ScienceDirect	2022
[113]	Prediction	Less dependency on first random solutions Accelerated process of getting excellent solutions Prevent useless search	Solve the last few iterations of the process High iterations	IEEE	2022
[114]	Multilevel Image Thresholding	Short running time Keep them up to date on the issue without confusing them Population diversity	High execution time Non-optimal updates of individual	MDPI	2022
[115]	Wireless Sensor Network	A few perfect the parameters Maintain a balance between exploration and exploitation Strong global search ability	Slow convergence rate High iterations	ScienceDirect	2022
[116]	Optimizing Parameters Of Power System	Short running time Keep them up to date on the issue without confusing them Population diversity	High iterations Non-optimal updates of individual	Tandfonline	2022
[117]	Feature Selection	Prevent useless search Short running time	High execution time Non-optimal updates of individual	IEEE	2022
[118]	Pid Controller	Short running time Keep them up to date on the issue without confusing them Population diversity	Slow convergence rate High iterations	MDPI	2022
[119]	Optimal Energy Management	Increase the efficiency of the fitness function Low likelihood of being mired in a local optimum	Solve the last few iterations of the process High iterations	Springer	2022

Table 3 (continued)

Ref	Application	Advantages	Weaknesses	Publisher	Year
[120]	Optimal Energy Management	Keep them up to date on the issue without confusing them Increase the efficiency of the fitness function	High iterations Non-optimal updates of individual	Tandfonline	2022
[121]	Optimal Energy Management	Increase the efficiency of the fitness function Low likelihood of being mired in a local optimum	Slow convergence rate High iterations	IEEE	2022
[122]	Optimal Energy Management	Prevent useless search Good convergence	High execution time Non-optimal updates of individual	MDPI	2022
[123]	Photovoltaic Power	A few perfect the parameters Maintain a balance between exploration and exploitation Strong global search ability	Slow convergence rate High iterations	MDPI	2022
[124]	Economic Load Dispatch Problems	Faster convergence Good convergence Strong global search ability	Slow convergence rate High iterations	MDPI	2022
[125]	Multilevel Image Thresholding	Short running time Prevent useless search Maintain a balance between exploration and exploitation	High execution time Non-optimal updates of individual	Springer	2022
[126]	Engineering Optimization Problems	Strong global search ability Low likelihood of being mired in a local optimum	Slow convergence rate Solve the last few iterations of the process	Springer	2022
[127]	Wireless Sensor Network	A few perfect the parameters Maintain a balance between exploration and exploitation Strong global search ability	Slow convergence rate High iterations	Springer	2021
[128]	Economic Load Dispatch Problems	Keep them up to date on the issue without confusing them Increase the efficiency of the fitness function	High execution time Non-optimal updates of individual	IEEE	2021
[129]	Load Frequency Control	High quality of solution and computation efficiency Accelerated process of getting excellent solutions	Slow convergence rate High iterations	IEEE	2021
[130]	Load Frequency Control	Prevent useless search Good convergence	Solve the last few iterations of the process High iterations	IEEE	2021
[131]	Engineering Optimization Problems	Short running time Prevent useless search Maintain a balance between exploration and exploitation	Non-optimal updates of individual Solve the last few iterations of the process	IEEE	2021
[132]	Economic Load Dispatch Problems	Faster convergence Good convergence Strong global search ability	Slow convergence rate Solve the last few iterations of the process	IEEE	2021
[133]	Optimizing Parameters Of Power System	Prevent useless search Good convergence	Solve the last few iterations of the process High iterations	MDPI	2021
[134]	Global Optimization	Keep them up to date on the issue without confusing them Increase the efficiency of the fitness function	High iterations Non-optimal updates of individual	IEEE	2021
[135]	Optimal Energy Management	Accelerated process of getting excellent solutions Increase the efficiency of the fitness function	High execution time Non-optimal updates of individual	IEEE	2021

Table 3 (continued)

Ref	Application	Advantages	Weaknesses	Publisher	Year
[136]	Optimal Allocation	Faster convergence Good convergence Strong global search ability	Slow convergence rate Solve the last few iterations of the process	IEEE	2021
[137]	Load Frequency Control	Prevent useless search Less dependency on first random solutions Maintain a balance between exploration and exploitation	High execution time Non-optimal updates of individual	Tandfonline	2021
[138]	Optimal Energy Management	Prevent useless search Less dependency on first random solutions Maintain a balance between exploration and exploitation	Slow convergence rate High iterations	Wiley	2021
[139]	Optimal Parameter Estimation	Prevent useless search Good convergence	Solve the last few iterations of the process High iterations	Wiley	2021
[140]	Photovoltaic Power	Faster convergence Good convergence Strong global search ability	High iterations Non-optimal updates of individual	ScienceDirect	2021
[141]	Photovoltaic Power	A few perfect the parameters Population diversity	Slow convergence rate Solve the last few iterations of the process	ScienceDirect	2021
[142]	Engineering Optimization Problems	Global optimization capability Powerful neighborhood search characteristic Increase the efficiency of the fitness function	Non-optimal updates of individual Solve the last few iterations of the process	Wiley	2021
[143]	Engineering Optimization Problems	Low likelihood of being mired in a local optimum Maintain a balance between exploration and exploitation	Solve the last few iterations of the process High iterations	ScienceDirect	2021
[144]	Optimal Energy Management	Population diversity Low likelihood of being mired in a local optimum	Slow convergence rate Solve the last few iterations of the process	IEEE	2021
[145]	Economic Load Dispatch Problems	A few perfect the parameters Maintain a balance between exploration and exploitation Strong global search ability	Solve the last few iterations of the process High iterations	Springer	2021
[146]	Mri Segmentation	High quality of solution and computation efficiency Less dependency on first random solutions Strong global search ability	Slow convergence rate High iterations	IEEE	2021
[147]	Mobile Robots	Global optimization capability Powerful neighborhood search characteristic Increase the efficiency of the fitness function	High execution time Non-optimal updates of individual	ScienceDirect	2021
[148]	Global Optimization	Global optimization capability Prevent useless search Powerful neighborhood search characteristic	High iterations High execution time	Others	2021
[149]	Feature Selection	Population diversity Low likelihood of being mired in a local optimum	Solve the last few iterations of the process High iterations	IEEE	2021
[150]	Prediction	Faster convergence Good convergence Strong global search ability	High iterations Non-optimal updates of individual	IEEE	2021

Table 3 (continued)

Ref	Application	Advantages	Weaknesses	Publisher	Year
[151]	Optimal Energy Management	Global optimization capability Powerful neighborhood search characteristic Increase the efficiency of the fitness function	High iterations High execution time	IEEE	2021
[152]	Engineering Optimization Problems	High quality of solution and computation efficiency Less dependency on first random solutions Strong global search ability	High execution time Non-optimal updates of individual	IEEE	2021
[153]	Pid Controller	Keep them up to date on the issue without confusing them Increase the efficiency of the fitness function	High execution time Non-optimal updates of individual	IEEE	2021
[154]	Photovoltaic Power	Global optimization capability Powerful neighborhood search characteristic Increase the efficiency of the fitness function	Slow convergence rate High iterations	Others	2021
[155]	Engineering Optimization Problems	Powerful neighborhood search characteristic Global optimization capability	High iterations Non-optimal updates of individual	IEEE	2021
[156]	Security Problems	Prevent useless search Less dependency on first random solutions Maintain a balance between exploration and exploitation	Non-optimal updates of individual Solve the last few iterations of the process	MDPI	2021
[157]	Security Problems	Powerful neighborhood search characteristic Increase the efficiency of the fitness function	Slow convergence rate High iterations	IEEE	2021
[158]	Security Problems	Global optimization capability Powerful neighborhood search characteristic Increase the efficiency of the fitness function	High execution time Non-optimal updates of individual	Wiley	2021
[159]	Engineering Optimization Problems	Powerful neighborhood search characteristic Global optimization capability	High iterations High execution time	Wiley	2021
[160]	Engineering Optimization Problems	A few perfect the parameters Maintain a balance between exploration and exploitation Strong global search ability	High iterations Non-optimal updates of individual	Wiley	2021
[161]	Engineering Optimization Problems	Maintain a balance between exploration and exploitation Prevent useless search	Slow convergence rate Solve the last few iterations of the process	Springer	2021
[162]	Engineering Optimization Problems	Less dependency on first random solutions Accelerated process of getting excellent solutions Prevent useless search	Non-optimal updates of individual Solve the last few iterations of the process	Springer	2021
[163]	Prediction	A few perfect the parameters Short running time Faster convergence	High iterations High execution time	Springer	2021
[164]	Scheduling	A few perfect the parameters Maintain a balance between exploration and exploitation Strong global search ability	Slow convergence rate Solve the last few iterations of the process	IEEE	2020

Table 3 (continued)

Ref	Application	Advantages	Weaknesses	Publisher	Year
[165]	Global Optimization	Keep them up to date on the issue without confusing them Increase the efficiency of the fitness function	High iterations High execution time	IEEE	2020
[166]	Engineering Optimization Problems	A few perfect the parameters Short running time Faster convergence	Slow convergence rate High iterations	Tandfonline	2021
[167]	Optimal Allocation	Global optimization capability Powerful neighborhood search characteristic Increase the efficiency of the fitness function	Non-optimal updates of individual Solve the last few iterations of the process	Springer	2020
[168]	Optimizing Parameters Of Power System	Maintain a balance between exploration and exploitation Prevent useless search	High iterations Non-optimal updates of individual	IEEE	2020
[169]	Optimizing Parameters Of Power System	A few perfect the parameters Maintain a balance between exploration and exploitation Strong global search ability	High iterations High execution time	IEEE	2020
[170]	Economic Load Dispatch Problems	Powerful neighborhood search characteristic Global optimization capability	Slow convergence rate High iterations	Springer	2020
[171]	Photovoltaic Power	Global optimization capability Powerful neighborhood search characteristic Increase the efficiency of the fitness function	High iterations High execution time	ScienceDirect	2020

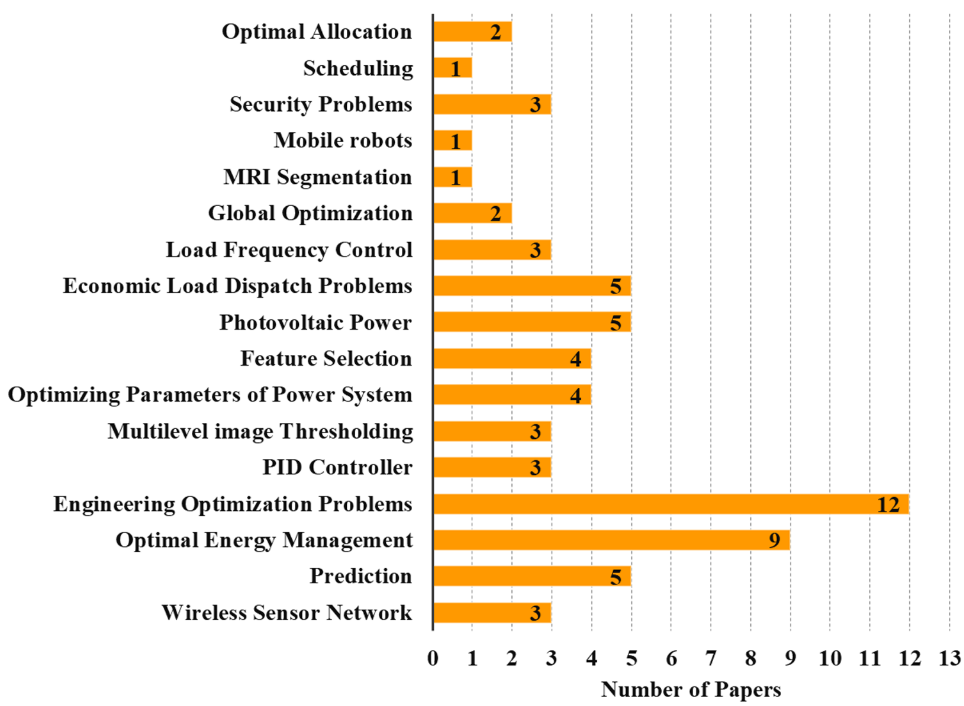


Fig. 18 Number of papers in different areas of Optimization based on SMA

the subject of engineering optimization issues is home to the most significant number of published publications. The field of optimum energy management has a total of nine papers, and it falls under the umbrella of the disciplines of electronics, mechanics, and civil engineering. SMA has also been used for optimization objectives in various domains, including wireless sensor networks, power systems, and forecasting.

4 Discussion

The optimization strategies mostly center on conventional optimization procedures, which may be restricted when used to Np-Hard issues due to their inherent complexity. Complex engineering problems generally include objective functions and probabilistic constraints that are highly nonlinear, and many of these issues have local optimum solutions. It causes traditional optimization algorithms to either converge prematurely or locally on an optimal solution, depending on the situation. NP-Hard problems may have discrete or mixed variables, making gradient-based optimization problems [172]. MAs are considered an alternative technique that is very popular in optimization fields. It is because MAs have an excellent performance for highly nonlinear problems, do not require derivatives, and are not affected by the starting solution's kind or the design parameters. Traditional optimization algorithms are considered to be the standard technique.

The proportion of SMA approaches based on each of the four central regions is shown in Fig. 19. Fifteen percent of the total was allocated to Hybridization, 36% to Improved, 7% to Variants of SMA, and 42% to Optimization Problems, respectively. The most significant proportion may be found in the Optimization Problems sector.

The main benefits and drawbacks of the SMA algorithm are outlined in Table 4, which may be found here. The SMA algorithm suffers from the issue of inconsistent operation in complicated situations, and the precision of the solution is often not adequate in the time necessary for the task. It is a problem since the SMA method was designed to solve simple problems.

There have been several different optimization algorithms have been proposed as possible answers to optimization problems. However, none can win against all of the other algorithms in the benchmark datasets. Optimization algorithms are being developed to tackle optimization issues to achieve a globally optimum solution while preventing premature convergence. Even though unimodal and multimodal situations may have distinct needs, these algorithms execute exploitation and exploration using specific mathematical equations and follow the same processes in both cases. An algorithm that addresses multi-modal issues will operate satisfactorily when used to solve unimodal difficulties. Because multi-modal problems could have more than one optimum solution, either globally or locally, it is necessary to conduct an exhaustive study of the search space to zero in on all optimal solutions [173]. As the issue's size grows, algorithms' difficulty in accomplishing the intended

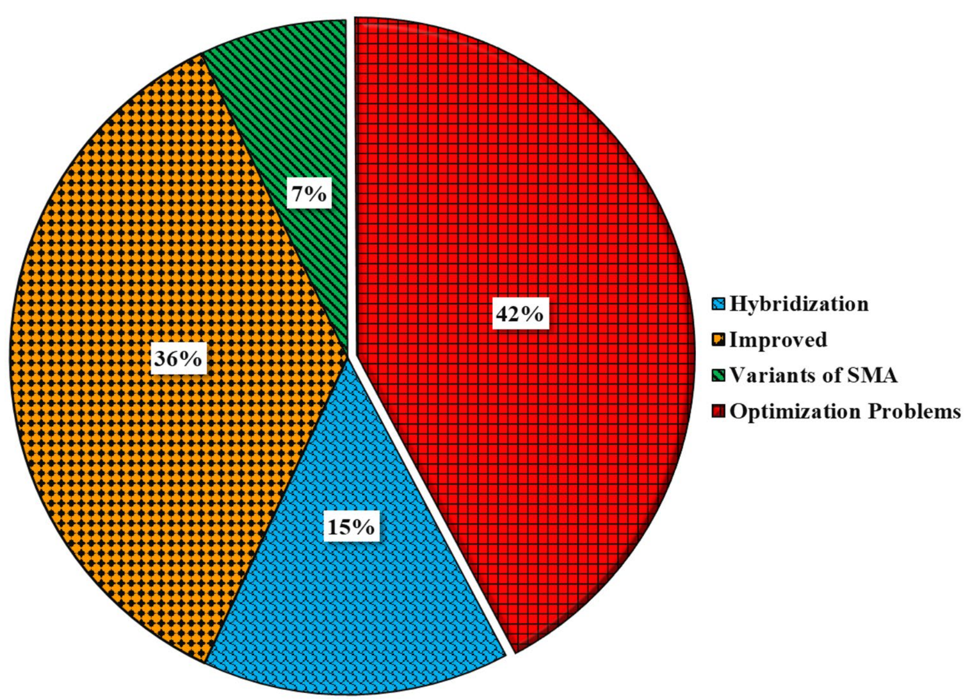


Fig. 19 Percentage of SMA methods based on four different areas

Table 4 SMA algorithm: Advantages and disadvantages

	Factors
Advantages	Easy to implement, with few parameters to set
	Superior efficiency in solving optimization issues
	For identifying optimum values, SMA is a fierce competitor
	Excellent convergence characteristics and cheap power production
	High-quality of solutions
	balance rule between exploration and exploitation
	short computational time
	Helpful to the balance between global search and local search
	The SMA optimizes convergence, decision-making, and precision during foraging
	Prevent the premature convergence
	Getting quality outcomes faster
	Accelerated process in finding excellent solutions
	The varied characteristics of the population
Disadvantages	Complex issue exploitation
	Getting stuck into local minimum regions
	Problem magnitude increases iteration

aim also grows. Therefore, combining a mechanism that produces variety with an algorithm that quickly converges works more suitably in the context of high-dimensional optimization problems.

Initialization, fitness assessment, weight update, reverse population fitness assessment, ranking, and position update are the primary components of Chaotic-SMA. It is primarily made up of these components. Initialization has a computational complexity of O(D). The fitness evaluation and inverse population fitness evaluation have a computational complexity of $O(Np + Np)$. The ranking has a computational complexity of $O(N \times PlogN)$. The computational complexity of the weight update has a computational complexity of $O(Np \times D)$, and the complexity of the position update has a computational complexity of $O(Np \times D)$. As a result, the overall complexity of MSMA is represented by the notation $O(D + T \times Np \times (2 + logN + D))$. The following is a list of the essential components of EOSMA [29]: initialization, fitness assessment, greedy selection, fitness sorting, fitness weight update, pool update, equilibrium position update, and mutation operator. Initialization has a computational complexity of $O(N \times Dim)$, greedy selection and equilibrium pool update take time complexity of O(N), updating fitness weight, updating location, and performing a mutation all have a computational complexity of $O(N \times Dim)$, and sorting fitness has a computational complexity of $O(N \times logN)$. If they assume that the fitness evaluation function has a time complexity of O(F), then the maximum number of iterations of EOSMA is $O(\max\_t(N \times Dim + N \times logN + F))$, where max t is the number of times the algorithm can be run, F is the time required to compute the fitness function once, Dim is the number of dimensions in the problem, and N is the population size. $O(N \times Dim)$ is the space complexity of EOSMA.

Multi-strategy has been presented as a means of improving the original SMA, which has several flaws, including a sluggish convergence time, a propensity to slip into local optimum, unstable optimization outcomes, etc. They include a chaotic elite search strategy to improve the algorithm's search capabilities and integrate a nonlinear convergence z parameter with a chaotic disturbance to strike a good compromise between the algorithm's global and local search capabilities. The results of optimizing 12 benchmark functions showed that CSMA demonstrates superior performances in terms of robustness, convergence speed, and solution accuracy. By using opponent search space location data, OBL-SMA performance is significantly strengthened. Since OBL-SMA has improved capabilities in both exploration and exploitation, it has shown superior convergence to other approaches. There is a trade-off between discovery and use in SMA, as in different meta-heuristic methods. The optimizer may more effectively globalize the search area thanks to the information gleaned from the exploration phase. However, the exploration phase often leads to new and improved solutions developed further during the exploitation phase. The implementation of chaotic-SMA was beneficial in increasing global convergence and avoiding being mired in a particular local solution. As a result of the tests, it has been theorized that substituting deterministic chaotic maps for random value generators is one strategy to improve the effectiveness of SMA.

The SMA-FA strategy enhances the SMA's local search with the FA's operators. This advancement incorporates the FA's method of incrementally modifying the SMA's underlying structure. This step is meant to provide the SMA algorithm more latitude in exploring the search domain and more variation, which help arrive at the optimal value more reasonably. The SMA-FA approach takes advantage of the FA's operators to improve the SMA's local search, preventing it from becoming stuck at local optima and speeding up the convergence process. Twenty different UCI datasets were utilized to evaluate the SMA-FA. It outperformed other algorithms in both simulation and experimental settings for exploring and exploiting space to locate optimal global solutions.

For problems with global optimization and reliability-based design optimization, a hybrid TLBOSMA was devised. This model is a mix of the SMA and the TLBO, and its purpose is to improve the SMA's capacity to converge on a solution. The search agents in the TLBOSMA have been split into two groups; the TLBO mechanism and the SMA mechanism are responsible for their respective updates. It is possible to improve the algorithm's capacity to converge and its resilience by modifying the subgroups used in TLBOSMA as the number of iterations progresses.

5 Conclusion and Future Works

This paper presented a detailed review of the SMA, demonstrating that it can solve various issues when used in multiple contexts. The material used in this review research was taken from various published works that were originally published between 2020 and 2022 when the first edition of SMA was introduced. This work showed one variation of SMA's adjustments and the algorithm's benefits, robustness, and constraints. So, the limitations of SMA were explored locally and globally to prevent the algorithm from becoming trapped in an optimal local solution and increase the convergence rate. In addition, we provided a comprehensive summary of the many issues that have been resolved by utilizing SMA. These issues include Wireless Sensor Networks, Prediction, Optimal Energy Management, Engineering Optimization Problems, PID Controller, Multilevel image Threshold, Optimizing Parameters of Power System, Feature Selection, Photovoltaic Power, Economic Load Dispatch Problems, Load Frequency Control, Global Optimization, MRI Segmentation, Mobile Robots, Security Problems. In addition, the SMA is regarded as one of the most meta-heuristic approaches. According to the conclusions drawn from the published papers, it has a high capacity to identify adequate solutions for the issues examined. This paper offers researchers who wish to present work based on SMA crucial information on how it may be utilized, its qualities, and its shortcomings to aid them with future presentations. The material may be used to improve the quality of the researchers' work. As a result, the SMA is adaptable and may be used in various new contexts. Last, we provided some intuitive future directions of SMA and its possible applications before we wrapped up this paper.

- The hybridizing results provide evidence of good behavior for the suggested strategy. By combining SMA with other MAs, it is possible to optimize each meta-heuristic algorithm's advantages while simultaneously reducing each algorithm's limitations and allowing the development of a wide range of practical applications. It is possible to enhance MAs with the help of the Lévy Flight by avoiding local optima and accelerating the convergence process. In the following work on this subject, an analysis of the potential implications of the Lévy flight will be carried out, and comprehensive suggestions for strengthening the SMA will be outlined.
- Multi-population approaches are not only straightforward, adaptable, and diverse. Still, they have also effectively resolved many issues that arise in the real world. Researchers presently working in these fields or who will work in them in the future have found that multi-population approaches are valuable to them. These methods have proved helpful to the optimization and engineering communities. However, multi-population SMA is not entirely understood, which has led to its establishment. Because it is a topic in which the current study is being conducted, SMA work also presents a viable alternative to methodologies inspired by nature.

By studying and exploring this paper, we concluded that for future works, hybrid algorithms should be used for NP-Hard and complex problems. Hybrid algorithms are very practical and useful for solving complex problems. According to the analysis, new meta-heuristic algorithms are more efficient compared to algorithms such as GA, PSO, and ABC. The researchers intend to use new meta-heuristic algorithms in solving complex problems for future studies.

Declarations

Conflict of interest There is no conflict of interest statement.

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