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Slime mould algorithm: A new method for stochastic optimization

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ABSTRACT

In this paper, a new stochastic optimizer, which is called slime mould algorithm (SMA), is proposed based on the oscillation mode of slime mould in nature. The proposed SMA has several new features with a unique mathematical model that uses adaptive weights to simulate the process of producing positive and negative feedback of the propagation wave of slime mould based on bio-oscillator to form the optimal path for connecting food with excellent exploratory ability and exploitation propensity. The proposed SMA is compared with up-to-date metaheuristics using an extensive set of benchmarks to verify its efficiency. Moreover, four classical engineering problems are utilized to estimate the efficacy of the algorithm in optimizing constrained problems. The results demonstrate that the proposed SMA benefits from competitive, often outstanding performance on different search landscapes. The source codes of SMA are publicly available at http://www.alimirjalili.com/SMA.html and https://tinyurl.com/Slime-mould-algorithm.

1. Introduction

Metaheuristic algorithms (MAs) have become prevalent in many applied disciplines in recent decades because of higher performance and lower required computing capacity and time than deterministic algorithms in various optimization problems [1–4]. Simple concepts are required to achieve favourable results, and it is facile to transplant to different disciplines. Also, the lack of randomness in the later stage of some deterministic algorithm makes it inclined to sink into local optimum, and random factors in MAs can make the algorithm search for all optimal solutions in search space, thus effectively avoiding local optimum. In linear problems, some gradient descent algorithms, such as work in [5] are more efficient than stochastic algorithms for the utilization of gradient information. The convergence speed of MAs will be less than gradient descent algorithms and can be considered as a drawback. In non-linear problems, however, MAs typically commence the optimization process with randomly generated solutions and do not demand gradient information, which makes the algorithm eminently suitable for practical problems when the derivative information is unknown. In real-world scenarios, the solution space of many problems is often indeterminate or infinite. It may be infeasible to find optimal solutions by traversing the solution space under current circumstances. MAs detect the proximate optimal solution of the problem by sampling the enormous solution space randomly in a certain way, to find or generate better solutions for the optimization problem under limited circumstances or computational capacity.

MAs are typically inspired by real-world phenomena to find better heuristic solutions for optimization problems by simulating physical rules or biological phenomena. MAs can be divided into two main categories: swam-based methods and evolutionary techniques. The first kind mainly simulates physical phenomena, apply mathematical rules or methodologies including Multi-Verse Optimizer (MVO) [6], Charged System Search (CSS) [7], Gravitational Search Algorithm (GSA) [8], Sine Cosine Algorithm (SCA) [9], Teaching-Learning-Based Optimization (TLBO) [10], Central Force Optimization (CFO) [11] and Tabu Search (TS) [12]. Nature-inspired methods mainly include two types: evolutionary methods and intelligent swarm techniques. The inspiration of the evolutionary algorithm (EA) originates from the process of biological evolution in nature. Compared with the traditional optimization algorithm, it is a global optimization method with better robustness and applicability.

Some of the widespread algorithms in the class of EA are Genetic Algorithm (GA) [13], Genetic Programming (GP) [14], Evolution Strategy (ES) [15], Evolutionary Programming (EP) [16] and Differential Evolution (DE) [17]. The application of ES and EP

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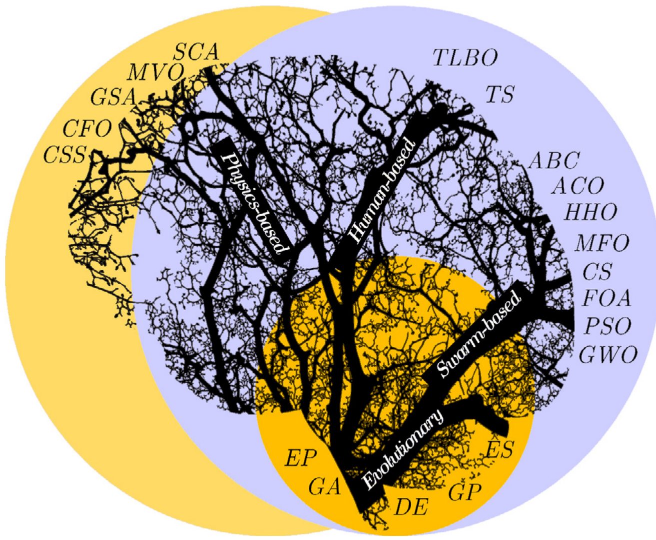

Fig. 1. Classification of evolutionary and SI methods.

and also swarm-intelligence methods in scientific research and practical problems is also becoming more and more extensive [18–20]. Swarm Intelligence (SI) [21] includes a collective or social intelligence that artificially simulates the decentralization of biological clusters in nature or the collective behaviour of self-organizing systems. In this class of algorithms, the inspiration usually comes from biological groups in nature that have collective behaviour and intelligence to achieve a certain purpose. Established and recent algorithms in this class are Particle Swarm Optimization (PSO) [22], Bat-inspired Algorithm (BA) [23], Grey Wolf Optimization (GWO) [24], Fruit Fly Optimization (FOA) [25], Moth Flame Optimization (MFO) [26], Ant Colony Optimization (ACO) [27], Harris Hawk Optimizer (HHO) [28], and Artificial Bee Colony (ABC) [29]. A schematic design for the classification of evolutionary and SI methods are shown in Fig. 1.

Although different MAs have some distinctness, they all have two identical stages in the search gradation: exploration and exploitation [30]. The exploration phase refers to the process of searching solution space as widely, randomly, and globally as possible. Exploitation phase refers to the competence of the algorithm to search more accurately in the area acquired by the exploration phase, and its randomness decreases while its precision increases. When the exploration ability of the algorithm is dominant, it can search the solution space more randomly and produce more differentiated solution sets to converge fleetly. When the exploitative ability of the algorithm is dominant, it searches more locally to enhance the quality and precision of the solution sets. However, when the exploration facility is improved, it will lead to reductions in the exploitation capability, and vice versa. Another challenge is that the balance of these two abilities is not necessarily identical to different problems. Therefore, it is relatively challenging to attain an appropriate balance between the two phases that are efficient for all optimization problems.

Despite the success of conventional and recent MAs, none of them can guarantee to find the global optimum for all optimization problems. This has been proven logically by the No-Free-Lunch (NFL) theory [31]. This theorem motivated numerous researchers to design a new algorithm and solve new classes of problems more efficiently. With the aspiration of proposing a more versatile and efficient algorithm, this paper introduces a new meta-heuristic algorithm: The slime mould algorithm (SMA). This method is aroused by the diffusion and foraging conduct of slime mould. An overall set of 33 benchmarks and four famous manufacturing design problems has rigorously verified the effectiveness and robustness of SMA.

The remainder of the paper is structured as below. Section 2 illustrated the concept of the source of slime mould algorithm, and the mathematical model was established. Section 3 firstly gave a qualitative analysis of the algorithm and made a comprehensive comparison of 33 benchmark functions, then tested it on four engineering design problems. Section 4 summarized the whole work and put forward some inspirations for future work.

2. Slime mould algorithm

In this section, the basic concept and conduct of slime mould will be introduced. Then a mathematical model inspired by its behaviour pattern will be established.

2.1. Originality

Before this article, some scholars have proposed similar naming algorithms, but the way of designing the algorithm and usage scenarios are quite different from the algorithms proposed in this paper. Monismith and Mayfield [32] solves the single-objective optimization problem by simulating the five life cycles of amoeba Dictyostelium discoideum: a state of vegetative, aggregative, mound, slug, or dispersal while using ε-ANN to construct an initial position-based mesh. Li et al. [33] proposed a method to construct wireless sensor networks by using two forms of slime mould tubular networks to correspond to two different regional routing protocols. Qian. et al. [34] combined the Physarum network with the ant colony system to improve the algorithm's competence to avoid local optimal values to handle the Travelling Salesman Problem better. Inspired by the diffusion of slime mould, Schmickland Crailsheim [35] proposed a bio-inspired navigation principle designed for swarm robotics. Becker [36] generated inexpensive and fault-tolerant graphs by simulating the foraging process of the slime mould Physarum polycephalum. As can be seen from the above discussion, most of the modelled slime mould algorithms were used in graph theory and generation networks. This living organism also inspired researchers in the area of graph optimization [37]. The algorithm used to optimize the problem [32] simulates the five life cycles of amoeba Dictyostelium discoideum, but the experiments and proofs in the article are slightly less.

The SMA proposed in this paper mainly simulates the behaviour and morphological changes of slime mould Physarum polycephalum in foraging and does not model its complete life cycle. At the same time, the use of weights in SMA is to simulate the positive and negative feedback generated by slime mould during foraging, thus forming three different morphotype, is a brand new idea. This paper also conducted a full experiment on the characteristics of the algorithm. The results in the next sections demonstrate the superiority of the SMA algorithm.

2.2. Concepts

The slime mould mentioned in this article generally refers to the Physarum polycephalum. Because it was first classified as a fungus, thus it was named "slime mould", which its life cycle was originally specified by Howard [38] in a paper published in 1931. Slime mould is a eukaryote that inhabits cold and humid places. The main nutritional stage is Plasmodium, the active and dynamic stage of slime mould, and also the main research stage of this paper. In this stage, the organic matter in slime mould seeks food, surrounds it, and secretes enzymes to digest it. During the migration process, the front end extends into a fan-shaped,

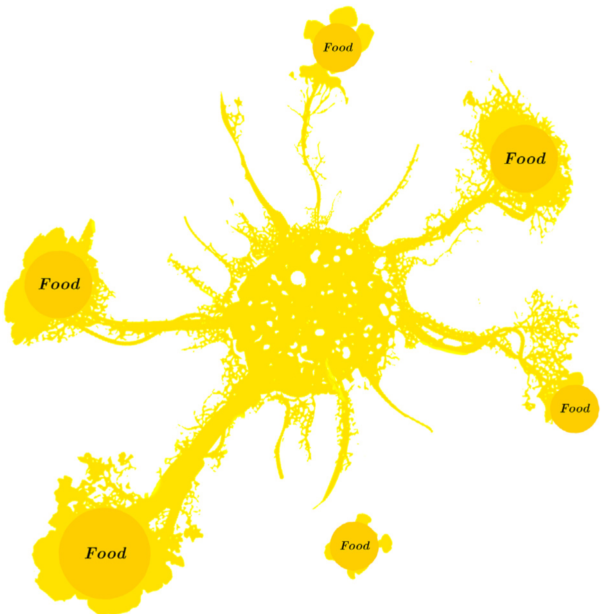

Fig. 2. Foraging morphology of slime mould.

followed by an interconnected venous network that allows cytoplasm to flow inside [39], as shown in Fig. 2. Because of their unique pattern and characteristic, they can use multiple food sources at the same time to form a venous network connecting them. If there is enough food in the environment, slime mould can even grow to more than 900 square centimetres [39].

Owing to the feature of slime mould can be easily cultured on agar and oatmeal [40], they were widely used as model organisms. Kamiya and his colleagues [41] was the first team to study the detailed process of the cytoplasmic flow of slime mould. Their work is of great help to our subsequent understanding of the way slime mould move and connects food in the environment. We now cognize that when a vein approaches a food source, the bio-oscillator produces a propagating wave [42] that increases the cytoplasmic flow through the vein, and the faster the cytoplasm flows, the thicker the vein. Through this combination of positive-negative feedback, the slime can establish the optimal path to connect food in a relatively superior way. Therefore, slime mould was also mathematically modelled and applied in graph theory and path networks [43–45].

The venous structure of slime mould develops along with the phase difference of the contraction mode [42], so there are three correlations between the morphological changes of the venous structure and the contraction mode of slime mould.

(1) Thick veins form roughly along the radius when the contraction frequencies vary from outside to inside.

(2) When the contraction mode is unstable, anisotropy begins to appear.

(3) When the contraction pattern of slime mould is no longer ordered with time and space, the venous structure is no longer present.

Therefore, the relationship between venous structure and contraction pattern of slime mould is consistent with the shape of naturally formed cells. The thickness of each vein is determined by the flow feedback of the cytoplasm in the Physarum solver [46]. The rise in the flow of cytoplasm leads to an increase in the diameter of veins. As the flow decreases, the veins contract because of the decrease of the diameter. Slime mould can build a stronger route where food concentration is higher, thus ensuring that they get the maximum concentration of nutrients. Recent studies have also revealed that slime mould has the competence of making foraging arrangements based on optimization theory [47]. When the quality of various food sources is different, slime mould can choose the food source with the highest concentration. However, slime mould also needs to weigh speed and risk in foraging. For instance, slime mould needs to make faster decisions in order to avoid environmental damage to them. Experiments have shown that the quicker the decision-making speed is, the possibilities of slime mould to find the prime food source is smaller [48]. Therefore, when deciding the source of food, slime mould obviously needs to weigh the speed and accuracy.

Slime mould needs to decide when to leave this area and search in another area when foraging. When lacking complete information, the best way for a slime mould to estimate when to leave the current position is to adopt heuristic or empirical rules based on the insufficient information currently available. Experience has shown that when slime mould encounter high-quality food, the probability of leaving the area is reduced [49]. However, due to its unique biological characteristics, slime mould can utilize a variety of food sources at the same time. Therefore, even if the slime mould has found a better source of food, it can still divide a component of the biomass to exploit both resources simultaneously when higher quality food is found [46].

Slime mould can also dynamically adjust their search patterns according to the quality of foodstuff provenience. When the quality of food sources is high, the slime mould will use the region-limited search method [50], thus focusing the search on the food sources that have been found. If the denseness of the food provenience initially found is low, the slime mould will leave the food source to explore other alternative food sources in the region [51]. This adaptive search strategy can be more reflected when different quality food blocks are dispersed in a region. Some of the mechanisms and characteristics of the slime mould mentioned above will be mathematically modelled in the subsequent sections.

2.3. Mathematical model

In this part, the mathematical model and method proposed will be described in details.

2.3.1. Approach food

The slime mould can approach food according to the odour in the air. To express its approaching behaviour in mathematical formulae, the following formulae are proposed to imitate the contraction mode:

$$\overrightarrow{X(t+1)} = \begin{cases} \overrightarrow{X_b(t)} + \overrightarrow{vb} \cdot \left(\overrightarrow{W} \cdot \overrightarrow{X_A(t)} - \overrightarrow{X_B(t)} \right), r < p \\ \overrightarrow{vc} \cdot \overrightarrow{X(t)}, r \geq p \end{cases} \tag{2.1}$$

where $\overrightarrow{vb}$ is a parameter with a range of $[-a, a]$, $\overrightarrow{vc}$ decreases linearly from one to zero. t represents the current iteration, $\overrightarrow{X_b}$ represents the individual location with the highest odour concentration currently found, $\vec{X}$ represents the location of slime mould, $\overrightarrow{X_A}$ and $\overrightarrow{X_B}$ represent two individuals randomly selected from slime mould, $\overrightarrow{W}$ represents the weight of slime mould.
The formula of p is as follows:

$$p = \tanh |S(i) - DF| \tag{2.2}$$

where $i \in 1, 2, \ldots, n$, $S(i)$ represents the fitness of $\vec{X}$, DF represents the best fitness obtained in all iterations.
The formula of $\overrightarrow{vb}$ is as follows:

$$\overrightarrow{vb} = [-a, a] \tag{2.3}$$

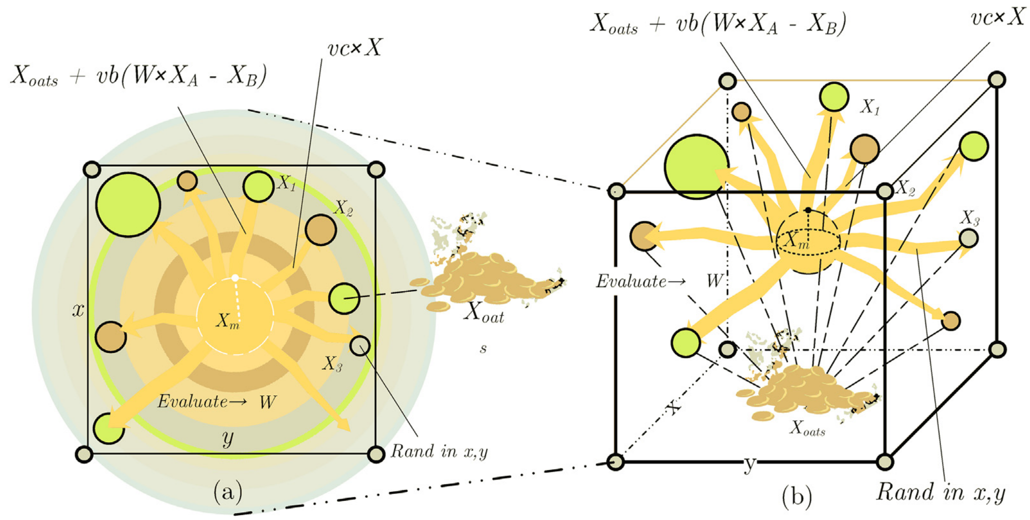

Fig. 3. Possible locations in 2-dimension and 3-dimension..

$$a = \operatorname{arctanh}(-\left(\frac{t}{\max\_t}\right) + 1) \tag{2.4}$$

The formula of $\overrightarrow{W}$ is listed as follows:

$$\overrightarrow{W(SmellIndex(i))} = \begin{cases} 1 + r \cdot log\left(\dfrac{bF - S\,(i)}{bF - wF} + 1\right), condition \\ 1 - r \cdot log\left(\dfrac{bF - S\,(i)}{bF - wF} + 1\right), \quad others \end{cases} \tag{2.5}$$

$$SmellIndex = sort(S) \tag{2.6}$$

where *condition* indicates that $S\,(i)$ ranks first half of the population, r denotes the random value in the interval of [0, 1], max_t shows maximum iteration, bF denotes the optimal fitness obtained in the current iterative process, wF denotes the worst fitness value obtained in the iterative process currently, *SmellIndex* denotes the sequence of fitness values sorted(ascends in the minimum value problem).

Fig. 3 visualizes the effects of Eq. (2.1). The location of searching individual $\vec{X}$ can be updated according to the best location $\overrightarrow{X_b}$ currently obtained, and the fine-tuning of parameters $\overrightarrow{vb}$, $\overrightarrow{vc}$ and $\overrightarrow{W}$ can change the location of the individual. Fig. 3 is also used to illustrate the position change of the searching individual in three-dimensional space. *rand*in the formula can make individuals form search vectors at any angle, that is, search solution space in any direction, so that the algorithm has the possibility of finding the optimum solution. Therefore, Eq. (2.1) enables the searching individuals to search in all possible directions near the optimal solution, thus simulating the circular sector structure of slime mould when approaching food. It is also applicable to extend this concept to Hyper-dimensional space.

2.3.2. Wrap food

This part simulates the contraction mode of venous tissue structure of slime mould mathematically when searching. The higher the concentration of food contacted by the vein, the stronger the wave generated by the bio-oscillator, the faster the cytoplasm flows, and the thicker the vein. Eq. (2.5) mathematically simulated the positive and negative feedback between the vein width of the slime mould and the food concentration that was explored. The component $r$in Eq. (2.5) simulates the uncertainty of venous contraction mode. *log* is used to alleviate the change rate of numerical value so that the value of contraction

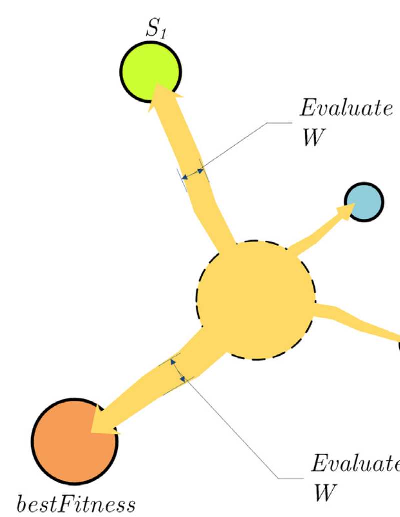

Fig. 4. Assessment of fitness.

frequency does not change too much. *condition* simulates the slime mould to adjust their search patterns according to the quality of food. When the food concentration is content, the weight near the region is bigger; when the food concentration is low, the weight of the region will be reduced, thus turning to explore other regions. Fig. 4 shows the process of evaluating fitness values for slime mould.

Based on the above principle, the mathematical formula for updating the location of slime mould is as follows:

$$\overrightarrow{X^*} = \begin{cases} rand \cdot (UB - LB) + LB, rand < z \\ \overrightarrow{X_b\,(t)} + \overrightarrow{vb} \cdot \left(W \cdot \overrightarrow{X_A\,(t)} - \overrightarrow{X_B\,(t)}\right), r < p \\ \overrightarrow{vc} \cdot \overrightarrow{X\,(t)}, r \geq p \end{cases} \tag{2.7}$$

where LB and UB denote the lower and upper boundaries of search range, *rand* and r denote the random value in [0,1]. The value of z will be discussed in the parameter setting experiment.

2.3.3. Oscillation

Slime mould mainly depends on the propagation wave produced by the biological oscillator to change the cytoplasmic flow in veins, so that they tend to be in a better position of food

Table 1
Unimodal and multimodal test functions of 23 standard benchmarks.

Functions	Dim	Range	f_{min}
$f_1(x) = \sum_{i=1}^{n} x_i^2$	n	[−100,100]	0
$f_2(x) = \sum_{i=1}^{n} \mid x_i \mid + \prod_{i=1}^{n} \mid x_i \mid$	n	[−10,10]	0
$f_3(x) = \sum_{i=1}^{n} \left(\sum_{j-1}^{i} x_j\right)^2$	n	[−100,100]	0
$f_4(x) = max_i \{\mid x_i \mid, 1 \le i \le n\}$	n	[−100,100]	0
$f_5(x) = \sum_{i=1}^{n-1} \left[100\left(x_{i+1} - x_i^2\right)^2 + (x_i - 1)^2\right]$	n	[−30,30]	0
$f_6(x) = \sum_{i=1}^{n} ([x_i + 0.5])^2$	n	[−100,100]	0
$f_7(x) = \sum_{i=1}^{n} ix_i^4 + random[0, 1]$	n	[−128,128]	0
$f_8(x) = \sum_{i=1}^{n} -x_i \sin\left(\sqrt{\mid x_i \mid}\right)$	n	[−500,500]	−418.9829*n
$f_9(x) = \sum_{i=1}^{n} \left[x_i^2 - 10\cos(2\pi x_i) + 10\right]$	n	[−5.12,5.12]	0
$f_{10}(x) = -20\exp(-0.2(\frac{1}{n}\sum_{i=1}^{n} x_i^2)^\wedge 0.5) - \exp\left(\frac{1}{n}\sum_{i=1}^{n}\cos(2\pi x_i)\right) + 20 + e$	n	[−32,32]	0
$f_{11}(x) = \frac{1}{4000}\sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n}\cos\left(\frac{x_i}{\sqrt{i}}\right) + 1$	n	[−600,600]	0
$f_{12}(x) = \frac{\pi}{n}\left\{10\sin(\pi y_1) + \sum_{i=1}^{n-1}(y_i - 1)^2\left[1 + 10\sin^2(\pi y_{i+1})\right] + (y_n - 1)^2\right\}$ $+ \sum_{i=1}^{n} u(x_i, 10, 100, 4), y_i = 1 + \frac{x_i+1}{4}$ $u(x_i, a, k, m) = \begin{cases} k(x_i - a)^m\ x_i > a \\ 0 - a < x_i < a \\ k(-x_i - a)^m\ x_i < a \end{cases}$	n	[−50,50]	0
$f_{13}(x) = 0.1\left\{\sin^2(3\pi x_1) + \sum_{i=1}^{n}(x_i - 1)^2\left[1 + \sin^2(3\pi x_i + 1)\right] + (x_n - 1)^2\left[1 + \sin^2(2\pi x_n)\right]\right\} + \sum_{i=1}^{n} u(x_i, 5, 100, 4)$	n	[−50,50]	0

concentration. For the purpose of simulating the variations of venous width of slime mould, we used $\overrightarrow{W}$, $\overrightarrow{vb}$ and $\overrightarrow{vc}$ to realize the variations.

$\overrightarrow{W}$ mathematically simulates the oscillation frequency of slime mould near one at different food concentration, so that slime mould can approach food more quickly when they find high-quality food, while approach food more slowly when the food concentration is lower in individual position, thus improving the efficiency of slime mould in choosing the optimal food source.

The value of $\overrightarrow{vb}$ oscillates randomly between $[-a, a]$ and gradually approaches zero as the increasement of iterations. The value of $\overrightarrow{vc}$ oscillates between [−1,1] and tends to zero eventually. The trend of the two values is shown as Fig. 5. Synergistic interaction between $\overrightarrow{vb}$ and $\overrightarrow{vc}$ mimics the selective behaviour of slime mould. In order to find a better source of food, even if slime mould has found a better source of food, it will still separate some organic matter for exploring other areas in an attempt to find a higher quality source of food, rather than investing all of it in one source.

Moreover, the oscillation process of $\overrightarrow{vb}$ simulates the state of slime mould deciding whether to approach the food source or find other food sources. Meanwhile, the process of probing food is not smooth. During this period, there may be various obstacles, such as light and dry environment, which restrict the spread of slime mould. However, it also improves the possibility of slime mould to find higher quality food and evades the trapping of local optimum.

The pseudo-code of the SMA is shown in Algorithm 1. The intuitive and detailed process of SMA is shown in Fig. 6. The General logic of SMA is also shown in Fig. 7.

There are still many mechanisms that can be added to the algorithm, or more comprehensive simulation of the life cycle of slime mould. However, to enhance the extensibility of the algorithm, we simplify the process and operators of the algorithm, leaving only the simplest algorithm as possible.

Algorithm 1 Pseudo-code of SMA

Initialize the parameters *popsize*, $Max\_iteraition$;
Initialize the positions of slime mould $X_i (i = 1,2, \dots, n)$;
While $(t \le Max\_iteraition)$
    Calculate the fitness of all slime mould;
    $update\ bestFitness,\ X_b$
    Calculate the W by **Eq.** (2.5);
    For $each\ search\ portion$
        $update\ p, vb, vc$;
        $update\ positions\ by$ **Eq.** (2.7);
    End For
    $t = t + 1$;
End While
Return $bestFitness,\ X_b$;

2.3.4. Computational complexity analysis

SAM mainly consists of the subsequent components: initialization, fitness evaluation, sorting, weight update, and location update. Among them, N denotes the number of cells of slime mould, D denotes the dimension of functions, and T denotes the maximum number of iterations. The computation complexity of initialization is $O(D)$, the computation complexity of fitness evaluation and sorting is $O(N + N\ log\ N)$, the computational complexity of weight update is $O(N \times D)$, the complexity of location update is $O(N \times D)$. Therefore, the total complexity of SMA is $O(D + T * N * (1 + log\ N + D))$.

3. Experimental results and analyses

In this sector, we compared the SMA with some competitive MAs on an all-inclusive set of 33 benchmark cases. The experimentations were ran on the operating system of Windows Server 2012 R2 Datacenter with 128 GB RAM and CPU of Intel (R) Xeon (R) E5−2650 v4 (2.20 GHz). The algorithms for comparison were coded by MATLAB R2018b.

Table 2
Unimodal and simple multimodal functions of CEC2014.

Functions	Dim	Range	f_{min}
$f_{14}(x)$ = Rotated High Conditioned Elliptic Function	n	[−100,100]	100
$f_{15}(x)$ = Rotated Bent Cigar Function	n	[−100,100]	200
$f_{16}(x)$ = Shifted and Rotated(SR) Ackley's Function	n	[−100,100]	500
$f_{17}(x)$ = SR Weierstrass Function	n	[−100,100]	600
$f_{18}(x)$ = SR HappyCat Function	n	[−100,100]	1300
$f_{19}(x)$ = SR HGBat Function	n	[−100,100]	1400
$f_{20}(x)$ = SR Expanded Griewank'splus Rosenbrock's Function	n	[−100,100]	1500
$f_{21}(x)$ = SR Expanded Scaffer'sF6 Function	n	[−100,100]	1600

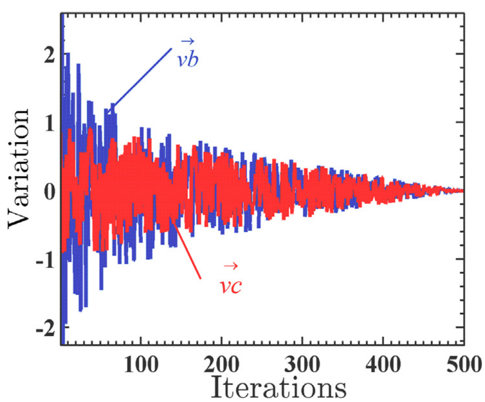

Fig. 5. Trends of $\overrightarrow{vb}$ and $\overrightarrow{vc}$.

3.1. Qualitative analysis

The qualitative analysis results of SMA in handling unimodal functions and multimodal functions are presented in Fig. 8 to intuitively analyse the position and fitness changes of slime mould during foraging. The figure is comprised of four concernment indicators: search history, the trajectory of the slime mould in the 1st dimension, the average fitness of slime mould, and convergence curve. Search history represents the location and distribution of slime mould in the iteration process. The trajectory of slime mould reveals the behaviour of the position change of slime mould in the first part of the first dimension. Average fitness indicates the variation trend of the average fitness of the slime mould colony changes with the iteration process. The convergence curve shows the optimal fitness value in the slime mould during the iteration process.

From the search history subplot, the slime mould in different benchmark functions put up a similar cross-type search trajectory clustered near the optimal value, thus accurately searching in reliable search areas and reflecting fast convergence. Meanwhile, the distribution of slime mould is mainly concentrated in multiple regions with local optimum, which shows the tradeoff of slime mould between multiple local optimums.

The trajectory of the first slime mould in the first dimension can be used as a representative of other parts of slime mould, revealing the primary exploratory behaviour of the slime mould. The fast oscillation in the prophase and the slight oscillation in the anaphase can ensure the fast convergence of slime mould and the accurate search near the optimal solution [52]. As can be perceived from the figure, the position curve of slime mould has a very large amplitude in the early iteration process, even up to 50% of the exploration space. In the later iteration period, if the function is smooth, the amplitude of the position of slime mould begins to decrease; if the amplitude of the function changes significantly, the position amplitude also changes much. This reflects the high adaptability and robustness of slime mould in different functions.

By observing the average fitness curve, the variation tendency of the fitness of slime mould during the iterative procedure can be visually observed. Although the average fitness curve of slime mould is oscillating, the average fitness value tends to decrease, and the oscillation frequency decreases inversely proportional to iterations, thus ensuring the rapid convergence of slime mould in the prophase and the precise search in the anaphase.

The convergence curve reveals the average fitness of the optimal fitness value searched by slime mould varies with iterations. By observing the downtrend of the curve, we can observe the convergence rate of slime mould and the time when it switches between the exploration and exploration gradation.

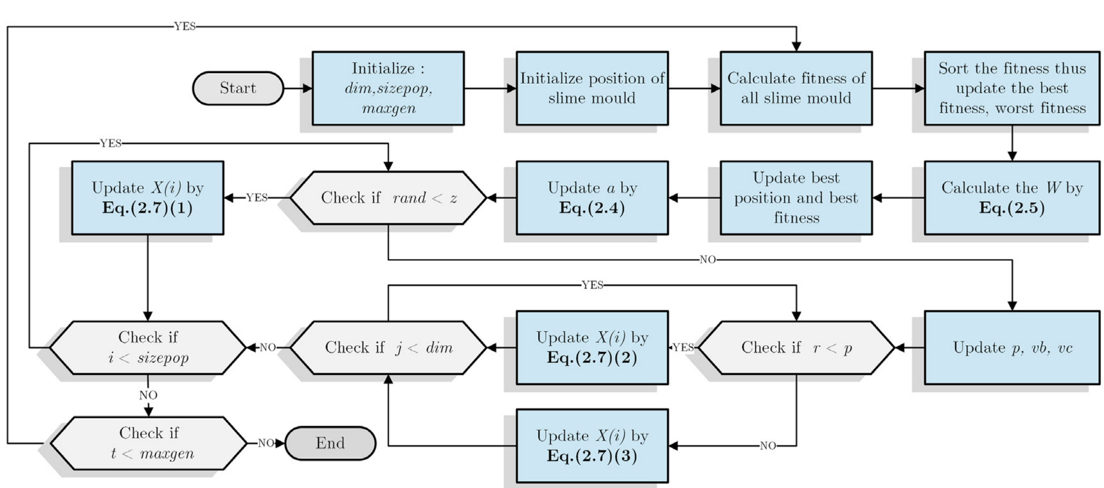

Fig. 6. Flowchart of SMA.

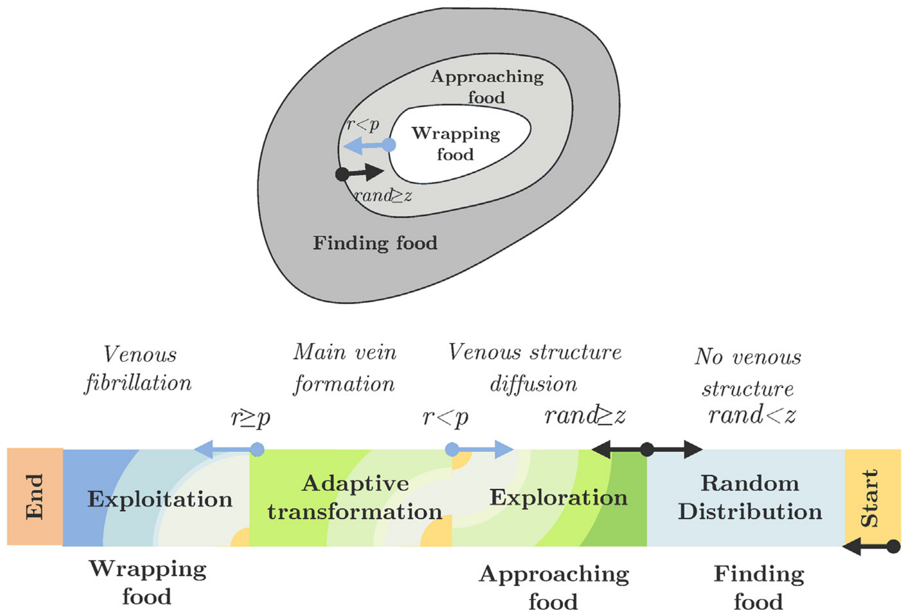

Fig. 7. The steps of SMA.

Table 3
Hybrid and composition functions of CEC 2014.

Functions	Dim	Range	f_{min}
$f_{22}(x)$ = Hybrid Function 1	n	[−100,100]	1700
$f_{23}(x)$ = Hybrid Function 2	n	[−100,100]	1800
$f_{24}(x)$ = Hybrid Function 3	n	[−100,100]	1900
$f_{25}(x)$ = Hybrid Function 4	n	[−100,100]	2000
$f_{26}(x)$ = Hybrid Function 5	n	[−100,100]	2100
$f_{27}(x)$ = Hybrid Function 6	n	[−100,100]	2200
$f_{28}(x)$ = Composite function 1	n	[−100,100]	2300
$f_{29}(x)$ = Composite function 2	n	[−100,100]	2400
$f_{30}(x)$ = Composite function 3	n	[−100,100]	2500
$f_{31}(x)$ = Composite function 4	n	[−100,100]	2600
$f_{32}(x)$ = Composite function 5	n	[−100,100]	2700
$f_{33}(x)$ = Composite function 6	n	[−100,100]	2800

Table 4
Parameter settings of counterparts.

Algorithm	Parameter settings
WOA	$a_1 = [2, 0]$; $a_2 = [-2, -1]$; $b = 1$
GWO	$a = [2, 0]$
MFO	$b = 1$; $t = [-1, 1]$; $a \in [-1, -2]$
BA	$A = 0.5$; $r = 0.5$
SCA	$A = 2$
FA	$\alpha = 0.5$; $\beta = 0.2$; $\gamma = 1$
PSO	$c_1 = 2$; $c_2 = 2$; $vMax = 6$
SSA	$c_1 \in [01]$; $c_2 \in [01]$;
MVO	*Existence probability* $\in [0.21]$; *travelling distance rate* $\in [0.61]$
ALO	$k = 500$
PBIL	*Learning rate* = 0.05; *elitism parameter* = 1; *probability vector mutation rate* = 0
DE	*Scaling factor* = 0.5; *crossover probability* = 0.5

3.2. Benchmark function validation

In this section, SMA was assessed on a comprehensive set of functions from 23 benchmarks and CEC 2014. These functions cover unimodal, multimodal, hybrid, and composite functions, as shown in Tables 1–3. Some composite functions of CEC 2014 are shown in Fig. 9. Dim denotes the dimension of function; Range denotes the definition domain of the function, and f_{min} denotes the optimal value of the function. The MAs used for comparison include well-regarded and recent ones: WOA [53], GWO [24], MFO [26], BA [23], SCA [9], FA [54], PSO [22], SSA [55], MVO [6], ALO [56], PBIL [57], DE [58] and advanced MAs: AGA [59], BLPSO [60], CLPSO [61], CBA [62], RCBA [63], CDLOBA [64], m_SCA [65], IWOA [66], LWOA [67], and CSSA [68]. The parameter setup of traditional MAs is detailed in Table 4. The parameter selection was based on the parameters used by the original author in the article or the parameters widely used by various researchers.

All algorithms were performed under the same conditions to achieve fairness in comparative experiments. Among them, the population was set to 30, the dimension and the iteration time was set to 30 and 1000 respectively. To reduce the impacts of random factors in the algorithm on the results, all the compared algorithms were run individually 30 times in each function and averaged as the final running result. On the purpose of measuring experiment results, Standard deviation (STD), Average results (AVG), and Median (MED) were employed to evaluate the results. Note that the best results will be bolded (take one in the case of juxtaposition).

3.2.1. Exploitation competence analysis

The data in Table 5 demonstrates that SMA ranked first or tied first on average when solving F1-5, F7, and F14. The convergence curves of F2 and F5 in Fig. 10 can be visually observed that SMA has the fastest convergence trend among all the comparative functions. The data in Table 6 demonstrates that SMA can still exhibit significant advantages even when compared to a modified MA, such as ranking first among other unimodal functions other than F5 and F14. These functions are unimodal functions in the benchmarks, reflecting SMA's efficient exploration capability. Moreover, in order to more fairly evaluate the local search efficiency of the algorithm, an evaluation version of the experiment has been added. The data in Table 7 demonstrate the experimental results obtained by 300,000 evaluations of the SMA with 10 other participants on the unimodal functions. In the experimental results, the values obtained by SMA were still better than those of other algorithms on F1-5 and F7. At the same time, the median values of the solutions were also consistent with the ranking of the optimal values, indicating the stability of the SMA.

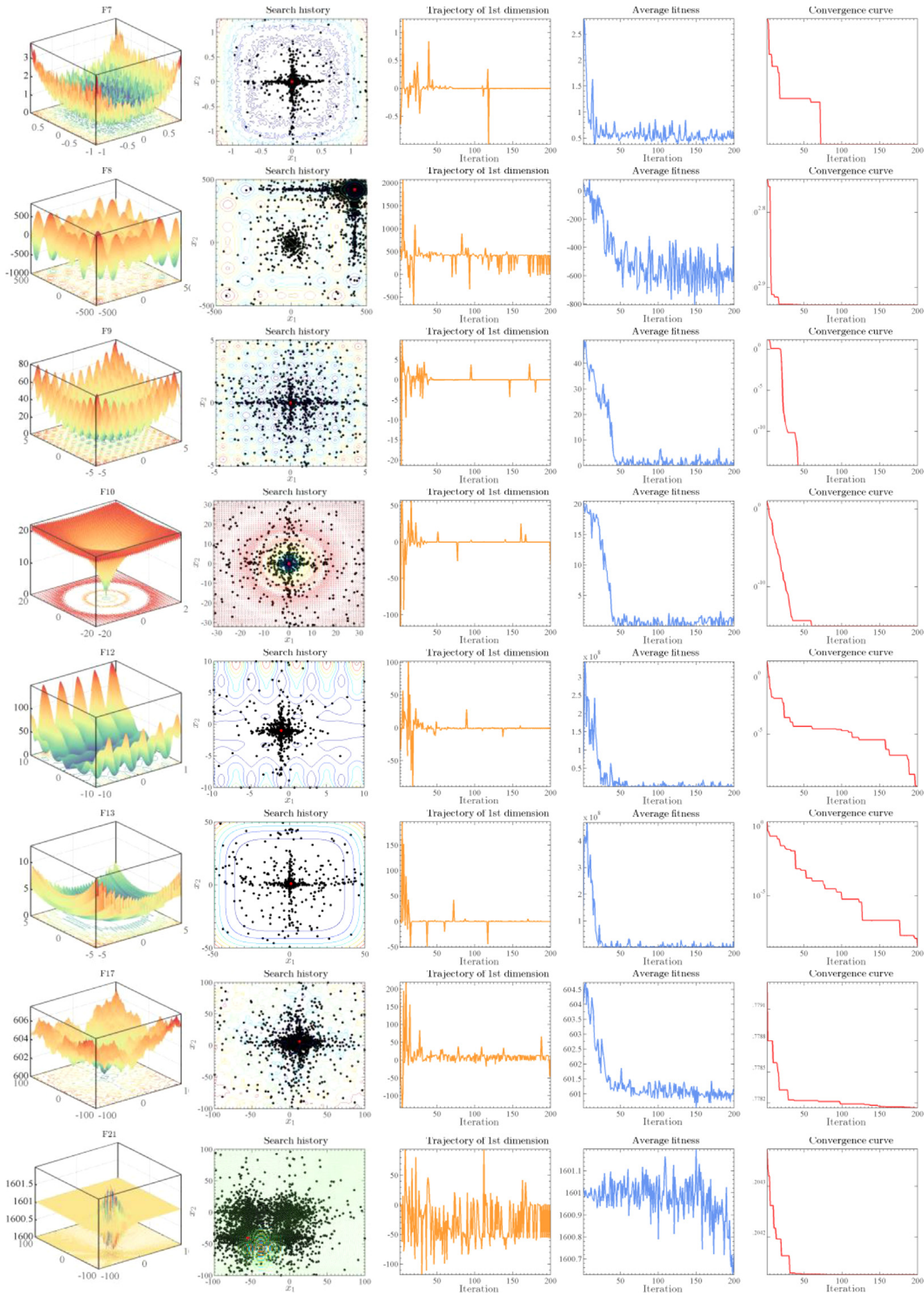

Fig. 8. Qualitative analysis.

3.2.2. Exploration competence analysis

The data in Table 8 represents that SMA is still competitive in multimodal functions. In F8–F11 and F20–21, the AVG of SMA was the smallest or the smallest in parallel compared with other algorithms. From the convergence curves of F8 and F21 in Fig. 10, it can be observed that SMA can search for the highest accuracy fitness value in these two multimodal functions, while some algorithms fail to obtain a superior solution after a certain amount of iterations. This is due to local optima stagnation, which illustrates that SMA can still show better exploration ability in case of preferable exploration. From the data in Table 9, it can be seen that the results of SMA in F9–F11, F17, and F20–21 are optimal, and only slightly lower than other algorithms in F8, F18, and F19, which indicates that SMA can still maintain its advantages over advanced algorithms and reflect SMA's capability to avoid local optimum solutions. Fig. 11 also shows that SMA can find a superior solution at a relatively fast convergence tendency in multimodal functions such as F9–11, F17, and F21. Table 10 illustrates the experimental results of SMA with 10 other comparators on the multimodal function. Among them, SMA obtained the best average and median results on F8–F11 compared with other algorithms, and AGA obtained the best average and median

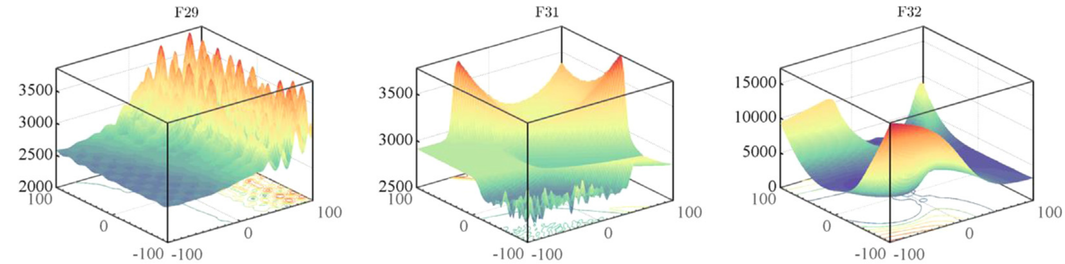

Fig. 9. Illustration of CEC 2014 composite functions.

Table 5
Comparison results on unimodal functions with traditional algorithms during 1000 iterations.

Algorithm	F1			F2			F3		
	AVG	STD	MED	AVG	STD	MED	AVG	STD	MED
SMA	**0.000000**	0.000000	**1.08E−64**	**5.330E−207**	0.000000	**5.93E−58**	**0.00000**	0.00000	8.22E−02
SCA	0.015244	0.029989	9.36E+01	1.150E−05	2.743E−05	8.06E−03	3261.99676	2935.03792	2.75E+04
SSA	1.231E−08	3.536E−09	1.83E+02	0.848146	0.941518	8.90E+00	236.62194	155.54710	2.94E+03
GWO	4.223E−59	1.081E−58	4.39E−46	1.128E−34	9.149E−35	7.07E−28	4.027E−15	1.418E−14	**1.50E−09**
MFO	2000.0006	4068.3807	2.04E+03	33.666839	20.253973	3.42E+01	24 900.5554	14 138.0477	2.91E+04
WOA	4.322E−153	2.276E−152	2.34E−54	5.032E−104	1.591E−103	3.42E−34	20 802.2782	10 554.3925	5.30E+04
GOA	7.670196	6.676643	1.27E+03	9.540510	14.128406	3.09E+01	1794.1195	1103.3922	7.64E+03
DA	1158.4940	600.8920	1.19E+03	14.313148	5.649106	1.45E+01	9612.3629	6188.5858	9.64E+03
ALO	1.050E−05	7.825E−06	7.10E+00	28.698940	42.100743	3.02E+01	1275.7431	596.2918	1.73E+03
MVO	0.318998	0.112060	9.40E+02	0.388930	0.137834	1.39E+01	48.11246	21.77526	4.61E+03
PBIL	46 908.0000	4218.6045	4.84E+04	95.200000	5.892134	9.80E+01	54 824.1	6552.855378	6.02E+04
PSO	128.803704	15.368375	1.42E+02	86.075426	65.298810	1.12E+02	406.96260	71.30926	6.06E+02
DE	3.030E−12	3.454E−12	4.01E−04	3.723E−08	1.196E−08	2.24E−03	24 230.5748	4174.3788	3.00E+04
Algorithm	F4			F5			F6		
	AVG	STD	MED	AVG	STD	MED	AVG	STD	MED
SMA	**2.301E−197**	0.000000	**1.31E−25**	**0.42779**	0.63700	**9.89E+00**	0.000879	0.000415	5.97E−01
SCA	20.532489	11.046644	7.53E+01	532.7126	1907.4456	1.58E+06	4.550121	0.357049	3.37E+01
SSA	8.254602	3.287966	1.62E+01	135.5698	174.1213	7.77E+03	0.000000	0.000000	2.04E+02
GWO	1.776E−14	2.228E−14	9.01E−12	27.10029	0.86432	2.73E+01	0.726058	0.278337	9.75E−01
MFO	64.420279	8.689356	6.47E+01	5 348 258	20 289 785	5.35E+06	1656.708	5277.651	1.68E+03
WOA	45.706343	26.935040	4.61E+01	27.26543	0.57447	2.73E+01	0.100557	0.110525	1.01E−01
GOA	12.596514	4.317304	2.35E+01	1631.1583	2241.1368	2.58E+05	4.884661	4.512327	1.36E+03
DA	23.631736	8.191777	2.37E+01	127 371	96 386	1.31E+05	1330.292	632.470	1.34E+03
ALO	12.133214	3.585375	1.32E+01	298.8031	431.1446	5.00E+02	0.000012	0.000011	7.49E+00
MVO	1.076968	0.310884	1.40E+01	407.9465	615.3290	8.63E+04	0.323756	0.097394	9.34E+02
PBIL	79.666667	4.088110	8.00E+01	143 346 156	31 547 349	1.51E+08	45 881.833	4850.932	4.77E+04
PSO	4.498158	0.329339	4.79E+00	154 736	36 039	1.85E+05	132.779	15.189	1.45E+02
DE	1.965929	0.430531	1.32E+01	46.12942	27.29727	1.40E+02	**3.096E−12**	1.461E−12	**4.11E−04**
Algorithm	F7			F14			F15		
	AVG	STD	MED	AVG	STD	MED	AVG	STD	MED
SMA	**8.839E−05**	7.118E−05	**4.08E−04**	**9 549 563**	6 529 870	2.97E+07	22 233.8245	14 144.9575	5.47E+07
SCA	0.024382	0.020732	6.04E−01	425 718 766	116 756 947	7.06E+08	2.689E+10	5.427E+09	3.97E+10
SSA	0.095541	0.050530	1.59E−01	20 297 116	8 153 518	6.91E+07	11 222.8121	11 173.7583	3.37E+08
GWO	0.000869	0.000435	1.46E−03	88 751 868	66 700 399	1.29E+08	2.254E+09	1.759E+09	3.98E+09
MFO	4.620163	13.076256	4.77E+00	87 010 749	137 363 574	1.00E+08	1.341E+10	7.685E+09	1.35E+10
WOA	0.000986	0.001147	2.66E−03	160 431 438	69 271 930	1.62E+08	2.154E+09	1.086E+09	2.17E+09
GOA	0.024028	0.011253	2.96E−02	33 807 500	14 819 986	1.28E+08	17 667 580	11 032 455	2.34E+09
DA	0.326978	0.138556	3.31E−01	305 164 519	121 919 102	3.05E+08	6.363E+09	2.751E+09	6.37E+09
ALO	0.103373	0.034257	1.06E−01	12 505 761	5 184 932	**1.69E+07**	12 378	9058	1.25E+07
MVO	0.020859	0.009584	1.42E−01	14 860 094	6 244 884	5.89E+07	566 570	210 025	1.45E+09
PBIL	282.1349	43.2693	2.93E+02	574 020 990	128 317 251	7.02E+08	4.961E+10	5.107E+09	5.32E+10
PSO	111.0068	21.5378	1.11E+02	17 174 833	5 483 990	2.16E+07	191 733 286	23 903 821	2.09E+08
DE	0.026937	0.006322	5.44E−02	100 597 441	31 636 302	1.78E+08	**1601.8022**	3314.1727	**1.97E+05**

on F16–21. Compared with AGA, SMA has a more significant advantage in unimodal functions, while AGA has a preferable performance in multimodal functions.

3.2.3. Analysis of avoiding locally optimal solutions

All functions in Tables 11–12, as fix-dimension multimodal functions, have multiple local optima, which are challenging for MAs, thus can discriminate the overall efficacy of algorithms in exploration and exploration. According to the data in Tables 11–12, SMA ranked first in AVG on F28, F29, F30, F32, and F33, which show a very potential comprehensive ability. It can also be seen from the optimum curve of F28–33 in Fig. 10 that SMA achieves superior solutions faster than other counterparts, thus well coordinating the ability of exploration and exploitation. The statistics of Tables 13–14 illustrate that SMA can also maintain certain advantages in composition functions compared with the advanced algorithm, which further reflects that SMA can avert falling into local optimum with fast convergence. F25, F32, and F33 in Fig. 11 also intuitively incarnate the performance preponderance of SMA in composition functions.

Table 6
Comparison results on the unimodal functions with advanced algorithms.

Algorithm	F1			F2			F3		
	AVG	STD	MED	AVG	STD	MED	AVG	STD	MED
SMA	**0.000000**	0.000000	4.72E−37	**4.20E−187**	0.000000	**1.24E−66**	**0.000000**	0.000000	**1.19E−02**
BLPSO	2208.3313	397.7883	5.00E+03	17.665054	1.905407	3.35E+01	13 540.48	1672.45	1.82E+04
CLPSO	596.7364	150.3595	5.15E+03	11.846531	1.669288	4.09E+01	16 836.42	3085.75	2.71E+04
CBA	0.113583	0.454545	4.38E−01	305 804	1 652 847	5.73E+05	73.709725	31.029467	2.54E+02
RCBA	0.201488	0.052889	5.31E−01	10.958358	28.471304	2.77E+01	95.544912	43.376020	7.44E+02
CDLOBA	0.005957	0.002133	1.88E−02	3781.932	15 086.168	1.24E+04	1.791342	6.166318	3.50E+02
m_SCA	2.521E−46	1.378E−45	8.14E−04	3.478E−33	1.420E−32	2.01E−06	8.991E−16	3.188E−15	5.82E+03
IWOA	8.130E−146	4.370E−145	**1.00E−53**	2.385E−102	6.585E−102	1.44E−33	15 410.3	7420.1	3.62E+04
LWOA	6.743E−07	7.589E−07	1.55E−01	2.801E−07	3.833E−07	6.54E−02	43 293.10	13 505.91	9.25E+04
CSSA	0.017344	0.027805	1.74E−02	0.061732	0.027609	6.21E−02	2.926441	3.133898	2.95E+00
Algorithm	F4			F5			F6		
	AVG	STD	MED	AVG	STD	MED	AVG	STD	MED
SMA	**8.84E−183**	0.00000	**1.80E−36**	1.27571	4.90297	**1.22E+01**	**0.000880**	0.000407	9.26E−01
BLPSO	27.66310	2.40967	3.54E+01	520 889	178 483	2.75E+06	2207.564	410.182	5.20E+03
CLPSO	42.44490	4.41014	5.61E+01	113 820	39 571	2.95E+06	563.251	138.054	5.26E+03
CBA	17.03820	7.72324	2.20E+01	197.6163	360.2440	2.58E+02	0.001823	0.007886	1.16E−01
RCBA	9.00594	3.41186	1.49E+01	148.2466	122.4613	2.29E+02	0.187352	0.054118	4.62E−01
CDLOBA	46.10460	7.48538	4.81E+01	138.1210	178.6248	2.29E+02	0.005940	0.001899	**1.79E−02**
m_SCA	2.248E−13	1.223E−12	1.53E+01	27.62609	0.84321	3.34E+01	2.540097	0.499546	4.06E+00
IWOA	13.12456	16.19609	2.26E+01	26.57003	0.66075	2.70E+01	0.036361	0.069578	6.17E−02
LWOA	11.12439	14.63066	2.69E+01	25.63874	6.59153	2.90E+01	0.009637	0.002992	4.25E−01
CSSA	0.03301	0.01983	3.45E−02	**0.17508**	0.16603	1.76E−01	0.030982	0.062573	3.11E−02
Algorithm	F7			F14			F15		
	AVG	STD	MED	AVG	STD	MED	AVG	STD	MED
SMA	**8.21E−05**	7.16E−05	**3.24E−04**	9 689 581	7 904 687	3.20E+07	**15 808.97**	10 533.48	5.40E+07
BLPSO	0.59346	0.17290	1.50E+00	1.72E+08	3.74E+07	2.98E+08	3.718E+09	5.932E+08	8.78E+09
CLPSO	0.26201	0.05157	1.74E+00	1.77E+08	6.19E+07	4.28E+08	1.985E+09	4.391E+08	1.47E+10
CBA	0.47023	0.31242	7.47E−01	1.15E+07	5 802 441	1.80E+07	513 564.79	1 056 309.50	2.80E+06
RCBA	0.61360	0.25709	1.02E+00	5 943 596	2 275 351	**1.06E+07**	372 942.94	107 512.69	8.44E+05
CDLOBA	26.93780	39.54585	6.71E+01	**4 469 831**	2 849 244	1.07E+07	18 462.13	9920.05	**3.57E+04**
m_SCA	0.00071	0.00053	2.02E−02	1.15E+08	6.69E+07	3.52E+08	1.048E+10	4.703E+09	2.38E+10
IWOA	0.00185	0.00236	3.92E−03	9.34E+07	4.72E+07	1.19E+08	1.047E+09	8.576E+08	1.43E+09
LWOA	0.00650	0.00439	3.44E−02	8.81E+07	3.31E+07	4.11E+08	3.334E+08	1.326E+08	2.21E+10
CSSA	0.00019	0.00016	6.78E−04	1.68E+09	2.36E+08	1.68E+09	8.837E+10	6.958E+09	8.84E+10

3.2.4. Significance of superiority analysis

Wilcoxon sign-rank test method [69] was exerted to verify whether SMA has obvious advantages over pairwise comparison. If the *p*-value produced by the comparison is below the significant level of 0.05 in this case, it means that the achievements of the algorithm in pairwise comparison have obvious superiority in the statistical sense. Otherwise, it is considered that the discrepancies between the two contestants are inconspicuous in a statistical sense. In order to draw further comprehensive conclusions and control the family-wise error rate (FWER), the true statistical significance (#TSS) of the combined pairwise comparison is shown in Eq. (3.1) [70]:

$$p = 1 - \prod_{i=1}^{k-1} 1 - p_{H_1} \tag{3.1}$$

The p value achieved from this expression is shown in Table 15, where the TSS in F1-8, F10, F12, F15, F28–30, and F32–33 were all less than 0.05 when compared with traditional algorithms. Therefore, SMA has significant differences in these functions compared to the traditional algorithms. TSS in Table 15, when compared with advanced algorithms indicates that SMA outperforms other algorithms in F1-8, F10, F17, F19–22, F25, F28–30, F32–33.

Although pairwise comparisons can be used for comparisons between algorithms, the FWER generated during the experiment cannot be corrected in advance, and the choice of algorithms in multiple comparisons can greatly affect the results of the analysis. In order to reduce the effect of algorithm selection in each result set, multiple comparison processes are used to modify FWER. In multiple comparisons, first, check whether the results obtained by the algorithm are unequal. When inequality exists, then perform post-hoc analysis to know which algorithms have significant differences. Therefore, non-parametric Friedman's test [71] was utilized. Table 16 illustrates the average ranking of the results of the algorithms on the benchmarks based on three sets of experiments. In a non-hypothesis, there is equality between all algorithms, so if the hypothesis is reversed, it means that there are differences between the algorithms being compared. Then we chose Holm's test [72] as the method of post hoc analysis, which is a multiple comparison method that can be used for control algorithms. Using the z-value obtained in Table 17 to find the corresponding *p*-value from the normal distribution table and compare it with the corrected α value. Take SMA as a control algorithm and compared it with other algorithms. The p-values have been sorted according to their significance. If the *p*-value is lower than the corresponding significant level α, the corresponding hypothesis is reversed, that is, the algorithm is significantly different. This paper selected two significant level $\alpha = 0.10$ and $\alpha = 0.05$, which indicate that there are marginal and significant differences between the two methods. As can be seen from Table 17, compared with the traditional algorithms other than DE, the z-value is smaller than the corrected value with $\alpha = 0.05$ as the significant level, that is, there are significant differences in benchmarks. Compared with advanced algorithms other than LWOA, there are significant differences among the benchmark functions, and slightly different from LWOA. In the experiments with other algorithms in the evaluation version, SMA is slightly different compared to GWO and WOA, not significantly different from AGA and DE, while significantly different from the remaining algorithms.

Table 7
Comparison results on unimodal functions during 3E5 evaluations.

Algorithm	F1			F2			F3		
	AVG	STD	MED	AVG	STD	MED	AVG	STD	MED
SMA	**0.00000**	0.00000	**2.150E−268**	**0.00000**	0.00000	1.999E−141	**0.00000**	0.00000	**7.427E−244**
SCA	5.33E−52	2.92E−51	1.325E−19	3.28E−60	9.54E−60	1.256E−28	2.65E+00	1.03E+01	2.763E+03
SSA	3.97E−09	7.20E−10	6.629E+01	2.20E−01	5.24E−01	4.818E+00	6.21E−08	1.97E−08	5.697E+02
GWO	0.00000	0.00000	0.000E+00	0.00000	0.00000	**1.002E−286**	8.62E−174	0.00000	1.908E−125
MFO	1.67E+03	3.79E+03	1.667E+03	3.53E+01	2.45E+01	3.533E+01	1.58E+04	1.08E+04	1.579E+04
WOA	0.00000	0.00000	0.000E+00	0.00000	0.00000	0.000E+00	2.15E+01	5.44E+01	1.755E+03
GOA	1.37E−03	7.51E−04	7.244E+02	4.93E−01	5.10E−01	1.954E+01	1.15E+02	3.94E+02	2.836E+03
MVO	3.11E−03	7.04E−04	5.957E+02	3.84E−02	1.30E−02	1.113E+01	3.70E−01	1.10E−01	1.613E+03
PSO	1.01E+02	1.43E+01	1.113E+02	4.69E+01	3.54E+00	5.156E+01	1.85E+02	2.76E+01	2.205E+02
DE	1.46E−159	3.86E−159	4.314E−76	2.02E−94	2.33E−94	1.359E−45	1.39E+03	7.73E+02	6.275E+03
AGA	2.38E−02	2.48E−02	5.567E−02	1.18E−02	3.99E−03	1.701E−02	4.51E−02	4.92E−02	8.333E−02
Algorithm	F4			F5			F6		
	AVG	STD	MED	AVG	STD	MED	AVG	STD	MED
SMA	**0.00000**	0.00000	2.648E−131	**2.22E−03**	9.67E−04	1.837E−01	9.61E−06	4.23E−06	1.583E−02
SCA	4.46E−03	1.34E−02	1.490E+01	2.73E+01	6.99E−01	2.793E+01	3.70E+00	2.72E−01	4.367E+00
SSA	3.72E−01	7.06E−01	7.726E+00	7.27E+01	9.68E+01	2.160E+03	3.86E−09	9.08E−10	6.799E+01
GWO	1.79E−152	8.68E−152	**2.593E−126**	2.61E+01	9.13E−01	2.632E+01	4.64E−01	2.81E−01	6.100E−01
MFO	6.54E+01	1.03E+01	6.536E+01	2.69E+06	1.46E+07	2.686E+06	2.99E+03	7.91E+03	2.990E+03
WOA	3.68E+00	7.91E+00	4.832E+00	2.44E+01	3.14E−01	2.437E+01	5.89E−06	2.44E−06	5.896E−06
GOA	2.45E+00	2.03E+00	1.366E+01	1.52E+02	3.50E+02	6.639E+04	1.52E−03	7.49E−04	7.702E+02
MVO	8.89E−02	3.43E−02	9.891E+00	6.68E+01	9.45E+01	3.591E+04	3.05E−03	7.30E−04	6.130E+02
PSO	3.81E+00	2.16E−01	3.993E+00	8.98E+04	1.83E+04	1.085E+05	9.85E+01	8.65E+00	1.094E+02
DE	3.54E−15	5.37E−15	7.076E−07	3.08E+01	1.81E+01	3.259E+01	**0.00000**	0.00000	**0.000E+00**
AGA	3.17E−02	2.19E−02	6.531E−02	5.10E−02	6.04E−02	**1.262E−01**	1.58E−02	1.69E−02	1.145E−01
Algorithm	F7			F14			F15		
	AVG	STD	MED	AVG	STD	MED	AVG	STD	MED
SMA	**9.53E−06**	8.25E−06	**5.830E−05**	2.15E+06	7.66E+05	9.335E+06	1.09E+04	1.28E+04	5.209E+06
SCA	2.43E−03	2.30E−03	1.570E−02	2.35E+08	5.63E+07	3.955E+08	1.65E+10	3.59E+09	2.586E+10
SSA	8.58E−03	4.21E−03	2.034E−02	1.72E+06	6.73E+05	2.440E+07	1.21E+04	9.72E+03	1.130E+08
GWO	6.07E−05	4.25E−05	9.191E−05	5.78E+07	3.28E+07	8.364E+07	2.18E+09	2.05E+09	3.621E+09
MFO	3.64E+00	5.34E+00	3.660E+00	9.51E+07	1.18E+08	9.580E+07	1.05E+10	7.21E+09	1.054E+10
WOA	1.38E−04	1.36E−04	3.663E−04	2.67E+07	1.08E+07	2.686E+07	4.45E+06	7.57E+06	4.481E+06
GOA	1.70E−03	9.63E−04	2.530E−03	1.31E+07	9.07E+06	4.304E+07	2.27E+07	1.24E+08	1.157E+09
MVO	2.99E−03	1.04E−03	6.692E−02	2.78E+06	1.07E+06	2.863E+07	1.55E+04	1.05E+04	9.453E+08
PSO	1.02E+02	2.89E+01	1.022E+02	8.12E+06	2.06E+06	1.019E+07	1.51E+08	1.61E+07	1.643E+08
DE	2.48E−03	6.04E−04	4.437E−03	2.05E+07	6.27E+06	3.310E+07	8.91E+02	1.81E+03	9.373E+02
AGA	1.77E−04	1.22E−04	3.056E−04	**1.73E+02**	8.34E+01	**2.952E+02**	**2.40E+02**	5.14E+01	**2.971E+02**

3.3. Wall-clock time analysis

In this section of the experimentations, SMA was compared with the other 11 participants in the calculation of time-consuming experiments in the 33 benchmarks mentioned above. The time-consuming calculation approach is that all participants independently run 10 times on each function and recorded the results in Table 18. As can be observed from the data in the table, the computation of SMA takes relatively more extended time, because the calculation of the oscillation factor requires more computing power. However, SMA can still outperform some algorithms while taking less time, such as GOA, DA, and ALO. In general, even if it is relatively time-consuming, SMA still possess tremendous effectiveness advantages over other algorithms, so the time results are expected.

3.4. Parameter sensitivity analysis

In this section, parameter sensitivity test was utilized to evaluate the impacts of population size, iterations and parameter z on the algorithm. The range of parameter z is [0,0.1], and there are 11 values at intervals of [0, 0.01]. The population size was set to 5,10,30,50,100 and 200. The number of iterations was set to 50,100,200,500,1000 and 2000. Under other conditions remained, different values of parameter z were tested on F1–13 and the results are shown in Table 19. SMA0 indicates that z takes a value of 0, SMA1 indicates that z takes a value of 0.01, and so on. The values in the table are ranking. From the results in Table 20, it can be recognized that the result of the algorithm is superior when z was taken as 0.03, because the probability maintains the balance between exploration and exploitation. Experimenter can also take different values for z according to specific problems.

To explore the influence of populations and iterations on the algorithm, we chose F13 to test the synergistic effect of the two parameters on the algorithm. As can be seen visually from Fig. 12, as the population size and iterations increased, the average became better. The reason is that the increase in the number of populations improves search efficiency, and the increase in iterations leads to an incensement in the times of searches and the accuracy of subsequent searches. However, the results were not increased proportionally when the population size and iterations continue to grow due to the global approximate optimal solution has been roughly discovered. Researchers can select the appropriate populations and iterations based on specific questions.

3.5. Experiments on engineering design problems

Methods based on different logics should be solved using at least a proper numerical validation [73–78]. Most problems have constraints in the real production environment. The process of considering constraints of equality and inequality during optimization is called constraints processing. The candidate solutions of the heuristic algorithm can be divided into feasible and infeasible according to the constraints. There are currently several types of constraint methods: death penalty, annealing,

Table 8
Results on multimodal functions with traditional algorithms during 1000 iterations.

Algorithm	F8			F9			F10		
	AVG	STD	MED	AVG	STD	MED	AVG	STD	MED
SMA	**−12 569.4**	0.1	**−1.26E+04**	**0.00000**	0.00000	9.96E−01	**8.882E−16**	0.00000	**8.88E−16**
SCA	−3886.1	225.6	−3.82E+03	18.35521	21.43693	7.22E+01	11.32308	9.66101	1.42E+01
SSA	−7816.8	842.3	−6.98E+03	56.61307	12.89967	1.38E+02	2.25688	0.72068	5.03E+00
GWO	−6088.7	859.4	−3.83E+03	0.06990	0.38287	**1.12E−01**	0.00000	0.00000	1.62E−14
MFO	−8711.6	827.4	−8.71E+03	162.06619	49.63022	1.63E+02	15.79421	6.91218	1.60E+01
WOA	−11 630.6	1277.5	−1.15E+04	0.00000	0.00000	0.00000	3.967E−15	2.030E−15	4.09E−15
GOA	−7430.4	761.2	−5.33E+03	86.74360	31.98704	2.35E+02	4.63913	1.06742	9.76E+00
DA	−5631.8	590.7	−5.62E+03	155.13449	38.31121	1.56E+02	8.64831	1.22491	8.72E+00
ALO	−5610.1	438.7	−5.61E+03	80.88997	20.29005	8.49E+01	2.00733	0.77081	2.90E+00
MVO	−7744.9	693.4	−5.59E+03	112.71842	24.57189	2.33E+02	1.14572	0.70341	7.70E+00
PBIL	−4046.4	331.0	−3.87E+03	150.36667	19.01267	1.55E+02	18.44223	0.19901	1.85E+01
PSO	−6728.1	650.2	−6.72E+03	369.24464	18.68261	3.73E+02	8.41508	0.41051	8.75E+00
DE	−12 409.8	149.2	−9.93E+03	59.28367	6.07679	8.60E+01	4.638E−07	1.383E−07	5.66E−03
Algorithm	F11			F12			F13		
	AVG	STD	MED	AVG	STD	MED	AVG	STD	MED
SMA	**0.00000**	0.00000	**0.00000**	0.001195	0.001422	1.42E−02	0.001577	0.003000	1.45E−01
SCA	0.23534	0.22480	1.29E+00	2.290194	2.958865	3.48E+07	518.6869	2782.8453	1.78E+07
SSA	0.01009	0.01067	2.75E+00	5.542545	3.122247	2.17E+01	1.010473	4.701096	9.51E+01
GWO	0.00028	0.00156	3.30E−04	0.037303	0.019955	5.70E−02	0.488377	0.174343	6.85E−01
MFO	22.63478	42.31343	2.82E+01	0.470607	0.782326	3.78E+02	6792.354	37 201.162	8.22E+03
WOA	0.00000	0.00000	0.00000	0.005205	0.003512	5.21E−03	0.181197	0.166955	1.81E−01
GOA	0.83124	0.15983	1.29E+01	6.489011	2.717562	4.07E+03	26.3886	16.5919	1.36E+05
DA	9.87794	4.37600	1.00E+01	306.688	1096.994	3.10E+02	4.571E+04	1.022E+05	4.73E+04
ALO	0.00994	0.01271	1.07E+00	9.456697	3.198074	1.28E+01	2.193406	7.919110	3.25E+00
MVO	0.57543	0.08747	8.98E+00	1.294524	1.103471	1.27E+01	0.081286	0.043182	1.78E+03
PBIL	416.755	48.474	4.25E+02	2.667E+08	7.771E+07	2.99E+08	5.860E+08	9.982E+07	6.40E+08
PSO	1.03228	0.00489	1.04E+00	4.80322	0.86670	5.16E+00	23.191583	4.195613	2.88E+01
DE	9.761E−11	2.126E−10	7.56E−03	**3.633E−13**	3.399E−13	**5.03E−05**	**1.691E−12**	1.165E−12	**2.44E−04**
Algorithm	F16			F17			F18		
	AVG	STD	MED	AVG	STD	MED	AVG	STD	MED
SMA	521.0056	0.109097	5.21E+02	618.2822	3.265441	**6.23E+02**	1300.6543	0.117872	**1.30E+03**
SCA	521.0427	0.053484	5.21E+02	636.9826	2.244227	6.40E+02	1303.9293	0.374149	1.30E+03
SSA	520.0584	0.107997	5.21E+02	622.8313	4.728569	6.28E+02	1300.5756	0.148959	1.30E+03
GWO	521.0410	0.054652	5.21E+02	616.6474	2.512406	6.24E+02	1300.6905	0.549189	1.30E+03
MFO	520.2870	0.170908	**5.20E+02**	622.7437	2.701796	6.23E+02	1301.3678	1.019364	1.30E+03
WOA	520.7787	0.119860	5.21E+02	637.7305	2.887311	6.38E+02	1300.5741	0.260727	1.30E+03
GOA	520.1390	0.082631	5.21E+02	622.1088	4.176909	6.30E+02	1300.5707	0.149671	1.30E+03
DA	520.9891	0.094995	5.21E+02	637.2321	2.789804	6.37E+02	1301.4935	1.087595	1.30E+03
ALO	**520.0494**	0.093898	5.21E+02	626.0851	3.620101	6.27E+02	**1300.4614**	0.100828	1.30E+03
MVO	520.5350	0.102963	5.21E+02	**614.4619**	3.437751	6.25E+02	1300.6110	0.114900	1.30E+03
PBIL	521.0393	0.043185	5.21E+02	640.6707	1.407127	6.41E+02	1305.2666	0.311548	1.31E+03
PSO	521.0618	0.054837	5.21E+02	624.8413	3.071015	6.26E+02	1300.5438	0.095901	1.30E+03
DE	520.7948	0.090515	5.21E+02	629.2747	1.350482	6.32E+02	1300.5363	0.050040	1.30E+03
Algorithm	F19			F20			F21		
	AVG	STD	MED	AVG	STD	MED	AVG	STD	MED
SMA	1400.6670	0.361757	**1.40E+03**	**1510.9564**	3.012250	**1.52E+03**	**1611.4845**	0.567778	**1.61E+03**
SCA	1473.0029	15.520309	1.51E+03	16 869	13 476.33	1.26E+05	1613.2141	0.241155	1.61E+03
SSA	1400.4157	0.238649	1.40E+03	1513.1155	4.171347	1.53E+03	1612.2034	0.537832	1.61E+03
GWO	1407.2551	8.107508	1.42E+03	1949.1287	920.5966	2.05E+03	1611.7755	0.656408	1.61E+03
MFO	1430.1235	20.716796	1.43E+03	208 671	416 720.09	2.17E+05	1612.6679	0.536141	1.61E+03
WOA	1405.0142	6.261895	1.41E+03	1727.0908	122.1192	1.73E+03	1612.8485	0.463174	1.61E+03
GOA	1400.4834	0.331069	1.40E+03	1519.1245	6.359294	2.07E+03	1612.5397	0.510917	1.61E+03
DA	1422.6359	10.796483	1.42E+03	9188.8893	11 460.10	9.19E+03	1613.1921	0.298363	1.61E+03
ALO	**1400.2530**	0.047583	1.40E+03	1513.5362	4.828335	1.52E+03	1612.6442	0.572926	1.61E+03
MVO	1400.5551	0.403115	1.40E+03	1512.5460	3.700993	1.54E+03	1612.2971	0.526756	1.61E+03
PBIL	1525.2857	13.420862	1.54E+03	1 435 558	748 053.04	1.65E+06	1613.3661	0.212279	1.61E+03
PSO	1400.3217	0.095276	1.40E+03	1519.8378	1.631079	1.52E+03	1612.5422	0.412383	1.61E+03
DE	1400.4031	0.089745	1.40E+03	1517.1531	1.278695	1.52E+03	1612.5367	0.196986	1.61E+03

static, dynamic, co-evolutionary, and adaptive. Although useful information may be lost in the process of abandonment, we still adopted a relatively simple method of the death penalty with low computational cost to deal with search individuals who violated constraints and then re-assigned them a relatively large target value.

In the following sections, SMA has been tested on four engineering-constrained design problems: a welded beam problem, a pressure vessel problem, a cantilever, and I-beam.

3.5.1. Welded beam structure problem

The main purpose of the problem is to constrain side constraints, end deflection of the beam (δ), buckling load on the bar (P_c), bending stress in the beam (θ), moreover, shear stress (τ) with the least economic cost of welded beams.

There are four variables, for instance, the thickness of the weld (h), length of the attached bar (l), the height of the bar (t), the thickness of the bar (b). The design diagram for this problem is shown in Fig. 13. The formulations were listed below:

Table 9
Comparison results on the multimodal functions with advanced algorithms.

Algorithm	F8			F9			F10		
	AVG	STD	MED	AVG	STD	MED	AVG	STD	MED
SMA	−12 569.4	0.068790	−1.25E+04	0.00000	0.00000	**0.00000**	**8.88E−16**	0.00000	**8.88E−16**
BLPSO	−4544.5	400.3510	−3.87E+03	207.3039	17.0015	2.30E+02	10.22852	0.69752	1.30E+01
CLPSO	−8295.7	351.9193	−6.10E+03	139.7601	15.8072	2.17E+02	8.16910	0.64983	1.43E+01
CBA	−7355.4	720.5161	−7.32E+03	133.1773	40.7382	1.44E+02	14.91852	3.56105	1.50E+01
RCBA	−7248.6	814.7588	−7.24E+03	77.4955	14.5193	1.07E+02	6.76084	6.62622	9.76E+00
CDLOBA	−7236.3	600.1951	−7.23E+03	243.8551	62.2823	2.72E+02	19.57830	0.77234	1.97E+01
m_SCA	−5925.7	986.2730	−3.94E+03	0.00000	0.00000	1.11E+01	5.35800	9.03538	1.34E+01
IWOA	−11 252.0	1780.6529	−1.12E+04	0.00000	0.00000	0.00000	3.73E−15	2.17E−15	3.73E−15
LWOA	−10 775.8	1141.9779	−1.02E+04	5.12692	18.79066	2.12E+01	4.81E−05	2.84E−05	1.03E−01
CSSA	**−12 569.5**	0.000239	**−1.26E+04**	7.14583	39.06861	7.15E+00	0.03173	0.03027	3.21E−02

Algorithm	F11			F12			F13		
	AVG	STD	MED	AVG	STD	MED	AVG	STD	MED
SMA	**0.00000**	0.00000	0.00000	0.00095	0.00101	2.68E−02	0.00135	0.00211	1.16E−01
BLPSO	21.49704	3.65806	4.49E+01	4441.072	7073.234	3.24E+05	378 616.22	235 965.32	3.39E+06
CLPSO	6.33968	0.91129	4.95E+01	20.05685	8.11078	5.40E+05	11 963.83	13 926.90	4.89E+06
CBA	0.22145	0.11045	7.77E−01	15.33572	7.52799	1.59E+01	43.5008	21.1814	4.59E+01
RCBA	0.02800	0.00947	6.72E−02	13.56632	4.54840	1.47E+01	0.09299	0.03609	2.19E−01
CDLOBA	145.5030	96.9037	1.74E+02	20.17146	6.03281	2.08E+01	35.8588	11.9314	3.85E+01
m_SCA	0.00000	0.00000	5.52E−02	0.19369	0.16449	9.82E−01	1.58065	0.19641	2.40E+00
IWOA	0.00264	0.01100	**3.70E−03**	0.00930	0.02578	1.18E−02	0.16079	0.13761	2.07E−01
LWOA	0.02455	0.04926	4.54E−01	0.00063	0.00024	1.78E−02	0.01660	0.01442	2.05E−01
CSSA	0.02723	0.03762	2.74E−02	**5.98E−05**	5.33E−05	**6.03E−05**	**0.00090**	0.00086	**9.06E−04**

Algorithm	F16			F17			F18		
	AVG	STD	MED	AVG	STD	MED	AVG	STD	MED
SMA	521.0127	0.069163	5.21E+02	**619.4282**	2.915833	**6.24E+02**	1300.6589	0.145401	1.30E+03
BLPSO	521.0920	0.070988	5.21E+02	629.3125	1.805214	6.34E+02	1300.9286	0.138697	1.30E+03
CLPSO	521.0176	0.059879	5.21E+02	629.7237	1.356299	6.35E+02	1300.6655	0.089057	1.30E+03
CBA	**520.3188**	0.287026	**5.20E+02**	641.6516	3.410418	6.42E+02	1300.5091	0.134277	1.30E+03
RCBA	520.3774	0.123562	5.21E+02	640.2023	3.196174	6.41E+02	**1300.4976**	0.123416	**1.30E+03**
CDLOBA	521.0056	0.064721	5.21E+02	636.2815	2.936580	6.37E+02	1300.5098	0.146951	1.30E+03
m_SCA	520.9230	0.085023	5.21E+02	625.2555	2.906023	6.37E+02	1301.7144	0.980372	1.30E+03
IWOA	520.7061	0.096424	5.21E+02	634.7725	3.121824	6.36E+02	1300.5275	0.096831	1.30E+03
LWOA	520.7827	0.071113	5.21E+02	633.6692	3.853306	6.40E+02	1300.6093	0.123410	1.30E+03
CSSA	521.0604	0.088972	5.21E+02	644.9713	1.825103	6.45E+02	1309.5241	0.830936	1.31E+03

Algorithm	F19			F20			F21		
	AVG	STD	MED	AVG	STD	MED	AVG	STD	MED
SMA	1400.6565	0.361610	1.40E+03	**1510.5477**	2.46585	**1.52E+03**	**1611.5995**	0.70239	**1.61E+03**
BLPSO	1410.4409	2.902210	1.43E+03	1802.5795	180.2212	4.48E+03	1613.0067	0.23416	1.61E+03
CLPSO	1403.5324	2.812311	1.45E+03	1952.4155	304.9825	4.26E+04	1613.0049	0.22798	1.61E+03
CBA	1400.3048	0.092093	1.40E+03	1562.3666	18.85652	1.56E+03	1613.5381	0.36317	1.61E+03
RCBA	1400.2943	0.060668	**1.40E+03**	1538.9490	7.61211	1.54E+03	1613.6523	0.32500	1.61E+03
CDLOBA	1400.3181	0.058475	1.40E+03	1753.9951	117.6904	1.76E+03	1613.5741	0.25668	1.61E+03
m_SCA	1426.1725	10.27231	1.46E+03	4997.7533	4929.0634	1.55E+04	1612.5383	0.51908	1.61E+03
IWOA	**1400.2787**	0.143274	1.40E+03	1625.8982	78.1816	1.67E+03	1612.9124	0.55626	1.61E+03
LWOA	1400.3289	0.095342	1.47E+03	1572.8452	27.80344	1.26E+04	1612.8272	0.52137	1.61E+03
CSSA	1680.8338	17.75465	1.68E+03	232 677.12	39 953.5	2.33E+05	1613.1690	0.24750	1.61E+03

Consider:

$X = [x_1, x_2, x_3, x_4] = [h\ l\ t\ b]$

Minimize:

$F(X) = 1.10471x_1^2x_2 + 0.04811x_3x_4(14.0 + x_2)$

Subject to:

$g_1(X) = \tau(X) - \tau_{max} \leq 0$

$g_2(X) = \sigma(X) - \sigma_{max} \leq 0$

$g_3(X) = \delta(X) - \delta_{max} \leq 0$

$g_4(X) = x_1 - x_4 \leq 0$

$g_5(X) = P - P_C(X) \leq 0$

$g_6(X) = 0.125 - x_1 \leq 0$

$g_7(X) = 1.10471x_1^2 + 0.04811x_3x_4(14.0 + x_2) - 5.0 \leq 0$

where

$$\tau(\vec{x}) = \sqrt{(\tau')^2 + 2\tau'\tau''\frac{x_2}{2R} + (\tau'')^2}$$

$$\tau' = \frac{P}{\sqrt{2}x_1x_2}, \tau'' = \frac{MR}{J}, \mathrm{M} = \mathrm{P}(\mathrm{L} + \frac{x_2}{2})$$

$$\mathrm{R} = \sqrt{\frac{x_2^2}{4} + \left(\frac{x_1 + x_3}{2}\right)^2}$$

$$J = 2\left\{\sqrt{2}x_1x_2\left[\frac{x_2^2}{4} + \left(\frac{x_1 + x_3}{2}\right)^2\right]\right\}$$

$$\sigma(\vec{x}) = \frac{6PL}{x_4x_3^2}, \delta(\vec{x}) = \frac{6PL^3}{Ex_3^2x_4}$$

$$P_C(\vec{x}) = \frac{4.013E\sqrt{\frac{x_3^2x_4^6}{36}}}{L^2}(1 - \frac{x_3}{2L}\sqrt{\frac{E}{4G}})$$

Table 10
Comparison results on multimodal functions during 3E5 evaluations.

Algorithm	F8			F9			F10		
	AVG	STD	MED	AVG	STD	MED	AVG	STD	MED
SMA	**−1.26E+04**	2.48E−04	**−1.257E+04**	**0.00000**	0.00000	**0.000E+00**	**8.88E−16**	0.00000	**8.882E−16**
SCA	−4.41E+03	2.15E+02	−4.288E+03	0.00000	0.00000	3.499E+00	1.26E+01	9.43E+00	1.610E+01
SSA	−7.79E+03	7.06E+02	−7.419E+03	6.54E+01	1.50E+01	9.676E+01	1.81E+00	8.07E−01	3.901E+00
GWO	−6.38E+03	7.23E+02	−4.403E+03	0.00000	0.00000	0.000E+00	7.64E−15	1.08E−15	7.638E−15
MFO	−8.37E+03	7.59E+02	−8.366E+03	1.65E+02	3.28E+01	1.651E+02	1.58E+01	7.02E+00	1.576E+01
WOA	−1.21E+04	9.04E+02	−1.207E+04	0.00000	0.00000	0.000E+00	3.38E−15	2.12E−15	3.375E−15
GOA	−7.56E+03	6.06E+02	−6.158E+03	1.04E+02	4.22E+01	1.742E+02	2.71E+00	8.89E−01	7.415E+00
MVO	−8.18E+03	7.17E+02	−6.424E+03	8.27E+01	2.44E+01	1.772E+02	1.08E−01	3.58E−01	6.771E+00
PSO	−7.07E+03	8.27E+02	−7.067E+03	3.43E+02	1.69E+01	3.469E+02	7.78E+00	2.41E−01	8.041E+00
DE	−1.24E+04	1.31E+02	−1.243E+04	3.32E−02	1.82E−01	3.317E−02	7.64E−15	1.08E−15	7.994E−15
AGA	−8.38E+02	9.72E−03	−8.379E+02	9.94E−03	0.00000	1.655E−02	1.64E−02	0.00000	1.644E−02

Algorithm	F11			F12			F13		
	AVG	STD	MED	AVG	STD	MED	AVG	STD	MED
SMA	**0.00000**	0.00000	**0.000E+00**	7.55E−06	8.36E−06	2.780E−04	6.77E−06	3.68E−06	2.418E−03
SCA	8.03E−11	4.36E−10	6.453E−02	3.27E−01	5.08E−02	6.351E+03	1.98E+00	1.11E−01	2.375E+00
SSA	1.18E−02	1.10E−02	1.577E+00	1.41E+00	1.70E+00	6.100E+00	5.06E−03	6.75E−03	3.688E+00
GWO	2.49E−04	1.36E−03	2.514E−04	2.56E−02	1.20E−02	3.778E−02	4.01E−01	1.95E−01	5.442E−01
MFO	3.31E+01	5.55E+01	3.312E+01	2.29E−01	4.75E−01	2.288E−01	6.15E−01	1.11E+00	6.152E−01
WOA	6.58E−04	2.52E−03	6.577E−04	1.09E−06	4.07E−07	1.087E−06	3.84E−04	2.00E−03	3.836E−04
GOA	1.81E−02	1.51E−02	7.615E+00	1.93E+00	1.50E+00	1.380E+01	9.33E−01	3.86E+00	5.700E+03
MVO	2.76E−02	1.33E−02	6.603E+00	1.64E−01	5.09E−01	7.007E+00	4.06E−03	5.30E−03	3.389E+01
PSO	1.02E+00	1.27E−02	1.022E+00	3.38E+00	3.70E−01	3.822E+00	1.57E+01	1.83E+00	1.729E+01
DE	0.00000	0.00000	0.000E+00	**1.57E−32**	5.57E−48	**1.571E−32**	**1.35E−32**	5.57E−48	**1.350E−32**
AGA	2.14E−02	1.37E−02	3.063E−02	2.17E−02	2.82E−02	5.744E−02	1.13E−02	9.89E−03	1.987E−02

Algorithm	F16			F17			F18		
	AVG	STD	MED	AVG	STD	MED	AVG	STD	MED
SMA	5.21E+02	2.27E−01	5.210E+02	6.15E+02	3.06E+00	6.188E+02	1.30E+03	1.26E−01	1.301E+03
SCA	5.21E+02	5.60E−02	5.210E+02	6.33E+02	2.39E+00	6.364E+02	1.30E+03	3.71E−01	1.304E+03
SSA	5.20E+02	1.07E−01	5.210E+02	6.19E+02	4.24E+00	6.234E+02	1.30E+03	1.45E−01	1.301E+03
GWO	5.21E+02	5.11E−02	5.210E+02	6.14E+02	3.27E+00	6.210E+02	1.30E+03	3.11E−01	1.301E+03
MFO	5.20E+02	1.73E−01	5.203E+02	6.23E+02	3.53E+00	6.231E+02	1.30E+03	1.26E+00	1.302E+03
WOA	5.20E+02	1.61E−01	5.204E+02	6.36E+02	4.15E+00	6.363E+02	1.30E+03	1.05E−01	1.301E+03
GOA	5.20E+02	7.96E−02	5.210E+02	6.17E+02	3.63E+00	6.250E+02	1.30E+03	6.95E−02	1.301E+03
MVO	5.20E+02	4.14E−02	5.210E+02	6.10E+02	3.97E+00	6.214E+02	1.30E+03	1.24E−01	1.301E+03
PSO	5.21E+02	4.59E−02	5.210E+02	6.23E+02	3.42E+00	6.231E+02	1.30E+03	7.31E−02	1.300E+03
DE	5.21E+02	4.46E−02	5.206E+02	6.20E+02	2.07E+00	6.226E+02	1.30E+03	4.04E−02	1.300E+03
AGA	**5.00E+02**	4.82E−01	**5.005E+02**	**6.00E+02**	1.68E−02	**6.000E+02**	**1.30E+03**	2.53E−02	**1.300E+03**

Algorithm	F19			F20			F21		
	AVG	STD	MED	AVG	STD	MED	AVG	STD	MED
SMA	1.40E+03	3.13E−01	1.401E+03	1.51E+03	1.83E+00	1.517E+03	1.61E+03	7.14E−01	1.612E+03
SCA	1.44E+03	7.88E+00	1.466E+03	4.96E+03	4.20E+03	2.681E+04	1.61E+03	2.17E−01	1.613E+03
SSA	1.40E+03	2.22E−01	1.400E+03	1.51E+03	2.10E+00	1.523E+03	1.61E+03	6.27E−01	1.612E+03
GWO	1.40E+03	7.60E+00	1.410E+03	1.89E+03	7.48E+02	1.960E+03	1.61E+03	6.66E−01	1.612E+03
MFO	1.43E+03	2.55E+01	1.435E+03	3.14E+05	5.20E+05	3.141E+05	1.61E+03	5.10E−01	1.613E+03
WOA	1.40E+03	1.23E−01	1.400E+03	1.57E+03	2.49E+01	1.575E+03	1.61E+03	5.51E−01	1.613E+03
GOA	1.40E+03	3.31E−01	1.401E+03	1.51E+03	2.20E+00	1.531E+03	1.61E+03	7.46E−01	1.612E+03
MVO	1.40E+03	3.32E−01	1.401E+03	1.51E+03	2.26E+00	1.527E+03	1.61E+03	5.89E−01	1.612E+03
PSO	1.40E+03	9.78E−02	1.400E+03	1.52E+03	1.38E+00	1.517E+03	1.61E+03	4.48E−01	1.612E+03
DE	1.40E+03	1.24E−01	1.400E+03	1.51E+03	1.10E+00	1.513E+03	1.61E+03	2.18E−01	1.612E+03
AGA	**1.40E+03**	1.21E−02	**1.400E+03**	**1.50E+03**	7.70E−03	**1.500E+03**	**1.60E+03**	9.19E−03	**1.600E+03**

$P = 60001$ b, $L = 14$ in. $\delta_{max} = 0.25$ in. $E = 30 \times 1^6$ psi,

$G = 12 \times 10^6$ psi

$\tau_{max} = 13600$ psi, $\sigma_{max} = 30000$ psi

In this problem, SMA was compared with MFO [26], SSA [55], Random [79], Siddall [80], Ragsdell [79], Coello and Montes [81], GWO [24], WOA [53], GSA, Simplex [79] and David [79]. Table 20 illustrates that SMA can obtain the optimal value among the competitors.

3.5.2. Pressure vessel structure problem

The intention of the problem is to find the parameters of cylindrical pressure vessels which can minimize the total cost of production and meet the pressure requirements. The parameters including the thickness of the shell (T_s), inner radius (T_h), the thickness of the head (T_h) and the length of the cylindrical portion. Both ends of the container are covered with a hemispherical shell at one end. Fig. 14 illustrates the design of the object and its corresponding parameters.

The formulations of four constraints are listed as follow:
Consider:

$$X = [x_1\ x_2\ x_3\ x_4] = [T_s\ T_h\ R\ L]$$

Objective:

$$f(X)_{min} = 0.6224x_1x_3x_4 + 1.7781x_3x_1^2 + 3.1661x_4x_1^2 + 19.84x_3x_1^2$$

Subject to:

$$g_1(X) = -x_1 + 0.0193x_3 \leq 0$$
$$g_2(X) = -x_3 + 0.00954x_3 \leq 0$$

Table 11
Comparison results on the Hybrid functions of CEC 2014 with traditional algorithms.

Algorithm	F22			F23			F24		
	AVG	STD	MED	AVG	STD	MED	AVG	STD	MED
SMA	1 981 009	955 714	3.35E+06	23 768.042	9648.796	2.41E+05	1916.4612	20.81879	**1.92E+03**
SCA	1.475E+07	7 203 070	2.36E+07	2.767E+08	1.768E+08	7.00E+08	2025.9911	29.94193	2.08E+03
SSA	1 105 845	643 830	3.04E+06	10 164.216	8416.726	5.28E+06	1920.6469	18.54917	1.93E+03
GWO	3 134 418	3 888 996	4.44E+06	1.721E+07	2.683E+07	4.25E+07	1959.2308	39.30239	1.97E+03
MFO	3 685 312	5 224 753	4.56E+06	3.014E+07	1.146E+08	3.10E+07	1971.9869	47.63181	1.97E+03
WOA	1.704E+07	1.559E+07	1.73E+07	435 824	298 836	4.45E+05	1996.2181	42.52503	2.00E+03
GOA	1 438 154	1 067 917	4.32E+06	6928.741	5474.188	5.04E+07	1916.6548	2.61108	1.94E+03
DA	1.179E+07	8 700 286	1.18E+07	1.213E+07	1.867E+07	1.23E+07	1998.5264	63.45143	2.00E+03
ALO	1 218 376	902 036	1.58E+06	3771.512	1977.571	**1.54E+05**	1922.1569	20.15628	1.92E+03
MVO	**648 113**	423 330	2.31E+06	11 057.398	8877.483	3.04E+07	1913.1472	2.24974	1.93E+03
PBIL	1.987E+07	5 897 960	2.61E+07	1.090E+09	4.562E+08	1.33E+09	2153.5319	42.97329	2.18E+03
PSO	721 353	340 828	**1.11E+06**	3 733 762	1 011 652	4.15E+06	1917.9437	2.40252	1.92E+03
DE	5 502 647	2 468 774	8.31E+06	199 823	164 718	6.71E+05	**1911.6762**	2.02980	1.92E+03
Algorithm	F25			F26			F27		
	AVG	STD	MED	AVG	STD	MED	AVG	STD	MED
SMA	26 151.83	14 592.587	3.50E+04	691 037.74	447 817.80	1.12E+06	2785.9438	200.10440	2.82E+03
SCA	42 036.30	23 681.495	1.14E+05	3 774 544	2 456 159	6.71E+06	3295.8542	153.63191	3.52E+03
SSA	28 121.80	15 931.602	3.37E+04	378 039	364 201	8.50E+05	2733.8257	195.24839	2.83E+03
GWO	26 371.89	17 760.819	3.15E+04	1 401 869	3 144 566	1.93E+06	2681.9022	164.02295	2.83E+03
MFO	68 807.98	34 415.152	7.04E+04	909 632.7	874 394.6	1.07E+06	2988.3818	304.13153	2.99E+03
WOA	141 181.82	150 095.222	1.42E+05	9 190 469	11 782 812	9.53E+06	3196.0473	259.04790	3.20E+03
GOA	15 217.92	11 721.455	2.85E+04	386 067	274 805	1.22E+06	2721.2340	196.75397	2.99E+03
DA	170 066.67	177 342.58	1.70E+05	4 046 744	4 943 178	4.05E+06	3238.7712	336.86424	3.24E+03
ALO	44 576.07	18 719.138	4.76E+04	416 024	304 543	5.44E+05	3023.7395	188.96878	3.03E+03
MVO	7113.7952	3345.696	2.22E+04	233 142	208 201	6.68E+05	2636.7226	181.32671	2.82E+03
PBIL	100 886.52	83 601.365	1.64E+05	6 032 360	2 197 809	8.28E+06	3545.4177	245.28854	3.70E+03
PSO	19 948.16	7799.1853	3.10E+04	324 137	191 521	**4.32E+05**	2934.5667	216.35151	2.97E+03
DE	12 477.50	4695.8815	**1.57E+04**	880 050	356 197	1.61E+06	**2594.1841**	115.53194	**2.77E+03**

Table 12
Comparison results on composite functions of CEC2014 with traditional algorithms.

Algorithm	F28			F29			F30		
	AVG	STD	MED	AVG	STD	MED	AVG	STD	MED
SMA	**2500.0000**	0.00000	**2.50E+03**	**2600.0000**	0.00000	**2.60E+03**	**2700.0000**	0.00000	**2.70E+03**
SCA	2712.2094	24.49225	2.80E+03	2612.5376	16.11479	2.66E+03	2734.7826	10.58302	2.76E+03
SSA	2632.2624	11.99882	2.66E+03	2644.8211	7.39515	2.65E+03	2717.7099	4.57908	2.72E+03
GWO	2644.1677	15.52070	2.65E+03	2600.0269	0.00904	2.60E+03	2709.8706	6.60434	2.71E+03
MFO	2672.0010	55.23865	2.67E+03	2678.9946	29.86466	2.68E+03	2718.0092	9.84490	2.72E+03
WOA	2680.3948	54.85251	2.68E+03	2611.4760	7.24474	2.61E+03	2717.4700	20.81026	2.72E+03
GOA	2636.9870	8.96575	2.69E+03	2645.5150	5.40226	2.67E+03	2717.0876	4.91578	2.73E+03
DA	2721.4771	44.95443	2.72E+03	2661.0711	14.44841	2.66E+03	2743.0074	14.56249	2.74E+03
ALO	2629.0815	8.44167	2.63E+03	2651.7113	7.91597	2.65E+03	2726.5079	7.20090	2.73E+03
MVO	2624.2212	6.19267	2.65E+03	2635.7205	6.61514	2.66E+03	2708.2693	1.65495	2.72E+03
PBIL	3031.2435	81.13515	3.08E+03	2827.7418	25.17373	2.83E+03	2760.6456	11.08699	2.77E+03
PSO	2619.6398	1.46590	2.62E+03	2631.7808	6.40174	2.63E+03	2718.6208	5.72742	2.72E+03
DE	2615.2456	0.00132	2.62E+03	2628.8256	2.71282	2.63E+03	2722.3177	3.27296	2.73E+03
Algorithm	F31			F32			F33		
	AVG	STD	MED	AVG	STD	MED	AVG	STD	MED
SMA	2700.7493	0.11128	**2.70E+03**	**2900.0000**	0.00000	**2.90E+03**	**3000.0000**	0.00000	**3.00E+03**
SCA	2703.5386	0.42894	2.70E+03	3824.0615	291.2901	3.95E+03	5546.0181	481.5436	5.59E+03
SSA	**2700.5370**	0.14086	2.70E+03	3530.3707	215.6535	3.62E+03	4170.5366	395.2774	4.47E+03
GWO	2766.6830	68.52197	2.77E+03	3401.0954	122.9196	3.59E+03	4250.4859	411.0486	4.75E+03
MFO	2702.0134	1.45934	2.70E+03	3622.4093	196.0596	3.62E+03	3955.0668	198.3093	3.96E+03
WOA	2717.0896	37.72566	2.72E+03	3902.6457	357.3971	3.90E+03	5395.1711	768.3897	5.41E+03
GOA	2772.4391	72.70589	2.78E+03	3534.0606	204.6178	3.68E+03	4454.6468	563.7650	4.87E+03
DA	2744.5288	66.71856	2.74E+03	3906.7882	348.4316	3.91E+03	6418.4644	759.2642	6.42E+03
ALO	2720.5156	40.82834	2.72E+03	3570.0454	291.1912	3.59E+03	5699.9910	503.7231	5.77E+03
MVO	2743.7298	71.22152	2.75E+03	3390.4461	148.2171	3.60E+03	4137.0810	330.4390	4.68E+03
PBIL	2704.7340	0.37452	2.71E+03	3931.9655	192.1610	3.97E+03	4535.2650	415.0320	4.62E+03
PSO	2790.8757	30.60922	2.79E+03	3487.2364	302.7920	3.51E+03	7526.0776	944.8788	7.80E+03
DE	2700.5562	0.06268	2.70E+03	3439.1447	117.3664	3.56E+03	3727.8590	34.29086	3.78E+03

$$g_3(X) = -\pi x_4 x_3^2 - \frac{4}{3}\pi x_3^3 + 1296000 \le 0$$

$$g_4(X) = x_4 - 240 \le 0$$

Variable ranges:

$0 \le x_1 \le 99$, $0 \le x_2 \le 99$, $10 \le x_3 \le 200$, $10 \le x_4 \le 200$

From the data of Table 21, it is obvious that SMA can obtain fairly superior optimal values compared with MFO [26], BA [82], HPSO [83], CSS [7], CPSO [84], ACO [85], GWO [24], WOA [53], MDDE [86], Lagrangian multiplier [87] and Branch-bound [88].

Table 13
Comparison results on the Hybrid functions of CEC 2014 with advanced algorithms.

Algorithm	F22			F23			F24		
	AVG	STD	MED	AVG	STD	MED	AVG	STD	MED
SMA	1 804 495	975 279	2.92E+06	19 731.57	12 366.188	2.85E+05	**1924.4016**	29.9388	**1.93E+03**
BLPSO	5.95E+06	2.79E+06	1.01E+07	2.03E+07	7.71E+06	9.85E+07	1940.2723	7.4647	1.98E+03
CLPSO	9.36E+06	4.32E+06	2.15E+07	2.35E+07	1.66E+07	2.67E+08	1973.9754	18.5819	2.07E+03
CBA	875 955	682 022	1.41E+06	19 590.62	55 097.347	4.37E+04	1930.5601	26.3854	1.93E+03
RCBA	536 209	287 301	9.14E+05	27 035.80	48 215.716	4.05E+04	1929.3577	27.4688	1.93E+03
CDLOBA	**253 257**	159 357	**5.29E+05**	**14 436.39**	8148.226	**2.05E+04**	1983.8732	37.8347	1.99E+03
m_SCA	3 405 875	2.39E+06	1.58E+07	5.42E+07	6.44E+07	3.95E+08	1974.7719	29.9192	2.03E+03
IWOA	1.11E+07	6.76E+06	1.42E+07	232 413.82	5.40E+05	5.39E+05	1974.5125	48.0377	1.98E+03
LWOA	1.13E+07	7 452 363	2.92E+07	588 224.18	2.66E+06	7.46E+07	1954.6903	42.1280	2.12E+03
CSSA	2.34E+08	7.53E+07	2.34E+08	7.83E+09	2.67E+09	7.83E+09	2599.1453	124.8102	2.60E+03
Algorithm	F25			F26			F27		
	AVG	STD	MED	AVG	STD	MED	AVG	STD	MED
SMA	**20 184.423**	11 536.23	**2.74E+04**	566 429.1	440 779.47	8.85E+05	2853.3837	275.30887	**2.88E+03**
BLPSO	40 020.222	17 226.38	6.37E+04	1 443 418	637 791.49	3.44E+06	3039.7382	166.89957	3.27E+03
CLPSO	35 837.420	13 506.64	8.72E+04	1 678 372	755 401.12	5.09E+06	2852.1935	155.80947	3.31E+03
CBA	47 394.400	21 444.35	6.74E+04	425 055.3	394 927.78	6.04E+05	3470.7820	389.88490	3.47E+03
RCBA	31 728.076	17 810.98	5.27E+04	353 013.1	266 894.62	5.93E+05	3385.7049	345.09736	3.40E+03
CDLOBA	49 593.385	25 881.81	6.28E+04	**158 313.0**	1.68E+05	**2.95E+05**	3280.2697	252.07423	3.28E+03
m_SCA	25 033.409	11 116.37	6.57E+04	903 524.0	975 927	3.32E+06	**2710.7381**	185.83183	3.26E+03
IWOA	54 586.150	24 987.96	6.40E+04	3 798 947	3 041 196	5.53E+06	3025.7726	243.33062	3.05E+03
LWOA	45 846.654	23 789.30	2.51E+05	2 379 875	1 411 692	1.57E+07	3021.9632	251.61117	3.37E+03
CSSA	4.00E+06	4.34E+06	4.00E+06	1.47E+08	1.33E+08	1.47E+08	55 417.05	53 372.36	5.54E+04

Table 14
Comparison results on composite functions of CEC2014 with advanced algorithms.

Algorithm	F28			F29			F30		
	AVG	STD	MED	AVG	STD	MED	AVG	STD	MED
SMA	**2500.0000**	0.00000	**2.50E+03**	**2600.0000**	0.00000	**2.60E+03**	**2700.0000**	0.00000	**2.70E+03**
BLPSO	2642.6104	5.72836	2.68E+03	2667.7295	2.33812	2.68E+03	2729.1590	3.76596	2.74E+03
CLPSO	2641.0387	6.17469	2.73E+03	2660.4964	3.06098	2.69E+03	2723.7881	4.81229	2.74E+03
CBA	2618.5576	2.10126	2.62E+03	2672.7287	32.2058	2.67E+03	2738.8447	16.6010	2.74E+03
RCBA	2616.5451	1.59102	2.62E+03	2671.7927	31.5474	2.67E+03	2734.0323	12.9174	2.73E+03
CDLOBA	2619.8273	5.91180	2.63E+03	2701.7423	41.3677	2.70E+03	2724.5749	12.1083	2.73E+03
m_SCA	2657.6041	18.7651	2.70E+03	2600.0082	0.00530	2.60E+03	2717.9183	3.76490	2.74E+03
IWOA	2653.0880	16.8268	2.66E+03	2607.2619	5.28645	2.61E+03	2714.2469	16.8627	2.72E+03
LWOA	2635.7620	26.8390	2.81E+03	2610.4768	6.01548	2.61E+03	2712.9723	16.0958	2.72E+03
CSSA	2525.7607	121.6063	2.53E+03	2600.4211	0.21279	2.60E+03	2700.0573	0.03311	2.70E+03
Algorithm	F31			F32			F33		
	AVG	STD	MED	AVG	STD	MED	AVG	STD	MED
SMA	2700.7690	0.14584	**2.70E+03**	**2900.0000**	0.000000	**2.90E+03**	**3000.0000**	0.000000	**3.03E+03**
BLPSO	2719.8189	40.7556	2.73E+03	3639.7610	104.8236	3.78E+03	4689.9702	351.2075	5.46E+03
CLPSO	2703.1872	0.86410	2.71E+03	3255.3722	59.2992	3.45E+03	5394.7830	503.6760	6.86E+03
CBA	2714.7665	60.7392	2.72E+03	3992.4341	466.0520	4.00E+03	5749.7099	1087.8530	5.77E+03
RCBA	2731.0975	67.5372	2.75E+03	4088.5512	406.7701	4.11E+03	5820.2491	1076.0463	5.86E+03
CDLOBA	2715.7761	56.3032	2.72E+03	3902.9353	371.3979	3.91E+03	5346.9885	837.0278	5.36E+03
m_SCA	2701.3185	0.81232	2.70E+03	3324.8813	254.9219	3.52E+03	4280.9832	270.1009	4.87E+03
IWOA	2732.9019	77.0976	2.73E+03	3800.5003	342.5802	3.83E+03	5181.1074	676.4584	5.28E+03
LWOA	**2700.5873**	0.13596	2.70E+03	3865.9583	237.8645	4.00E+03	4457.1988	270.3753	4.91E+03
CSSA	2792.4644	23.3249	2.79E+03	4836.8934	344.1577	4.84E+03	8555.0615	3476.6646	8.56E+03

Table 15
True p-value obtained from comparison on thirty-three benchmarks.

Traditional MAs		F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11
	#TSS	2.08E−05	2.08E−05	2.08E−05	2.08E−05	2.08E−05	4.13E−03	2.68E−05	1.34E−04	1.00E+00	2.31E−05	1.00E+00
		F12	F13	F14	F15	F16	F17	F18	F19	F20	F21	F22
	#TSS	3.71E−05	5.23E−02	5.53E−02	6.34E−03	7.95E−01	1.32E−01	3.26E−01	2.24E−01	1.98E−01	6.88E−02	7.01E−01
		F23	F24	F25	F26	F27	F28	F29	F30	F31	F32	F33
	#TSS	4.53E−01	7.59E−01	9.96E−01	5.34E−01	4.96E−01	2.29E−05	2.08E−05	2.63E−04	4.36E−01	2.08E−05	2.16E−05
Advanced MAs		F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11
	#TSS	1.56E−05	1.56E−05	1.56E−05	1.56E−05	1.85E−02	1.40E−03	2.60E−03	1.60E−05	1.00E+00	2.74E−05	1.00E+00
		F12	F13	F14	F15	F16	F17	F18	F19	F20	F21	F22
	#TSS	1.83E−01	4.91E−01	1.25E−01	1.91E−01	9.93E−01	1.86E−05	7.57E−01	5.59E−04	1.56E−05	3.22E−05	2.04E−03
		F23	F24	F25	F26	F27	F28	F29	F30	F31	F32	F33
	#TSS	3.37E−01	5.58E−02	3.91E−02	3.62E−01	8.15E−01	1.56E−05	1.56E−05	7.49E−05	7.75E−01	1.56E−05	1.64E−05

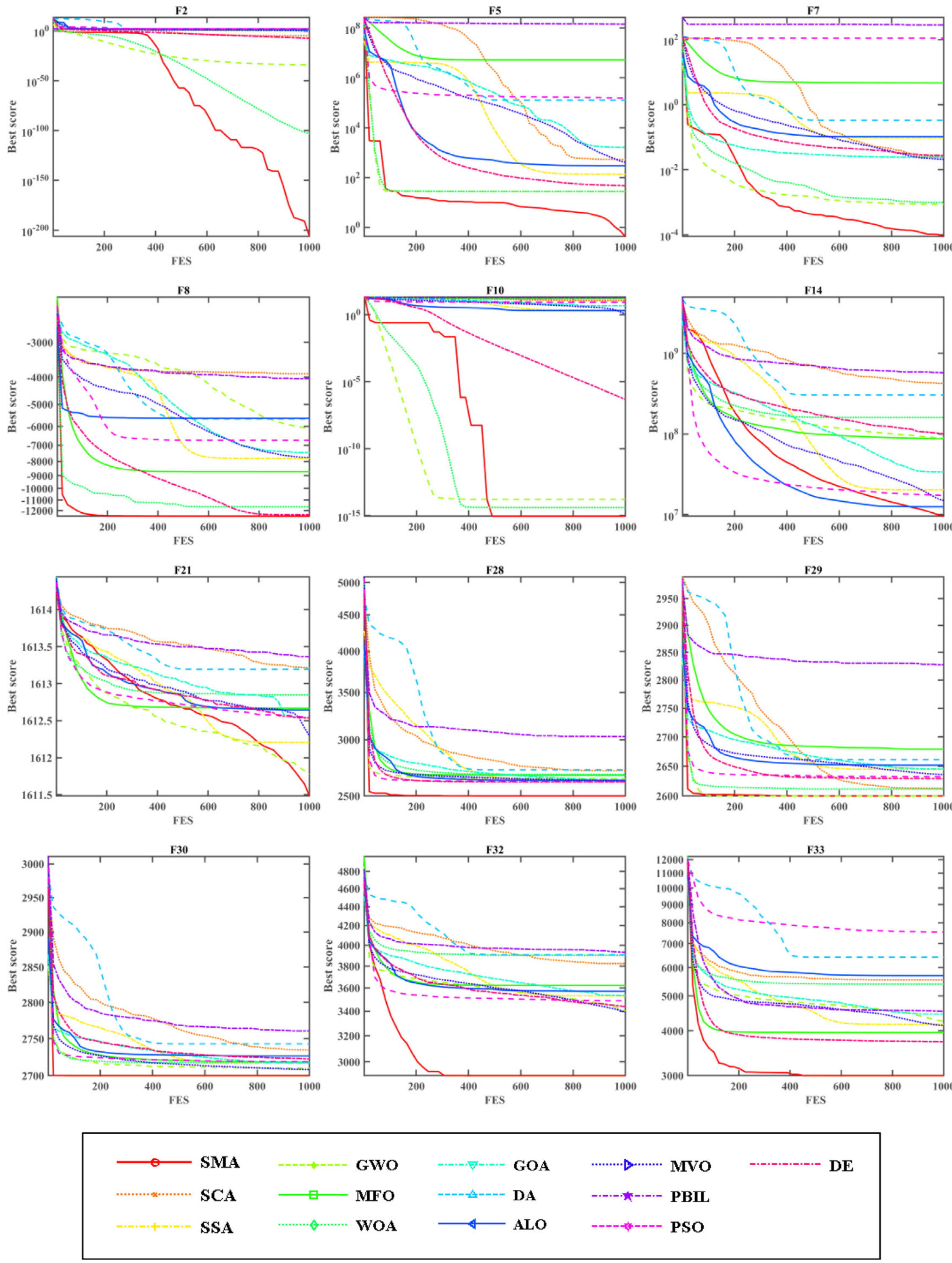

Fig. 10. Comparisons between SMA and traditional MAs.

3.5.3. Cantilever structure problem

The cantilever beam is made up of five hollow square cross-sections, as exhibited in Fig. 15. Since the thickness is fixed, only six parameters identified in the figure need to be considered. The intention of the problem is to dwindle the total mass of the cantilever beam when the bearing capacity is satisfied. The formulae of this optimization problem are listed as follow:

Consider:

$$X = [x_1\ x_2\ x_3\ x_4\ x_5]$$

Minimize:

$$F(X) = 0.6224(x_1 + x_2 + x_3 + x_4 + x_5)$$

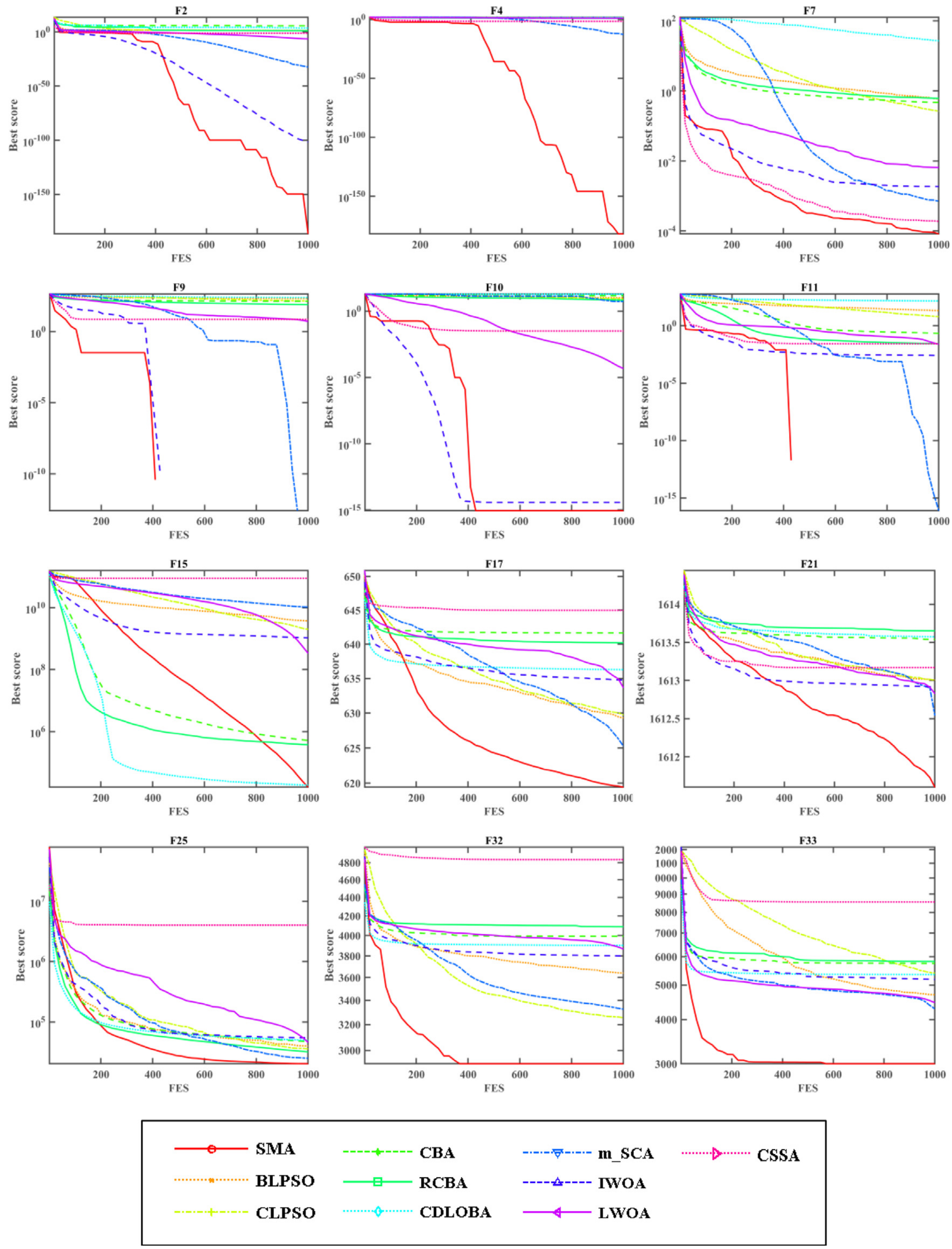

Fig. 11. Comparisons between SMA and advanced MAs.

Subject to:

$$G(X) = \frac{61}{x_1^3} + \frac{37}{x_2^3} + \frac{19}{x_3^3} + \frac{7}{x_4^3} + \frac{1}{x_5^3} \le 1$$

Variable ranges:

$$0.01 \le x_1.x_2, x_3, x_4, x_5 \le 100$$

Compared to MFO [26], SOS [89], CS [90], MMA [91] and GCA [91], SMA can achieve better results in the cantilever design problem, as shown in Table 22.

3.5.4. I-beam structure problem

The intention of this engineering problem is to minimize the vertical deviation of I-beam by adjusting four parameters as shown in Fig. 16.

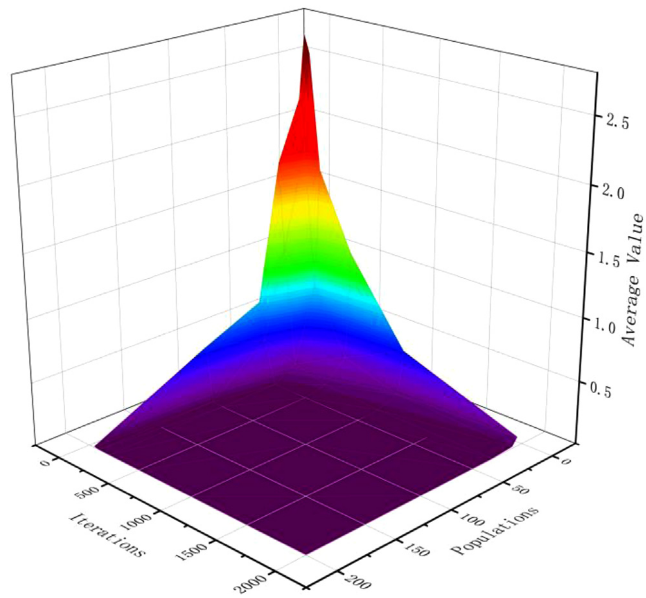

Fig. 12. The influence of populations and iterations.

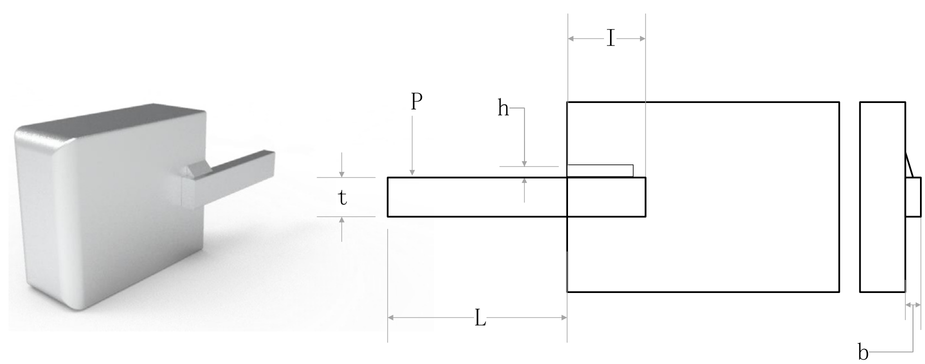

Fig. 13. Structure of welded beam design based on [26].

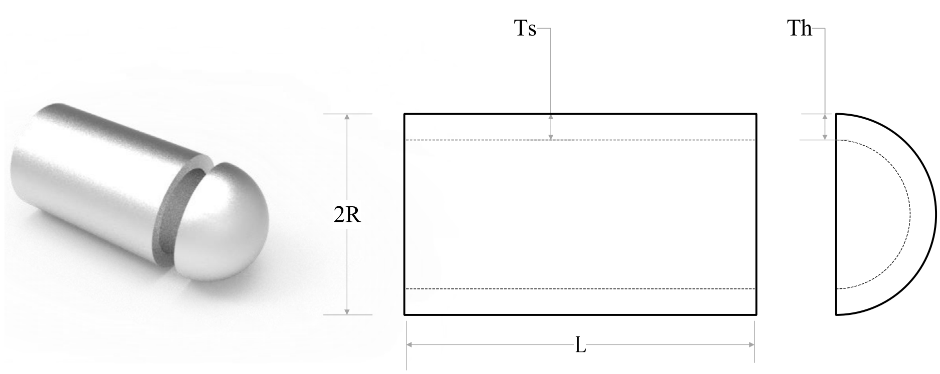

Fig. 14. Structure of pressure vessel based on [26].

Table 23 lists the optimization results for SMA compared to ARSM [92], SOS [89], CS [90] and IARSM [92]. The data reveals that SMA can obtain excellent optimal values in this engineering problem, reflecting the applicability of SMA to engineering problems.

4. Conclusions and future perspectives

This paper proposed an effective optmizer motivated by slime behaviour to tackle the optimization problems. The algorithm mainly uses the weights to simulate the positive and negative feedback of the bio-oscillator during the foraging to the food source to form a different thickness of the feeding vein network. The morphology of the slime mould also changes with three different contraction patterns.

To qualitatively analyse the algorithm, four metrics (search history, the trajectory of the first dimension, average fitness, and convergence curve) were applied. Then, the algorithm was evaluated in 33 benchmark functions consisting of unimodal, multimodal, fix-dimension multimodal, and composite functions. Most of the functions tested are composite functions. Wilcoxon sign-rank test and Friedman test were applied to estimate the efficacy of the algorithm more scientifically. The experimental results illustrate that SMA can guarantee the performance of explorations while achieving superior exploitations, thus maintaining an outstanding balance between exploitations and explorations,

Table 16
Results of Friedman test of iterative version and function evaluation version.

	Iterative version on F1-33												
	SMA	SCA	SSA	GWO	MFO	WOA	GOA	DA	ALO	MVO	PBIL	PSO	DE
Avg	3.057	9.396	5.180	5.280	8.037	6.735	6.690	10.580	6.124	5.013	12.228	7.865	4.815
Rank	1	11	4	5	10	8	7	12	6	3	13	9	2
	Iterative version on F1-33												
	SMA	BLPSO	CLPSO	CBA	RCBA	CDLOBA	m_SCA	IWOA	LWOA	CSSA			
Avg	2.297	7.578	6.996	5.507	5.408	6.100	5.000	4.710	4.907	6.497			
Rank	1	10	9	6	5	7	4	2	3	8			
	Evaluation version on F1–21												
	SMA	SCA	SSA	GWO	MFO	WOA	GOA	MVO	PSO	DE	AGA		
Avg	3.189	8.103	5.668	5.369	8.201	5.135	6.805	5.895	8.970	4.292	4.373		
Rank	1	9	6	5	10	4	8	7	11	2	3		

Table 17
Holms' test (take SMA as the control algorithm).

	SMAVS.	$z - value$	p-value	$\alpha/i, \alpha = 0.05$	$\alpha/i, \alpha = 0.10$
Traditional algorithms	PBIL	9.9878	8.6010E−24	0.0042	0.0083
	DA	8.2494	7.9860E−17	0.0045	0.0091
	SCA	6.9851	1.4240E−12	0.005	0.01
	MFO	6.7639	6.7120E−12	0.0056	0.0111
	PSO	4.9307	4.0900E−07	0.0063	0.0125
	WOA	4.2669	9.9060E−06	0.0071	0.0143
	GOA	3.8877	5.0540E−05	0.0083	0.0167
	ALO	3.7296	9.5740E−05	0.01	0.02
	GWO	2.9394	1.6460E−03	0.0125	0.025
	SSA	2.3389	9.6680E−03	0.0167	0.0333
	MVO	1.7384	0.04111	0.025	0.05
	DE	1.6436	0.05009	0.05	0.1
Advanced algorithms	BLPSO	12.0748	7.1760E−34	0.00556	0.01111
	CLPSO	10.7331	3.5580E−27	0.00625	0.0125
	CSSA	9.3915	2.9580E−21	0.00714	0.01429
	CDLOBA	8.0498	4.1460E−16	0.00833	0.01667
	CBA	6.7082	9.8520E−12	0.01	0.02
	RCBA	5.3666	4.0120E−08	0.0125	0.025
	IWOA	4.0249	2.8500E−05	0.01667	0.03333
	m_SCA	2.6833	0.00365	0.025	0.05
	LWOA	1.3416	0.08986	0.05	0.1
Evaluation	PSO	5.648039	8.1160E−09	0.005	0.01
	MFO	4.896673	4.8730E−07	0.0056	0.0111
	SCA	4.801299	7.8820E−07	0.00625	0.0125
	GOA	3.532738	2.0570E−04	0.0071	0.0143
	MVO	2.644126	0.0041	0.0083	0.0167
	SSA	2.422361	0.0077	0.01	0.02
	GWO	2.130033	0.0166	0.0125	0.025
	WOA	1.901289	0.0286	0.0167	0.0333
	AGA	1.156902	0.1237	0.025	0.05
	DE	1.077811	0.1406	0.05	0.1

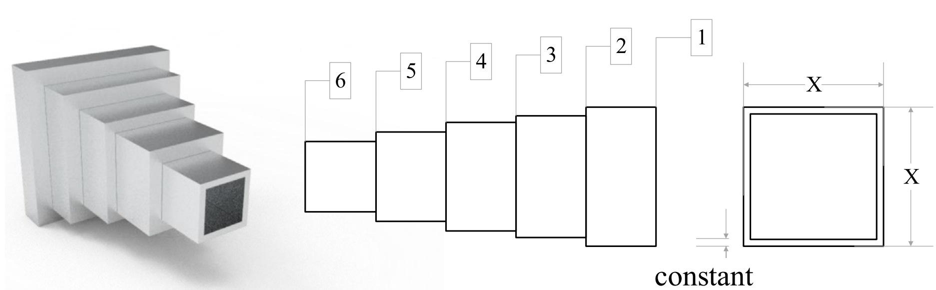

Fig. 15. Structure of cantilever beam based on [26].

which reflects the superior performance of the algorithm in a statistical sense compared with other algorithms.

Meanwhile, SMA was used in four classical engineering structural problems, including welded beam, pressure vessel, cantilever, and I-beam design problems. The results demonstrate that SMA is also applicable to engineering optimization problems in real life with satisfactory optimization results.

The accounts for the satisfactory performance of SMA in maintaining the balance of exploitation and exploration inclinations can be theoretically attributed to the following points:

Table 18
Wall-clock time costs of SMA and other candidates on 33 benchmarks.

	SMA	SCA	SSA	GWO	MFO	WOA	GOA	DA	ALO	MVO	PSO	DE
F1	14.040	1.310	0.811	1.825	1.513	0.562	119.466	90.262	218.355	3.822	0.967	5.054
F2	13.291	1.139	0.796	1.622	1.342	0.577	118.108	110.886	216.748	3.806	0.920	4.446
F3	13.478	2.480	2.215	2.839	2.636	2.278	110.012	116.268	207.606	4.165	1.919	5.288
F4	12.776	1.123	0.796	1.560	1.123	0.546	117.188	86.659	207.513	2.761	0.640	3.838
F5	12.995	1.404	1.030	1.950	1.466	0.780	123.646	115.768	233.112	3.401	0.874	4.976
F6	15.241	1.513	1.045	2.090	1.544	0.686	146.376	122.929	260.163	3.760	0.889	4.914
F7	16.037	2.356	1.919	2.855	2.465	1.638	141.665	118.857	257.995	4.883	1.794	5.678
F8	15.709	1.763	1.295	2.434	1.778	0.983	141.119	172.038	255.467	2.824	1.264	5.491
F9	16.115	1.576	1.123	2.028	1.669	0.764	142.133	136.657	259.305	3.994	1.139	4.742
F10	14.726	1.794	1.279	2.090	1.997	0.936	143.209	111.151	251.099	4.025	1.092	5.444
F11	16.115	2.215	1.607	2.309	1.981	0.998	144.878	121.338	264.063	4.040	1.217	5.600
F12	19.032	4.602	4.134	5.023	4.836	3.900	149.917	124.598	265.561	6.880	4.134	8.596
F13	18.939	4.852	4.274	5.101	4.243	3.604	149.153	126.205	266.684	6.833	4.087	8.518
F14	16.411	2.090	1.732	2.855	2.340	1.326	140.807	145.549	256.341	4.399	1.544	5.647
F15	15.725	2.106	1.498	2.465	1.950	1.108	144.894	136.080	261.583	4.524	1.373	5.990
F16	15.803	2.106	1.638	2.652	2.044	1.295	146.766	152.351	261.161	4.243	1.342	5.351
F17	31.715	16.677	15.943	17.254	16.224	15.678	163.832	185.080	281.145	19.438	16.021	20.686
F18	16.177	2.090	1.544	2.621	2.246	1.279	146.376	170.306	263.080	4.508	1.342	5.288
F19	16.006	2.075	1.560	2.434	1.872	1.092	142.554	130.791	263.767	4.446	1.435	5.850
F20	2.387	1.700	2.465	2.153	1.295	147.062	143.318	264.250	4.493	1.529	5.366	
F21	16.177	2.246	1.716	2.683	2.278	1.295	145.674	171.820	262.238	4.680	1.451	5.444
F22	15.897	2.231	1.654	2.808	2.340	1.513	145.097	172.787	258.665	4.446	1.654	5.881
F23	15.413	1.919	1.576	2.480	2.200	1.357	140.183	144.192	253.080	4.555	1.404	5.928
F24	19.531	5.054	4.633	5.491	4.976	4.072	150.635	128.264	268.993	7.940	4.586	9.064
F25	16.552	2.262	1.638	2.730	2.184	1.310	145.112	120.901	265.670	4.384	1.513	5.710
F26	13.057	2.168	1.529	2.168	1.763	1.154	118.015	119.450	206.592	3.697	1.498	4.836
F27	14.414	2.122	1.763	2.371	2.059	1.373	115.644	115.862	210.289	3.962	1.466	5.179
F28	16.833	4.477	3.572	4.914	4.618	3.385	125.331	128.810	216.873	5.632	3.182	7.784
F29	15.663	3.526	2.933	3.635	2.980	2.278	117.656	89.155	216.046	5.429	2.668	6.942
F30	17.831	4.274	3.448	4.711	4.228	3.292	141.462	165.829	248.775	6.646	3.869	7.847
F31	33.665	20.296	20.327	19.890	19.563	19.781	162.257	187.373	277.261	22.464	19.095	24.633
F32	33.915	20.530	19.656	20.155	19.438	19.251	164.488	187.700	280.474	22.729	19.594	23.681
F33	18.705	5.850	5.554	6.334	5.834	4.586	150.042	124.411	269.461	8.237	4.898	9.547

Table 19
Ranking of results with varied values of parameter z.

Function	SMA0	SMA1	SMA2	SMA3	SMA4	SMA5	SMA6	SMA7	SMA8	SMA9	SMA10
1	1	1	1	1	1	6	7	8	9	10	11
2	1	1	3	4	5	6	7	9	8	10	11
3	1	1	1	1	5	6	7	8	9	10	11
4	1	1	3	4	5	6	7	8	9	10	11
5	11	10	9	8	7	3	4	2	6	5	1
6	11	1	2	3	4	5	6	9	7	8	10
7	1	2	4	3	6	7	10	8	9	5	11
8	11	1	4	5	6	8	9	2	7	10	3
9	1	1	1	1	1	1	1	1	1	1	1
10	1	1	1	1	1	1	1	1	1	1	1
11	1	1	1	1	1	1	1	1	1	1	1
12	11	10	9	7	6	8	5	4	2	3	1
13	11	10	2	1	8	4	5	3	9	7	6
Average	4.85E+00	3.15E+00	3.15E+00	3.08E+00	4.31E+00	4.77E+00	5.38E+00	4.92E+00	6.00E+00	6.23E+00	6.08E+00
Rank	5	2	2	1	3	4	7	6	8	10	9

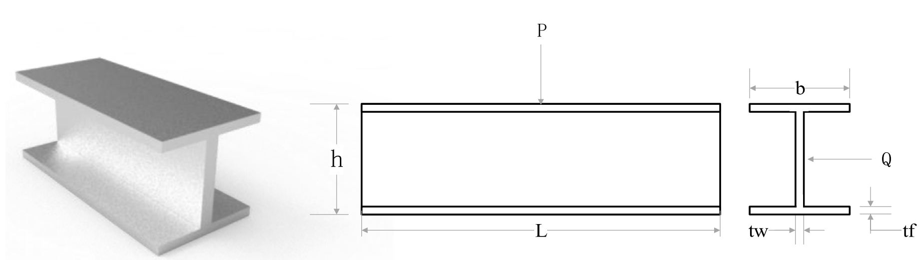

Fig. 16. Structure of I-beam based on [26].

- The adaptive weight W enables the SMA to maintain a certain disturbance rate while guaranteeing fast convergence, thus avoiding optimal local trapping during fast convergence.
- Vibration parameter $\overrightarrow{vb}$ allows the individual position of slime mould to contract in a specific way, thus ensuring the efficiency of the early exploration and the accuracy of the later exploitation.

Table 20
Results of welded beam structure problem compared with other competitors.

Algorithms	Optimum values for variables				Optimum cost
	h	l	t	b	
SMA	**0.2054**	**3.2589**	**9.0384**	**0.2058**	**1.69604**
MFO [26]	0.2057	3.4703	9.0364	0.2057	1.72452
SSA [55]	0.2057	3.4714	9.0366	0.2057	1.72491
Random [79]	0.4575	4.7313	5.0853	0.6600	4.11856
Siddall [80]	0.2444	6.2189	8.2915	0.2444	2.38154
Ragsdell [79]	0.2455	6.1960	8.2730	0.2455	2.38594
Coello and Montes [81]	0.2060	3.4713	9.0202	0.2065	1.72822
GWO [24]	0.2057	3.4784	9.0368	0.2058	1.72624
WOA [53]	0.2054	3.4843	9.0374	0.2063	1.73050
GSA	0.1821	3.8570	10.0000	0.2024	1.87995
Simplex [79]	0.2792	5.6256	7.7512	0.2796	2.53073
David [79]	0.2434	6.2552	8.2915	0.2444	2.38411

Table 21
Results of pressure vessel design problem compared with other competitors.

Algorithms	Optimum values for variables				Optimum cost
	T_s	T_h	R	L	
SMA	**0.7931**	**0.3932**	**40.6711**	**196.2178**	**5994.1857**
MFO [26]	0.8125	0.4375	42.0984	176.6366	6059.7143
BA [82]	0.8125	0.4375	42.0984	176.6366	6059.7143
HPSO [83]	0.8125	0.4375	42.0984	176.6366	6059.7143
CSS [7]	0.8125	0.4375	42.1036	176.5727	6059.0888
CPSO [84]	0.8125	0.4375	42.0912	176.7465	6061.0777
ACO [85]	0.8125	0.4375	42.1036	176.5727	6059.0888
GWO [24]	0.8125	0.4345	42.0892	176.7587	6051.5639
WOA [53]	0.8125	0.4375	42.0983	176.6390	6059.7410
MDDE [86]	0.8125	0.4375	42.0984	176.6360	6059.7017
Lagrangian multiplier [87]	1.1250	0.6250	58.2910	43.6900	7198.0428
Branch-bound [88]	1.1250	0.6250	47.7000	117.7010	8129.1036

Table 22
Results of cantilever beam structural problem in comparison with other competitors.

Algorithm	Optimum values for variables					Optimum cost
	X_1	X_2	X_3	X_4	X_5	
SMA	**6.017757**	**5.310892**	**4.493758**	**3.501106**	**2.150159**	**1.339957**
MFO [26]	5.9830	5.3167	4.4973	3.5136	2.1616	1.33998
SOS [89]	6.0188	5.3034	4.4959	3.4990	2.1556	1.33996
CS [90]	6.0089	5.3049	4.5023	3.5077	2.1504	1.33999
MMA [91]	6.0100	5.3000	4.4900	3.4900	2.1500	1.3400
GCA [91]	6.0100	5.3000	4.4900	3.4900	2.1500	1.3400

Table 23
Results of I-beam structural problem in comparison with other methods.

Algorithm	Optimum values for variables				Optimum cost
	b	h	T_w	T_f	
SMA	**49.998845**	**79.994327**	**1.764747**	**4.999742**	**0.006627**
ARSM [92]	37.0500	80.0000	1.7100	2.3100	0.0157
SOS [89]	50.0000	80.0000	0.9000	2.3218	0.0131
CS [90]	50.0000	80.0000	0.9000	2.3217	0.0131
IARSM [92]	48.4200	79.9900	0.9000	2.4000	0.1310

- The adequate utilization of individual fitness values allows SMA to make better decisions based on historical information.
- The location updating decision parameter p and three different location updating methods ensure better adaptability of the SMA in different search phases.

On the purpose of improving the extensibility of the algorithm, the development of the algorithm is established on the principle of being as simple as possible. In future work, various mutation mechanisms or acceleration mechanisms can be employed to enhance the efficacy of the algorithm. The binary version of the algorithm can also be developed for feature selection. Moreover, SMA can also be used to optimize parameters of classifiers such as kernel extreme learning machine or support vector machine.

Declaration of competing interest

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

CRediT authorship contribution statement

Shimin Li: Writing - original draft, Writing - review & editing, Software, Visualization, Investigation. **Huiling Chen:** Conceptualization, Methodology, Formal analysis, Investigation, Writing - review & editing, Funding acquisition, Supervision. **Mingjing Wang:** Writing - review & editing, Software. **Ali Asghar Heidari:** Methodology, Formal analysis, Investigation, Writing - original draft, Writing - review & editing, Software, Visualization. **Seyedali Mirjalili:** Supervision, Writing - review & editing, Investigation.

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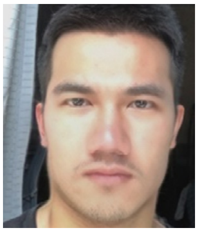

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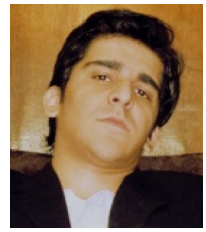

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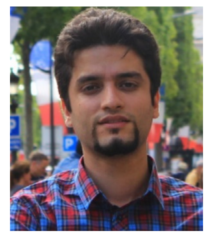

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