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Research article

Directional crossover hunger games search with adaptive Lévy diversity for network subculture

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Abstract: In this paper, we explore and analyze the network subculture in the youth and actively explore the new path of socialist core values to cultivate the values of college students. Through the effective questionnaire survey of college students, the prediction model of decision support is established by improving the metaheuristic algorithms. Hunger games search (HGS) is a metaheuristic algorithm widely used in many fields. However, the method converges slowly and veers toward the local optimum when presented with challenging problems. Therefore, there is room for HGS to develop. We introduce a brand-new HGS variant, denoted as SDHGS. This variant combines the directional crossover mechanism with an adaptive Lévy diversity strategy. The directed crossover mechanism endeavors to harmonize the interplay between exploration and exploitation, while the adaptive Lévy diversity facet enhances the range of variations within the population. The cooperation of these mechanisms within SDHGS concludes in an augmented convergence rate and heightened precision. SDHGS is compared to HGS, seven classic algorithms, and enhanced algorithms on the benchmark function set to evaluate and demonstrate the performance. Besides, various analytical techniques, such as the Friedman test and the Wilcoxon signed-rank test, are considered when analyzing the experimental results. The findings demonstrate that SDHGS with two techniques greatly enhances HGS performance. Finally, SDHGS is applied to discuss the internal relationship that affects the existence of youth subculture and establish a prediction model of decision support.

Keywords: hunger games search; adaptive Lévy diversity; network subculture; directional crossover

1. Introduction

With the rapid advancement of social networks and 5G technologies in the digital era of media integration in recent years, various unique youth-subcultural phenomena have been birthed. Milton Gordon, an American sociologist, was the one who initially conceived and described the idea of subculture. He further developed "culture-sub-area" in the Sociological Dictionary and used subculture to reclassify national culture, which refers to various cultures depending on social factors such as ethnicity, economy, religion, and geography. The core of culture is values. The important representation of youth subculture is the conflict of values, which is in an ambiguous relationship with the socialist core values we advocate. However, university teaching environments cannot always accept the multiplicity of adolescent subcultures. The collision of mainstream values and network subcultural values has a decisive impact on the shaping of values of teenagers and social behaviors and inevitably reduces the leading role of mainstream social culture in their values. Kolesnik and collaborators explored diverse realms of engagement between universities and youth subcultures. This encompassed the integration of fashionable elective courses within the academic domain, the cultivation of technological creativity through maker culture, and the promotion of student health through the introduction of sports subculture. As ideological and political educators in colleges and universities, they shoulder the mission of moral education for the university. However, they should not mindlessly blame the subversion, rebellion, and resistance of the youth subculture to the mainstream values. However, they should analyze the psychological essence and generation mechanism behind the subcultural values to reflect on the deficiency of the current education in the psychological adjustment mechanism of the youth.

In the realm of intellectual traditions, discussions and positive theoretical advancements coexist harmoniously with the flourishing empirical research on youth cultures and subcultures. Annually, a plethora of fresh publications, monographs, and edited compilations enrich our comprehension of global youth-subcultural phenomena [1]. Jeffrey used computer-sided content analysis to examine 735 newspaper articles on the punk subculture published over three decades and illustrated the utility between media and historical youth studies. Ron and colleagues posited the influence exerted by the internet and social media on subcultures among the younger generation [2]. Rahma studied the content of youth subculture to resist texts produced by cultural industries [3]. In this paper, the research and analysis are carried out on the representative of the extensive network subculture in the youth, and the new path of the socialist core values on the cultivation of values of college students is actively explored. Tan et al. used Raymond Williams' concept of "sensory structure" within the semiotics framework to understand the process of subjectivity formation and Sang subculture's emotional significance to participants, expressing the sense of loss of Chinese youth in their early years [4].

In the realm of optimization, methods can manifest as either multi-objective or single-objective [5]. Irrespective of their category, these methods can fall into two overarching classifications: Evolutionary (recognized as metaheuristics) or deterministic. We focus on the domain of single-objective evolutionary methods. In recent times, researchers have employed the hunger games search (HGS) paradigm to tackle intricate optimization problems. This optimizer is one of the recent metaheuristics (MAs) that have equipped with cores of exploration and exploitation. Scholars used several MAs to find optimal or suboptimal solutions without need to gradient info [6]. The family of MAs are widespread, and some popular ones are the hunger games search (HGS) [7], Archimedes optimization algorithm (AOA) [8], honey badger algorithm (HBA) [9], particle swarm optimizer (PSO) [10], henry gas solubility optimization (HGSO) [11], colony predation algorithm (CPA) [12], slime mould algorithm (SMA) [13], Runge Kutta optimizer (RUN) [14], Harris hawks optimization (HHO) [15], the weighted mean of vectors (INFO) [16], modified butterfly optimization algorithm with Lagrange interpolation (mLBOA) [17], multi-strategies boosted mutative crow search algorithm (CCMSCSA) [18], and so on. In regards to modifications made to HGS, Zhou et al. [19] introduced an enhanced iteration of HGS incorporating a chaotic initialization mechanism, a Gaussian barebone mechanism, and orthogonal learning to effectively address three intricate engineering design challenges. Li et al., on the other hand, proposed DECEHGS, a distinctive amalgamation of HGS with DE, chaotic local search, and evolutionary population dynamics techniques. This hybrid approach was tailored for engineering designs and global optimization [20]. Houssein et al. introduced a refined rendition of HGS aimed at elevating the performance of feature selection for support vector machines, particularly within the realm of chemical and medical datasets [21]. Ma et al., in a different vein, devised a multi-pronged strategy for HGS, employing its binary version to diminish data dimensionality efficiently [22]. In the same area of metaheuristics and mathematical models, Ghasemi and collaborators introduced a logistic management model at a bi-level, incorporating an evolutionary game that incorporates environmental feedback mechanisms [22], a cooperative game theory method [23], and a bi-level blood supply chain network [24]. Abdollah used a Stackelberg game with genetic algorithm (GA) and grey wolf optimization (GWO) [25].

Based on the observations derived from antecedent inquiries, the HGS algorithm exhibits the commendable attributes mentioned earlier. However, it is not impervious to the potential drawback of becoming entrapped in local minima due to its pronounced developmental capabilities. This study introduces SDHGS, an advanced algorithm meticulously designed to enhance convergence velocity, precision, and escape from local optima. Specifically, SDHGS integrates the directional crossover mechanism with the adaptive Lévy diversity strategy to improve the global search ability. The directional crossover mechanism accelerates the convergence rate, while the adaptive Lévy diversity strategy enriches population diversity.

Utilizing HGS, enhancements were implemented for configurations within a hybrid microgrid system. Additionally, a novel soft computing model was introduced for predicting the intensity of ground vibration caused by mine blasting. Despite its many advantages, such as those listed above, HGS may experience regional stagnation because of its high capacity for exploitation. Addressing the limitations of conventional HGS and enhancing the synchronization between global exploration and local exploitation, an innovative variant of HGS was suggested. This variation relied on the cautious union of the directional crossover mechanism with the adaptive Lévy diversity strategy. SDHGS is subjected to a comparative evaluation against HGS, traditional algorithms, and enhanced algorithms, all performed on the IEEE CEC 2017 function benchmark to assess its efficacy. The assessment employs statistical tools, including the Wilcoxon signed-rank test (WSRT) [26], the Friedman test (FT) [27], and the analysis of function convergence profiles. Moreover, the remarkable innovations introduced by this study are elucidated below.

- Based on the basic HGS, a unique form termed SDHGS is developed, which combines the adaptive Lévy diversity mechanism and the directed crossover method.
- SDHGS and the alternative excellent comparison algorithms are evaluated on CEC 2017 to

validate the superiority of the proposed approach.

- Two mechanisms are introduced to SDHGS to improve the global search ability effectively.
- The SDHGS-KNN prediction model is established for network subculture to the cultivation of values of college students.

The remainder of this research is organized as follows. Section 2 displays the dataset of the students from Wenzhou University. In Section 3, we explain the HGS concept, the adaptive Lévy diversity mechanism, and the directed crossover method. Section 4 introduces the structure of the SDHGS, KNN, and SDHGS-KNN models. Section 5 analyzes and presents the experimental data and comments. Section 6 concludes this work and discusses future work.

2. Data gathering and preparation

The data involved in this research come primarily from full-time undergraduate and graduate students of Wenzhou University. From these groups of college students, 650 students were selected randomly as research objects, and a total of 612 valid questionnaires were collected. Among them, 574 were aged between 18 and 22, 30 were aged between 23 and 27, 5 were aged between 28 and 32, and 3 were aged above 33. According to the gender, age, monthly income of the research object, the degree of understanding and acceptance of the network subculture, and the network subculture, the following questions arise: To what extent do you think the network subculture infiltrates into your life, and whether you will spend money on star chasing? What do you think about the money on star chasing? What is your attitude towards the network subculture and other indicators? In this paper, we discuss the internal relationship that affects the existence of youth subculture. We establish the prediction model of decision support on this basis. Table 1 describes the twenty attributes in detail.

Table 1. Nine attributes are described in detail.

Attribute	Question	Account
1	Gender	The numbers 1 and 2 denote male and female students, respectively.
2	Age	It is separated into four age groups: 18 to 22 years old, 23 to 27 years old, 28 to 32 years old, and over 33 years old, denoted by the letters 1, 2, 3, and 4, accordingly.
3	How much is your monthly income or living expenses?	It is divided into less than CNY 2000, CNY 2000 to CNY 4000, CNY 4000 to CNY 6000, and more than CNY 6000, represented by 1, 2, 3, and 4, respectively.
4	What do you know about the culture of the network subculture?	The categories are not well understood, well understood, moderately well understood, and very well understood, denoted by 1, 2, 3, 4, and 5, respectively.
5	How do you understand the network subculture?	It is divided into: fans love the same thing, spontaneous gathering, will discuss the development of it together; fans organize spontaneously or passively, organized action, but not limited to the expression of support, collective consumption, etc.; fans gather because they like to, but gradually evolve into a group of people who say nothing, attack opponents and often fight; others. They are denoted by 1, 2, 3, and 4, respectively.

Continued on next page

Attribute	Question	Account
6	Does the network subculture affect your daily life (positively or negatively)?	The effect is divided into a very large impact, with some impact, uncertain, no impact, and others, etc., denoted by 5, 4, 3, 2, and 1, respectively.
7	To what extent do you think the network subculture has penetrated your life?	It is divided into: No intersection, the difference between the network subculture and daily life is obvious; limited to network language; influence their consumption concept, aesthetic concept and completely into the daily life, represented by 0, 1, 2, and 3, respectively.
8	Will you spend money on chasing stars?	It is divided into: never spend any money, will spend a small amount of money, will spend a moderate amount of money, will spend a lot of money, and will spend all the available money. They are denoted by 1, 2, 3, 4, and 5, respectively
9	What kind of way do you usually follow the stars?	It is divided into: to the scene to watch concerts, plays, etc.; participating in book signings to buy products endorsed by celebrities; voting, making a list, brush data to the airport pickup; enjoying movies, music, and other works, denoted by 5, 4, 3, 2, and 1, respectively
10	What do you think about spending money on chasing stars?	It is divided into recognition, it is worth spending money for the person you like; moderate, in their own economic allow within the scope; neutral, neither for nor against; irrelevant to me, and irrational consumption, which should be resisted. They are denoted by 4, 3, 2, and 1, respectively.
11	What is your attitude toward the network subculture?	It is divided into: like, will participate in; understanding, but never participating; ignore does not involve, has nothing to do with me; don't like it, but will participate; dislike, try to avoid and reject, resist all related things. They are denoted by 6, 5, 4, 3, 2, and 1, respectively.
12–19	What do you think are the main influences of network subculture on youth groups?	Acquired some new skills (such as video editing, photoshop, making memes, etc.); found like-minded friends; more optimistic, harvest positive energy; enrich daily life, spiritual get a lot of satisfaction; take up a large part of your life and decrease your performance /productivity; being discriminated against or not understood by others; Idol excessive consumption of physical and mental exhaustion; Others, 0 means not selected and 1 means selected.
20–27	What do you think of the social image of the youth network subculture group? (Multiple choices)	It is divided into crazy and irrational, blindly following the trend, lack of self-control, optimism, youth in the new era, full of positive energy, promoting consumption; others, 0 means not selected and 1 means selected.
28	What do you think of the current cultural atmosphere of the network subculture?	It is divided into positive and healthy, we develop to a good side under the guidance of idols and establish correct values; harmonious coexistence, we do not interfere with each other, happy and harmonious; chaos, for their interests, torn and divided groups; some harmony and some confusion, denoted by 1, 2, 3 and 4, respectively.

Continued on next page

Attribute	Question	Account
29–34	What reasons for the formation of the current network subculture? (Multiple choices)	It can be divided into: The rapid development of the entertainment market and the Internet industry catalyzed the emergence of the network subculture; the demands of popular culture and youth subculture; in the process of youth growth, the specific psychological needs are not paid attention to, so they rely on the psychological satisfaction of the network subculture; the portrayal of idol stars by new media such as Weibo and doujin makes entertainment culture rooted in the hearts of young people; operation of idol star team; others. 0 means not selected and 1 means selected.
35–40	What are the problems of the current network subculture? (Multiple choices)	It is divided into: fans pick up too many people, disrupt social order; “private food” too much, invasion of personal privacy; blindly follow the trend, irrational consumption; spending too much time, affecting work and study; fans fight seriously, disrupting the order of the Internet; others. 0 means not selected and 1 means selected.
41–48	Which of the following behaviors do you think belong to the abnormal network subculture? (Multiple choices)	It is divided into control evaluation, investment, fund-raising assistance; tight network subculture class; from time to time to the surrounding friends Amway their favorite stars; verbal abuse between teams of fans; inciting minors to krypton; Internet abuse of people with different opinions; supporting a star despite breaking the law; others. 0 means not selected and 1 means selected.
49–53	What impact the deformed network subculture may have on the youth group? (Multiple choices)	It is divided into narrow and distorted youth values; it causes young people to engage in extreme behaviors such as cyberbullying, chasing stars through loans, and abandoning their studies; makes young people develop bad habits, causing bad effects on later life; it makes young people rely on the virtual space of the network, which hurts real life and interpersonal communication; there is no effect. 0 means not selected and 1 means selected.
54–60	What does a healthy network subculture look like? (Multiple choices)	It can be divided into: stars, as public figures, should play a role in promoting positive energy to fans; to keep up with their idols, fans work harder and study harder; follow their idols to do public welfare activities within their power; proper discussion, there is no meaningless network subculture activities occur; fans appropriately chase stars, do not exceed their consumption power; the atmosphere of public opinion in the network subculture is good, and there is no big fan to take the lead in inciting; Others, 0 means not selected and 1 means selected.
61–67	What measures can be taken to improve the influence of the network subculture on young people (Multiple choices)?	It is divided into: individuals should establish a rational concept of chasing stars; parents should give correct guidance in time; schools should strengthen ideological and political education; stars should establish a good image as public figures; entertainment companies should make correct norms and strengthen constraints; The marketing public account shall be marketed appropriately; others. 0 means not selected and 1 means selected.

3. Materials and methods

3.1. Hunger games search (HGS)

Yang et al. suggested HGS [23] with stable characteristics and competitive performance in 2021. It is a simple and efficient mathematical model regarding behavioral choices and hunger-driven activity. The mathematical model of the HGS algorithm is built on approaching food and hunger roles.

Thus, the HGS individual approaches food based on hunger-driven behavior, and the expression is defined as follows.

$$X(t+1) = \begin{cases} X(t) \cdot (1 + randn(1)), & r_1 < l \quad (1) \\ W_1 \cdot X_b + R \cdot W_2 \cdot |X_b - X(t)|, & r_1 > l, r_2 > E \quad (2) \\ W_1 \cdot X_b - R \cdot W_2 \cdot |X_b - X(t)|, & r_1 > l, r_2 < E \quad (3) \end{cases} \tag{1}$$

$$E = \text{sech}(|F(i) - BF|) \tag{2}$$

$$\text{sech}(x) = \frac{2}{e^x + e^{-x}} \tag{3}$$

$$R = 2 \times a \times rand - a \tag{4}$$

$$a = 2 \times \left(1 - \frac{t}{MaxFEs}\right) \tag{5}$$

where R represents a random number which is defined as Eq (4); r_1, r_2 denote two independent random numbers in the range of [0, 1], respectively; $randn(1)$ indicates the random number that generates a normal distribution; t denotes the current iteration; W_1 and W_2 are two weights of hunger; X_b is the best position for this iteration; $X(t)$ represents the position of the hungry search agent in the *tth* iteration; $F(i)$ represents the fitness of the ith individual, and BF denotes the best fitness at present; $rand$ indicates a number ranging from [-1, 1] randomly and $MaxFEs$ stands for the maximum iterations.

The $|X_b - X(t)|$ emulates the spatial range within which the present foraging agent operates at the current moment and is scaled by the factor W_2 to modulate the impact of hunger on the activity span of the agent. The $X(t)(1 + randn(1))$ illustrates how a hungry agent might venture in search of sustenance in a stochastic manner within its current locale. The parameter l serves the purpose of enhancing the performance of the method.

The controller R is employed to delimit the ambit of the movements of the agent, as a hungry agent terminates its quest once nourishment is procured. The scope of R progressively diminishes, ultimately converging to 0. The extent of the activity range is adjusted based on $W_1 \cdot X_b$ indicating the responsiveness of the agents to the insights of the companions when navigating to the food source and its subsequent resumption of food exploration at its current position post-acquisition. As demonstrated in Eq (6), W_1 signifies the discrepancy in determining the actual position. The formulation for W_2 is presented in Eq (7).

$$W_1 = \begin{cases} hungry(i) \cdot \frac{N}{SHungry} \times r_4, & r_3 < l \quad (1) \\ 1, & r_3 > l \quad (2) \end{cases} \tag{6}$$

$$W_2 = \left(1 - exp(-|hungry(i) - SHungry|)\right) \times r_5 \times 2 \tag{7}$$

where $hungry$ shows each hunger agent; N is the number of agents; $SHungry$ represents the total hunger, that is $sum(hungry)$. r_3, r_4 and r_5 represent three random numbers in the range of [0, 1], independently. The $hungry(i)$ equation can be written as follows.

$$hungry(i) = \begin{cases} 0, & AllFitness(i) == BF \\ hungry(i) + H, & AllFitness(i)! = BF \end{cases} \tag{8}$$

$$TH = \frac{F(i) - BF}{WF - BF} \times r_6 \times 2 \times (UB - LB) \tag{9}$$

$$H = \begin{cases} LH \times (1 + r), & TH < LH \\ TH, & TH \geq LH \end{cases} \tag{10}$$

where $AllFitness(i)$ represents the fitness of each individual so far; r_6 stands for a random number between 0 and 1; $F(i)$ represents the ith individual's fitness; BF is the best fitness currently; WF retains the poorest fitness throughout the evolution method; UB and LB represent the upper and lower bounds, and hunger H has a lower bound value LH. On Algorithm 1, the pseudocode of the hunger games search is displayed.

Algorithm 1: Pseudocode of hunger games search (HGS)

Initialize the parameters $N, MaxFEs, l, FEs, D, SHungry$
Initialize the positions of agents X_i $(i = 1, 2, \cdots, N)$
While $(FEs \leq MaxFEs)$
    Compute the fitness of all agents
    Update BF, WF, X_b, BI
    Set $Hungry$ by Eq (8)
    Set W_1 by Eq (6)
    Set W_2 by Eq (7)
  For $each\ individual$
      Calculate E by Eq (2)
      Compute R by Eq (4)
      Update the position by Eq (1)
  End for
$FEs = FEs + N;$
End while
Return BF, X_b

3.2. Directional crossover strategy

The concept of a directional crossover tactic (DX) encompasses a mutation mechanism derived from genetic algorithms (GA), drawing inspiration from its GA counterpart. The directional crossover strategy within the realm of GA has been documented for its remarkable capacity for extensive global exploration. Mathematically formulated, the DX technique entails guiding the current individual, p_{best}, according to the orientation of another individual. Key attributes defining the directional crossover strategy comprise the crossover rate (p_c), the likelihood of variables' crossover (p_{cv}), the directional probability ((p_d), and a multiplying factor (α). These defining traits are delineated by Eqs (11) and (12).

$$val = \begin{cases} 1 - 0.5^{e^{\left[\frac{\left|p_1^j - p_2^j\right|}{\left(ub_j - lb_j\right)}\right]}} & , if\ p_1^j \neq p_2^j\ and\ p_{best}^j \geq p_{mean}^j \\ 1 - 0.5^{e^{\left[\frac{\left|p_{best}^j - p_{mean}^j\right|}{\left(ub_j - lb_j\right)}\right]}} & , if\ p_1^j = p_2^j\ and\ p_{best}^j \neq p_{mean}^j \end{cases} \tag{11}$$

$$\beta = \frac{r_1}{\alpha^2} \tag{12}$$

where p_1^j and p_2^j stands for two randomly selected individuals from the population, $j \in [1, dimension]$. The average of p_1^j and p_2^j in the jth dimension is denoted by p_{mean}^j. p_{best}^j is the value of the jth dimension of the oriented individual p_{best}. $r_1 \in (0, 1)$ represents a random value. The upper and lower boundaries of the individual jth dimension are denoted by ub_j and lb_j. The DX method generates two new individuals, denoted by c_1 and c_2. The pseudocode of the DX strategy is shown in Algorithm 2.

3.3. Lévy strategy

Building upon the foundations of the Lévy flight distribution theory, the adaptive Lévy methodology was conceptualized. The concept underlying the adaptive Lévy diversity mechanism is explained through Eqs (13)–(17).

$$X = Levy(P, \lambda) \tag{13}$$

$$Z = \begin{cases} X_j & , if\ rand(d) = j \\ rand \cdot \left(ub_j - lb_j\right) + lb_j, & if\ rand(d) \neq j \end{cases} \tag{14}$$

$$Q = 1 - \frac{FEs}{MaxFEs} \tag{15}$$

$$P = \begin{cases} rand \cdot (ub - lb) + lb, & if\ rand < Q \\ Z & , if\ rand \geq Q \end{cases} \tag{16}$$

$$X^* = \begin{cases} P & , rand < Q \\ X_b(t) + vb \cdot \left(W \cdot X_A(t) - X_B(t)\right), & r < p\ and\ rand \geq Q \\ vc \cdot X(t) & , r \geq p\ and\ rand \geq Q \end{cases} \tag{17}$$

where P denotes the individual in the present. λ represents a constant, $\lambda = 1$. d stands for the dimension, $j \in [1, d]$. FEs indicates the number of current evaluations. Moreover, $MaxFEs$ represents the most evaluations. Algorithm 3 displays the pseudocode of the adaptive Lévy strategy.

Algorithm 2: Pseudocode [28] of DX strategy

Input: p_1 and p_2 with d dimensions, p_c, p_{cv}, p_d, p_{best}, α;
Output: offspring (c_1, c_2);
If $rand \leq p_c$
    For $j = 1{:}d$
        If $rand \leq p_{cv}$
            Update val and β by Eqs (11) and (12);
            If $\left|p_1^j - p_2^i\right| > 0$
              Compute the value of p_{mean}^j;
            If $p_{best}^j \geq p_{mean}^j$
                  Update individual c_1 and c_2 determined from p_d;

$$c_1 = val \cdot \left(p_1^j + p_2^j\right) \pm \alpha^{r_1} \cdot e^{(1-\beta)} \cdot (1 - val) \cdot \left|p_1^j - p_2^j\right|;$$

$$c_2 = (1 - val) \cdot \left(p_1^j + p_2^j\right) \pm \alpha^{(1-r_1)} \cdot e^{(-\beta)} \cdot val \cdot \left|p_1^j - p_2^j\right|;$$

              else
                  Update c_1 and c_2 as determined by p_d;

$$c_1 = val \cdot \left(p_1^j + p_2^j\right) \pm \alpha^{r_1} \cdot e^{(1-\beta)} \cdot (1 - val) \cdot \left|p_1^j - p_2^j\right|;$$

$$c_2 = (1 - val) \cdot \left(p_1^j + p_2^j\right) \pm \alpha^{(1-r_1)} \cdot e^{(-\beta)} \cdot val \cdot \left|p_1^j - p_2^j\right|;$$

              End if
            Else if $p_{best}^j \neq p_{mean}^j$
            Update c_1 and c_2 as determined by p_d;

$$c_1 = val \cdot \left(p_{best}^j + p_{mean}^j\right) \pm \alpha^{r_1} \cdot e^{(1-\beta)} \cdot (1 - val) \cdot \left(p_{best}^j - p_{mean}^j\right);$$

$$c_2 = (1 - val) \cdot \left(p_{best}^j + p_{mean}^j\right) \pm \alpha^{(1-r_1)} \cdot e^{(-\beta)} \cdot val \cdot \left(p_{best}^j - p_{mean}^j\right);$$

          else
              The updated individuals are equal to the parents p_1 and p_2;
          End if
      End if
else
The updated individuals are equal to the parents p_1 and p_2;
End if
End for
else
The updated individuals are equal to the parent individuals p_1 and p_2;
End if
Make transboundary adjustments

Algorithm 3: Pseudocode of adaptive Lévy mechanism

Input: Agent P, dim;
Output: P following the approach;
Calculate agent X using Eq (13);
Define $Z = zeros(1, dim)$, $J = randi([1, dim])$;
For $individual\ each\ dimension$
Calculate position using Eq (14);
End For
Calculate position using Eq (17);

4. The designed SDHGS method

In this section, we integrate the directional crossover approach and the adaptive Lévy strategy into the framework of HGS, alongside an exposition of the fundamental concept and architecture of SDHGS. The incorporation of the directional crossover mechanism and the adaptive Lévy diversity technique serves to elevate the diversity within the population. Moreover, these mechanisms can potentially harmonize the trade-off between exploratory and exploitative aspects within the search process.

4.1. The proposed SDHGS

Within this segment, the DX strategy and the adaptive Lévy diversity mechanism are seamlessly integrated into the HGS framework, resulting in what is referred to as the adaptive Lévy directional HGS (SDHGS). On the one hand, the DX strategy maintains a fresh balance between SDHGS's capacities for exploration and exploitation. On the other hand, the SDHGS can preserve population diversity thanks to the adaptive Lévy diversity mechanism. The pseudocode for SDHGS is provided in Algorithm 4 and is based on research on adaptive Lévy diversity and directed crossover methods. SDHGS's organizational structure is shown in Figure 1.

Comprising the substantial temporal intricacy of SDHGS are procedures such as initialization, fitness computation, sorting, original position refinement, the adaptive Lévy diversity procedure, and the directional crossover approach. The algorithm's population magnitude is represented as N, with T indicating the upper threshold for iterations. Simultaneously, the task dimension is denoted as d. The temporal complexity of initialization is bounded by $O(N)$. Moreover, the sorting operation entails a complexity of $O(N \times Nlog\, N)$. The complexity of calculating fitness is $O(N \times d)$. HGS's computational complexity is $O(N \times (1 + T \times N \times (2 + logN + 2 \times d)))$. The adaptive Lévy diversity strategy has an $O(N \times d)$ level of complexity. Additionally, the directional crossover strategy's complexity is $O(N \times d)$. As a result, the total complexity of SDHGS is equal to $O(N \times \left(1 + T \times N \times (2 + logN + 2 \times d)\right) + 2 \times d)$.

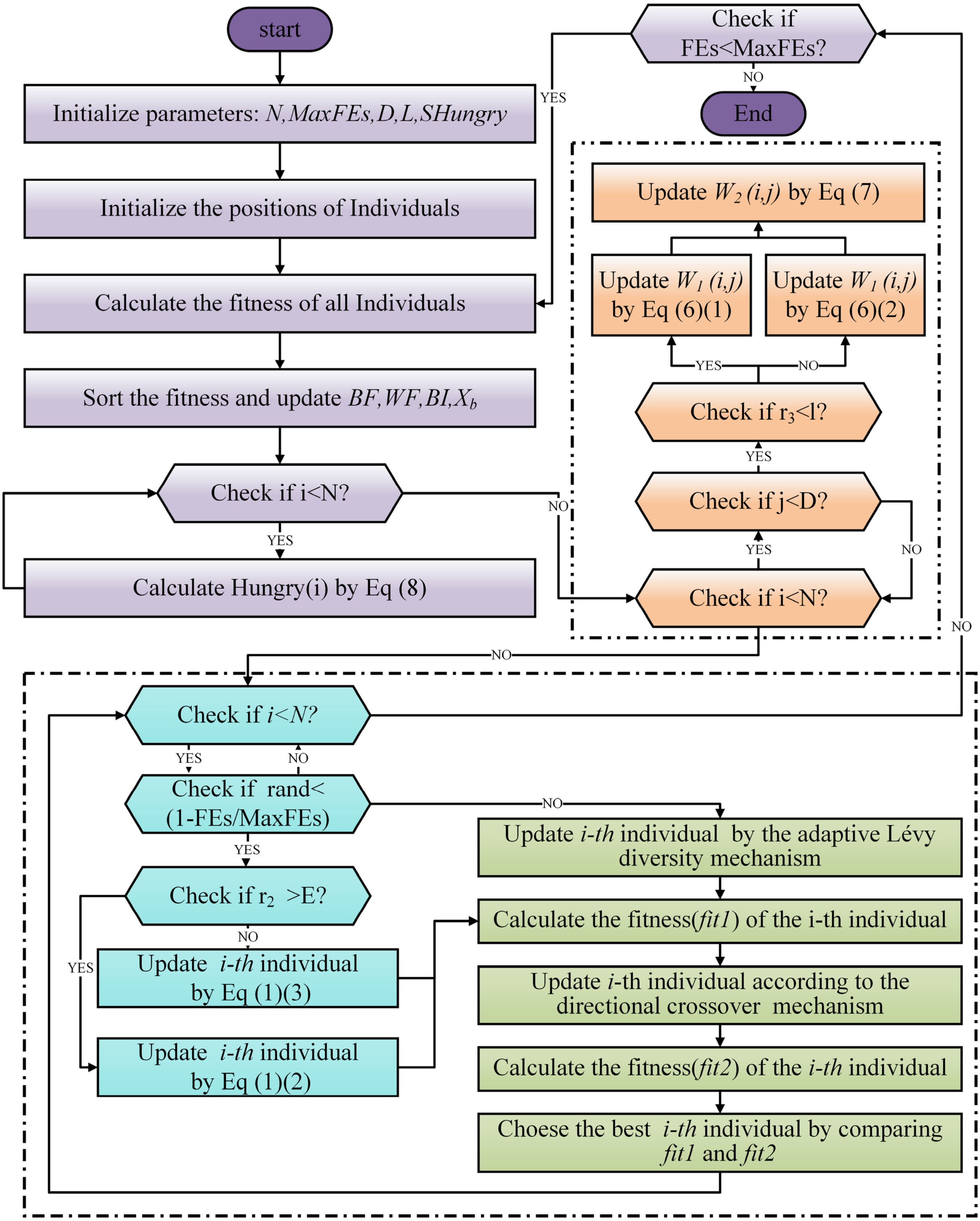

Figure 1. Flowchart of SDHGS.

Algorithm 4: Pseudocode of SDHGS

Initialize the parameters $N, MaxFEs, l, FEs, D, SHungry$
Initialize the positions of Individuals X_i $(i = 1, 2, \cdots, N)$
While $(FEs \leq MaxFEs)$
    Compute each agent's fitness
    Update BF, WF, X_b, BI
    Set $Hungry$ using Eq (8)
    Set W_1 using Eq (6)
    Set W_2 using Eq (7)
  For $each\ individual$
    If rand < 1 − $FEs/MaxFEs$
      Set the individuals using Algorithm 3
      Compute E using Eq (2)
      Calculate R using Eq (4)
      Adjust the position using Eq (1)
    End if
    Update the best position by Algorithm 2
End for
$FEs = FEs + N$;
End while
Return BF, X_b

4.2. K-nearest neighbor (KNN)

A straightforward, non-parametric, and successful learning algorithm called K-nearest neighbor (KNN) [29] produced good results in function classification and high classification accuracy [30]. Employing a k-nearest neighbor ensemble, this model predicts the classification of a novel instance through a consensus vote from the classes of its nearest neighbors. The classification outcome for the novel instance is ascertained by identifying the class associated with the nearest training point, determined through a proximity-based metric. The Euclidean distance is used to determine similarity and is frequently utilized in the literature. Equation (18) illustrates how to calculate the Euclidean distance between two D-dimensional points Z_1 and Z_2.

$$Distance\ (Z_1, Z_2) == \left(\sum_{i=1}^{D}(z_1^i - z_2^i)^2\right)^{1/2} \tag{18}$$

In this study, we assess the KNN classifier's classification accuracy due to its quick training times, simple implementation, and high efficiency.

4.3. SDHGS-KNN model

The described SDHGS represents an advanced iteration of HGS, utilizing a binary paradigm to classify crucial attributes. Through the collaborative utilization of the adaptive Lévy diversity technique and the directed crossover approach, it achieves an optimal solution for feature selection. This results in gathering critical attribute insights and enhancing classification precision. The application of SDHGS for feature selection adheres to a binary format, given the essential requirement of a binary domain, encompassing "0" and "1".

Within the optimization process, a solution is portrayed through an n-dimensional vector of the same length as the count of features within the dataset. Solution values can exclusively be "0" or "1", where "0" signifies the non-selection of the feature and "1" indicates its selection. Consequently, the proposed SDHGS transforms binary SDHGS (bSDHGS) using the transfer function (TF), as detailed in this study. Demonstrated to us is the utilization of transfer functions (TFs) as a means to convert a continuous variant into a binary rendition. The ensuing diagram illustrates the manner in which positional components within this manuscript undergo updates.

$$T\left(X_i^j(t)\right) = \left|\frac{2}{\pi}\arctan\left(\frac{\sqrt{\pi}}{2}X_i^j(t)\right)\right| \tag{19}$$

$$X_i^d(t+1) = \begin{cases} -X_i^d(t+1), & rand < T\left(x_i^d(t+1)\right) \\ X_i^d(t+1), & rand \geq T\left(x_i^d(t+1)\right) \end{cases} \tag{20}$$

where $X_i^j(t)$ is the population's ith member at the jth dimension. Thus, using the mechanism value $T\left(X_i^j(t)\right)$, Eq (20) updates the location for the following iteration. Equation (19) can be used to get the $T\left(X_i^j(t)\right)$.

Feature selection constitutes a pivotal phase in the preprocessing of data for both machine learning and data analysis [31]. It encompasses the identification and extraction of the most pertinent and informative features from a dataset, while eliminating irrelevant or redundant ones [32]. Within the realm of feature selection, the objectives of top significance encompass the count of selected attributes and the precision of classification, both of which are intrinsically distinct and separate [33]. Fewer features are chosen, indicating a more significant classification impact as the classification accuracy increases. Throughout each iteration, the quality of each solution is often evaluated using a fitness function. Finally, bSDHGS adeptly achieves equilibrium between the quantity of chosen attributes and classification accuracy. The resultant adaptive function is expressed as follows:

$$Fitness = \alpha \cdot \gamma_R + \beta\frac{|R|}{|N|} \tag{21}$$

where α represents a classification accuracy weight in the [0, 1] range, γ_R is regarded as the classification error rate, $\beta = 1 - \alpha$ means the importance of the number of features chosen, $|R|$ is the size of the subset of features chosen and $|N|$ means the total number of features. After many tests, the best effect was obtained under the condition of $\alpha = 0.05$ [34].

The dataset undergoes scaling to conform within the range of $[-1, 1]$ before being partitioned into distinct training and testing sets. Employing a ten-fold cross-validation methodology, which stands as the established norm, this research ensures a judicious and equitable experimental procedure. The population's dimensions in the bSDHGS algorithm align with the count of attributes present in the dataset, set before the random initialization of the binary SDHGS method's population. The binary value "1" holds significance as it dictates the identification of selected attributes. Validation of attribute correctness and the determination of population fitness entail the application of a KNN classifier. Subsequently, the internal stages of the bSDHGS unfold, uncovering optimal user sets for the algorithm. Further, employing the KNN classifier, the classification precision of the scenarios is gauged. Consequently, an optimal subset of attributes is meticulously fashioned.

5. Experimental results and discussion

In this section, an overview is provided regarding the 30 benchmark functions sourced from IEEE CEC2017, specifically designed to evaluate the efficacy of SDHGS. All these functions solely pertain to single objective boundary constraints, free of any additional constraints apart from the boundary limitations. The related contents of the functions are shown in Table 2, where the limit of the search space is in the range of [-100, 100], and *F (min)* is the best value. Functions F1 to F3 are characterized as unimodal functions. F4 to F10, on the other hand, represent simple multimodal functions, exhibiting numerous local optima. Moving forward, F11 to F20 are denoted as hybrid functions, while F21 to F30 are categorized as composition functions. Therefore, these 30 functions can test the performance of SDHGS to judge whether SDHGS can meet the needs of various problems and solve optimization problems.

A series of functional assessments, rooted in the IEEE CEC 2017 function suite, is conducted within this segment. Through the integration of a directional crossover mechanism and an adaptive Lévy diversity mechanism into HGS, the novel SDHGS variant is formulated. The comprehensive evaluation utilizing the IEEE CEC 2017 function suite results in a rigorous examination of algorithmic performance. Remarkably, these diverse functions reveal the algorithms' efficacy in terms of exploration and exploitation but also underscore their ability to harmonize these opposing facets.

The recently published algorithms include HGS, grey wolf optimization (GWO), INFO, SSA, RUN, SMA, and AOA, which are the algorithms for comparison. For the comparison tests, the advanced algorithms are WLSSA, CLSGMFO, OBLGWO, WDE, IGWO, SCADE, and CBA. In a word, analyses of mean value, variance, Wilcoxon signed-rank test [26], and Friedman test [27] are used to examine the experiment outcomes. Convergence analysis is a broad idea created to track performance that picks up steam over time, particularly in optimization problems [36]. The analytical results attest to the enhancements SDHGS exhibited regarding its acceleration of convergence, heightened precision, and augmented potential for escaping local optima.

The entire studies are carried out at the same levels to aid researchers in obtaining objective data [37]. The algorithms use evaluation principles (FEs) to reduce the number of calculations required. Furthermore, the experimentation is conducted utilizing a computing system equipped with a 12th Generation Intel (R) Core (TM) I7-12700H CPU running at 2.30 GHz and supported by a Windows 11 operating environment, complemented by a RAM capacity of 16.0 GB. In order to calculate the goal fitness, the algorithm multiplies the number of each evaluation. The experiment is assumed to be valid and reliable while the evaluation principle is in play. Thirty different iterations of each method are performed to reduce experimental error and eliminate unpredictability. Furthermore, there are 30 algorithms in the population. The measurement is 30. The algorithm's upper threshold for evaluations, designated as MaxFEs, is set at 300,000. The configurations of parameters for the contrastive algorithms are meticulously delineated in Table 3. To conduct a thorough statistical comparison, the Friedman test was employed to assess the potential differences and statistical significance in the performance of all comparison algorithms on the baseline function. The mean ranking value (ARV) resulting from the Friedman test served as a metric to gauge the average performance of the inspected method. At a significance level of 0.05, the Wilcoxon signed-rank test—a non-parametric statistical test—is utilized to ascertain the statistical significance of the modification. Statistical conformance tests are performed using Friedman tests. If a p-value is less than 0.05 is considered statistically significant. The symbols "+/=/-" describe that the method is superior, equal to, or worse than the other comparative methods.

Table 2. Functions of IEEE CEC2017 [35].

ID	Function name	F (min)
F1	Shifted and Rotated Bent Cigar Function	100
F2	Shifted and Rotated Sum of Different Power Function	200
F3	Shifted and Rotated Zakharov Function	300
F4	Shifted and Rotated Rosenbrock's Function	400
F5	Shifted and Rotated Rastrigin's Function	500
F6	Shifted and Rotated Expanded Scaffer's F6 Function	600
F7	Shifted and Rotated Lunacek Bi_Rastrigin Function	700
F8	Shifted and Rotated Non-Continuous Rastrigin's Function	800
F9	Shifted and Rotated Levy Function	900
F10	Shifted and Rotated Schwefel's Function	1000
F11	Hybrid Function 1 ($N = 3$)	1100
F12	Hybrid Function 2 ($N = 3$)	1200
F13	Hybrid Function 3 ($N = 3$)	1300
F14	Hybrid Function 4 ($N = 4$)	1400
F15	Hybrid Function 5 ($N = 4$)	1500
F16	Hybrid Function 6 ($N = 4$)	1600
F17	Hybrid Function 7 ($N = 5$)	1700
F18	Hybrid Function 8 ($N = 5$)	1800
F19	Hybrid Function 9 ($N = 5$)	1900
F20	Hybrid Function 10 ($N = 6$)	2000
F21	Composition Function 1 ($N = 3$)	2100
F22	Composition Function 2 ($N = 3$)	2200
F23	Composition Function 3 ($N = 4$)	2300
F24	Composition Function 4 ($N = 4$)	2400
F25	Composition Function 5 ($N = 5$)	2500
F26	Composition Function 6 ($N = 5$)	2600
F27	Composition Function 7 ($N = 6$)	2700
F28	Composition Function 8 ($N = 6$)	2800
F29	Composition Function 9 ($N = 3$)	2900
F30	Composition Function 10 ($N = 3$)	3000

Table 3. The specifications of algorithms for comparison.

Method	Parameter settings
SDHGS	$Q = 1 - FEs/MaxFEs$; $p_c = 0.9$; $p_{cv} = 0.9$; $\alpha = 0.95$; $p_d = 0.75/0.5$ $\beta = 1.5$; $\lambda = 1$
HGS	$l = 0.08$; $LH = 100$
GWO	$a = [2, 0]$
INFO	$c = 2$; d= 4
SSA	$c1 \in [0, 1]$; $c2 \in [0, 1]$
RUN	$a = 20$; $b = 12$
SMA	$z = 0.03$
AOA	$a = 5$
MFO	$b = 1$; $t = [-1, 1]$; $a \in [-1, -2]$

5.1. Balance analysis of SDHGS and HGS

The performance of the algorithms is thoroughly tested in this part through balance tests using SDHGS and HGS on IEEE CEC 2017 functions. HGS with a directed crossover mechanism and HGS with an adaptive Lévy diversity mechanism make up SDHGS. The balancing analysis of SDHGS and HGS can provide examples of these two mechanisms in HGS. The primary function uses the same parameter settings. The maximum number of evaluations is set at 300,000. Thirty agents make up the population, and 30 separate experiments are conducted. The outcomes of the diversity and balance analyses between SDHGS and HGS are shown in Figure 2. The IEEE CEC 2017 function sets F1, F4, F5, F8, F11, F14, and F21 functions have all been chosen for the balancing analysis. The entire balancing response is expressed as a percentage of exploration and exploitation. These values are computed for each iteration using Eqs (22) and (23).

$$\text{Exploration\%} = \left(\frac{\text{DIV}}{\text{DIV}_{\text{max}}}\right) * 10 \tag{22}$$

$$\text{Exploitation\%} = \left(\frac{|\text{DIV}_{\text{max}} - \text{DIV}|}{\text{DIV}_{\text{max}}}\right) * 10 \tag{23}$$

The highpoint diversity value observed throughout the model's optimization process is referred to as DIV_{max}. Exploratory tendencies are demonstrated through the relationship between iteration-based diversity and the highest diversity attained, quantified as $Exploration\%$. Conversely, the extent of exploitation is represented by the complementary percentage to $Exploitation\%$, as it is shaped by the gap between current iteration diversity and the maximum diversity—a consequence of agents' search concentration. This complements the measure of exploration to signify the degree of exploitation.

Illustrated in Figure 2, the present experiment undertakes a comprehensive analysis of the diversity and equilibrium attributes within SDHGS and HGS. The equilibrium assessment encompasses multiple facets such as exploration, exploitation, and incremental-decremental dynamics. These characteristics are discerned through the blue curves and red lines, which signify local exploitation and exploration, respectively, and the green lines represent incremental trends.

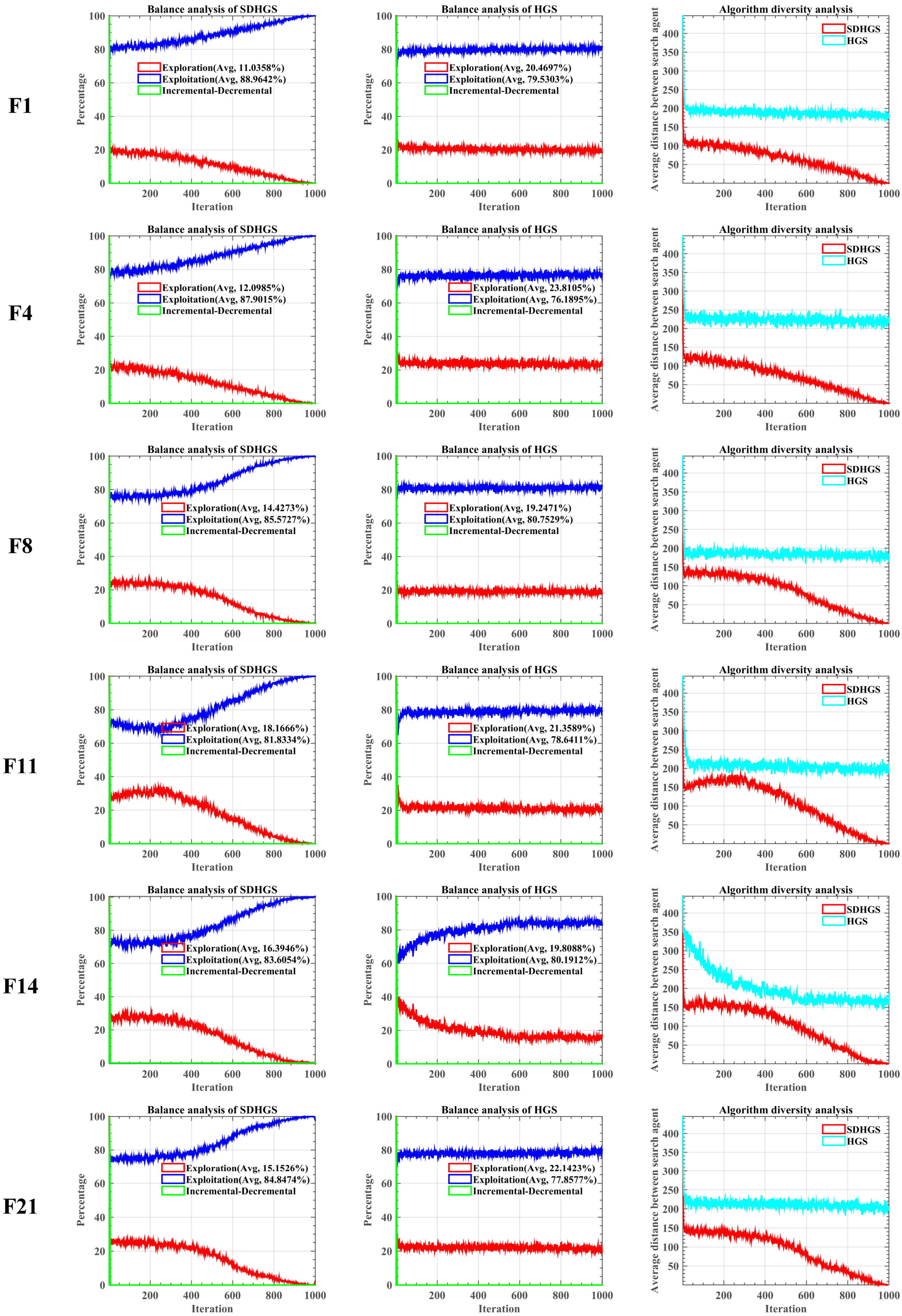

Figure 2. Analysis of diversity and balance between SDHGS and HGS.

Comparing SDHGS to HGS, a discernible disparity emerges in terms of their utilization patterns. SDHGS exhibits a more pronounced inclination towards small-scale exploitation searches and a diminished tendency towards expansive exploration searches. This observed behavior arises from the strategic integration of the directional crossover mechanism and the adaptive Lévy diversity approach into SDHGS. These mechanisms synergistically bolster the span of global and local searches, respectively, resulting in a refined equilibrium. The outcomes of the experimentation reinforce the underlying hypothesis. This is visualized through the ascending trajectory of the green curve when the emphasis on exploration surpasses that of exploitation and, conversely, a descending trend when exploration is equivalent to or less than exploitation. The temporal dimension exhibited in the image, featuring intervals of high or low iteration values, delineates the enduring impact of the search strategy's local exploitation and global exploration capabilities.

Due to the distinctive emphasis on local exploitation within SDHGS, its functions manifest a higher degree of exploitation when compared to those evaluated by HGS. In contrast, HGS is distinguished by its robust pursuit of global exploration, thereby substantiating its relatively elevated exploration proportion.

The final column within Figure 2 elucidates the diversity assessment for the functions F1, F4, F5, F8, F11, F14, and F21, as outlined earlier. The horizontal axis delineates the iteration count, while the vertical axis signifies the diversity metric. At the commencement of algorithms, a wide spectrum is encountered due to random initialization. However, with the progression of iterations, population diversity gradually wanes.

The observed outcomes underscore a distinctive pattern. After reaching a certain value, the diversity within HGS demonstrates a plateau, signifying its resilience to further diminution. Conversely, SDHGS portrays notably smaller and diminishing diversity metrics than HGS. The trajectory of diversity curves indicates that SDHGS exhibits swifter convergence, thereby advancing further within the realm of global exploration when juxtaposed with HGS.

5.2. Comparison with excellent original algorithms

In this section, we compare SDHGS with various traditional and newly reported methods on IEEE CEC 2017, including HGS, GWO, INFO, SSA, RUN, SMA, and AOA. Their mean value (Avg) and standard deviation (Std) results of Wilcoxon signed-rank test analysis are illustrated in Table 4. First, SDHGS obtains best mean value on F5–F9, F11, F13, F16, F17, F20–F23, F26, and F29. They are marked in bold. The experimental findings demonstrate that SDHGS has superior local search capability compared to HGS. In other words, SDHGS improves local and global search capabilities while maintaining a healthy balance. Thus, when addressing problems, SDHGS is more precise and stable than other conventional algorithms.

The p-values obtained from this experiment's WSRT analysis are displayed in Table 5. The majority of the p-values below 0.05 in this table are bolded. The p-values are less than 0.05 on most of the functions, which denotes that SDHGS compares with another algorithm significantly on IEEE CEC 2017. The WSRT of SDHGS is 2.333, ranking first. The experimental results of SMA, with a score of 3.6333, rank second. However, the HGS only ranks sixth, indicating that SDHGS is superior to HGS. The suggested SDHGS exhibits superior performance (+) in comparison to HGS across nineteen functions, and it demonstrates an equivalent level of performance (=) across eight functions. Consequently, SDHGS surpasses HGS across the entire spectrum of functions.

Table 4. Comparative results for SDHGS, HGS, GWO, INFO, SSA, RUN, SMA, and AOA.

Function	Metric	SDHGS	HGS	GWO	INFO	SSA	RUN	SMA	AOA
F1	Avg	1.9009E+04	8.4805E+03	1.2290E+09	**1.0000E+02**	2.0463E+03	4.8044E+03	7.3103E+03	4.3658E+10
	Std	1.7300E+04	6.1134E+03	8.5537E+08	**3.3078E-07**	2.6617E+03	4.4456E+03	6.9665E+03	4.0197E+09
F2	Avg	1.6406E+12	2.4646E+02	1.6424E+31	**2.0000E+02**	2.0110E+02	2.0000E+02	2.0060E+02	2.7356E+42
	Std	1.9842E+12	1.7050E+01	3.7140E+31	**3.4339E-04**	3.4911E+00	2.4850E-03	1.8782E+00	8.2789E+42
F3	Avg	5.9509E+03	3.9024E+02	3.3522E+04	3.0000E+02	**3.0000E+02**	3.0018E+02	3.0002E+02	7.5642E+04
	Std	1.7716E+03	1.3933E+02	1.3154E+04	2.3122E-06	**9.0931E-09**	8.3650E-02	8.6178E-03	8.1864E+03
F4	Avg	4.7688E+02	4.8882E+02	6.0714E+02	**4.3421E+02**	4.8867E+02	4.9377E+02	4.9107E+02	1.1079E+04
	Std	1.3109E+01	1.4777E+01	8.7481E+01	3.3452E+01	1.9717E+01	2.1452E+01	**8.9672E+00**	3.8796E+03
F5	Avg	**5.7761E+02**	6.2155E+02	5.9429E+02	6.5685E+02	5.9065E+02	6.9690E+02	5.9235E+02	8.1833E+02
	Std	1.4191E+01	2.3809E+01	2.2538E+01	3.4327E+01	**1.0415E+01**	2.8734E+01	2.1982E+01	3.9085E+01
F6	Avg	**6.0021E+02**	6.0370E+02	6.0743E+02	6.2426E+02	6.2707E+02	6.4208E+02	6.0116E+02	6.6507E+02
	Std	**1.1351E-01**	3.5140E+00	4.8305E+00	9.2022E+00	1.1594E+01	7.7414E+00	7.8024E-01	5.0347E+00
F7	Avg	**8.0540E+02**	8.9354E+02	8.6626E+02	9.7898E+02	8.7804E+02	9.9651E+02	8.4360E+02	1.2802E+03
	Std	**9.8237E+00**	3.9048E+01	4.4182E+01	6.6459E+01	5.2665E+01	6.8800E+01	3.4892E+01	9.6756E+01
F8	Avg	**8.6927E+02**	9.1674E+02	8.9999E+02	9.2885E+02	9.0397E+02	9.3919E+02	8.7970E+02	1.0358E+03
	Std	**6.4274E+00**	2.2384E+01	2.0735E+01	2.6558E+01	3.0603E+01	2.6392E+01	2.7288E+01	2.5132E+01
F9	Avg	**9.2537E+02**	3.7569E+03	1.8514E+03	3.2349E+03	2.9977E+03	3.6984E+03	1.7090E+03	5.7147E+03
	Std	**1.3454E+01**	9.3959E+02	6.0828E+02	6.9975E+02	1.2273E+03	5.9353E+02	7.2848E+02	7.6703E+02
F10	Avg	4.0501E+03	4.0757E+03	**3.8813E+03**	5.2503E+03	4.6609E+03	4.4958E+03	4.1632E+03	6.1485E+03
	Std	6.3904E+02	5.6309E+02	**4.3958E+02**	6.6871E+02	6.3782E+02	4.7502E+02	4.7226E+02	6.6051E+02
F11	Avg	**1.1650E+03**	1.2115E+03	2.0894E+03	1.2898E+03	1.2737E+03	1.1843E+03	1.2336E+03	3.1994E+03
	Std	**8.6900E+00**	4.6050E+01	7.4987E+02	5.7221E+01	4.4267E+01	1.9503E+01	5.7968E+01	1.0070E+03
F12	Avg	8.2024E+05	7.7511E+05	8.1598E+07	**2.2970E+04**	1.4026E+06	1.5809E+06	1.0982E+06	7.9176E+09
	Std	3.7926E+05	7.2806E+05	1.2269E+08	**1.0828E+04**	8.1147E+05	7.9259E+05	7.7200E+05	2.0326E+09
F13	Avg	**1.5105E+04**	3.4599E+04	6.7042E+04	2.3030E+04	6.8955E+04	2.5671E+04	3.5407E+04	4.3347E+04
	Std	**6.2236E+03**	2.6714E+04	4.4396E+04	1.7025E+04	2.8640E+04	1.0495E+04	2.6826E+04	1.6024E+04

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Function	Metric	SDHGS	HGS	GWO	INFO	SSA	RUN	SMA	AOA
F14	Avg	7.6106E+03	5.7245E+04	2.9108E+05	**1.6961E+03**	5.5782E+03	2.0274E+03	2.6566E+04	5.3909E+04
	Std	6.9278E+03	4.4007E+04	3.4591E+05	**1.4990E+02**	3.4664E+03	4.2154E+02	1.4216E+04	5.0094E+04
F15	Avg	2.8106E+03	1.9513E+04	3.0253E+04	**2.4008E+03**	6.5766E+04	1.6733E+04	2.5945E+04	2.4149E+04
	Std	**1.2173E+03**	1.5959E+04	1.0100E+04	2.0671E+03	3.2123E+04	1.6174E+03	1.2014E+04	9.1154E+03
F16	Avg	**2.2363E+03**	2.5656E+03	2.3314E+03	2.6447E+03	2.6024E+03	2.7220E+03	2.3431E+03	4.4999E+03
	Std	1.9626E+02	**1.6371E+02**	2.5244E+02	3.0513E+02	2.4308E+02	1.9902E+02	2.9695E+02	9.0229E+02
F17	Avg	**1.7983E+03**	2.3536E+03	1.9283E+03	2.3097E+03	1.9797E+03	2.1954E+03	2.1675E+03	2.8644E+03
	Std	**5.9097E+01**	2.0576E+02	8.8935E+01	2.0604E+02	1.2974E+02	2.1822E+02	2.3214E+02	2.0925E+02
F18	Avg	1.3220E+05	5.0966E+05	6.5196E+05	**7.9735E+03**	1.2669E+05	4.2138E+04	4.3445E+05	8.3449E+05
	Std	6.9463E+04	4.3089E+05	5.1270E+05	**8.9662E+03**	8.0153E+04	9.7900E+03	4.1865E+05	7.0542E+05
F19	Avg	5.3179E+03	2.6761E+04	2.8841E+05	**2.1228E+03**	3.5805E+05	7.3821E+03	2.9369E+04	1.0847E+06
	Std	2.2963E+03	2.6039E+04	2.3484E+05	**1.9608E+02**	2.3154E+05	3.6222E+03	2.2181E+04	1.5737E+05
F20	Avg	**2.2099E+03**	2.5023E+03	2.3634E+03	2.5773E+03	2.3840E+03	2.4269E+03	2.3788E+03	2.7160E+03
	Std	**7.3264E+01**	9.7058E+01	1.3035E+02	2.0785E+02	1.3242E+02	1.6721E+02	1.2403E+02	2.0837E+02
F21	Avg	**2.3574E+03**	2.4243E+03	2.3768E+03	2.4320E+03	2.3929E+03	2.4426E+03	2.4098E+03	2.5977E+03
	Std	**1.4179E+01**	2.4236E+01	1.8322E+01	2.9411E+01	3.1099E+01	3.2239E+01	2.4317E+01	5.0831E+01
F22	Avg	**2.3022E+03**	4.9738E+03	3.5561E+03	4.5763E+03	3.8422E+03	2.9874E+03	5.7344E+03	8.4597E+03
	Std	**1.4732E+00**	1.4784E+03	1.4807E+03	2.0792E+03	2.0704E+03	1.5391E+03	7.9969E+02	7.4222E+02
F23	Avg	**2.7164E+03**	2.7681E+03	2.7528E+03	2.8266E+03	2.7446E+03	2.7724E+03	2.7392E+03	3.4024E+03
	Std	**1.3420E+01**	1.6138E+01	3.1313E+01	5.9887E+01	1.7749E+01	2.5825E+01	2.1388E+01	1.0021E+02
F24	Avg	2.9030E+03	3.0299E+03	2.9485E+03	2.9697E+03	2.8977E+03	**2.8954E+03**	2.9199E+03	3.8708E+03
	Std	2.2510E+01	7.0617E+01	6.9409E+01	3.1396E+01	**1.9375E+01**	2.9493E+01	2.7738E+01	2.4302E+02
F25	Avg	2.9175E+03	**2.8867E+03**	2.9892E+03	2.9105E+03	2.8958E+03	2.9088E+03	2.8870E+03	4.5638E+03
	Std	2.1347E+01	4.1334E+00	2.7369E+01	2.5736E+01	1.7828E+01	1.7247E+01	**1.3025E+00**	2.7331E+02
F26	Avg	**3.9291E+03**	4.9937E+03	4.5713E+03	5.1859E+03	4.9057E+03	5.4520E+03	4.7677E+03	1.0208E+04
	Std	5.4443E+02	2.7528E+02	**1.8645E+02**	1.3362E+03	8.1926E+02	1.6189E+03	2.7453E+02	9.5081E+02

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Function	Metric	SDHGS	HGS	GWO	INFO	SSA	RUN	SMA	AOA
F27	Avg	3.2265E+03	3.2269E+03	3.2540E+03	3.2583E+03	3.2356E+03	3.2555E+03	**3.2094E+03**	4.5353E+03
	Std	1.3729E+01	1.5416E+01	2.3600E+01	3.0216E+01	1.9958E+01	1.8643E+01	**1.2711E+01**	3.5097E+02
F28	Avg	3.1993E+03	3.1953E+03	3.4360E+03	3.1577E+03	3.1930E+03	**3.1216E+03**	3.2379E+03	6.0700E+03
	Std	**1.8175E+01**	6.3185E+01	7.2310E+01	7.6154E+01	5.1474E+01	3.8582E+01	4.0958E+01	5.9282E+02
F29	Avg	**3.4308E+03**	3.8080E+03	3.7333E+03	4.0512E+03	3.8804E+03	3.9729E+03	3.7826E+03	6.3068E+03
	Std	**6.9964E+01**	2.8945E+02	1.6881E+02	2.6549E+02	2.4268E+02	2.7914E+02	2.0356E+02	6.0936E+02
F30	Avg	1.1931E+04	9.9488E+04	5.7459E+06	**6.4562E+03**	9.7232E+05	5.1099E+04	1.5452E+04	5.8682E+07
	Std	2.9173E+03	1.3482E+05	3.3840E+06	**1.3227E+03**	6.4939E+05	1.6106E+04	4.8028E+03	1.2396E+08

Table 5. P-values gained by Wilcoxon test.

Function	SDHGS	HGS	GWO	INFO	SSA	RUN	SMA	AOA
F1	~	2.3242E-01	**1.9531E-03**	**1.9531E-03**	1.9531E-02	6.4453E-02	1.3086E-01	**1.9531E-03**
F2	~	**1.9531E-03**	**1.9531E-03**	**1.9531E-03**	**1.9531E-03**	**1.9531E-03**	**1.9531E-03**	**1.9531E-03**
F3	~	**1.9531E-03**	**1.9531E-03**	**1.9531E-03**	**1.9531E-03**	**1.9531E-03**	**1.9531E-03**	**1.9531E-03**
F4	~	1.9336E-01	**1.9531E-03**	**1.9531E-03**	1.9336E-01	6.4453E-02	6.4453E-02	**1.9531E-03**
F5	~	**1.9531E-03**	2.7344E-02	**1.9531E-03**	1.3086E-01	**1.9531E-03**	2.3242E-01	**1.9531E-03**
F6	~	**1.9531E-03**	**1.9531E-03**	**1.9531E-03**	**1.9531E-03**	**1.9531E-03**	**1.9531E-03**	**1.9531E-03**
F7	~	**1.9531E-03**	**1.9531E-03**	**1.9531E-03**	**1.9531E-03**	**1.9531E-03**	1.3672E-02	**1.9531E-03**
F8	~	**1.9531E-03**	3.9063E-03	**1.9531E-03**	1.3672E-02	**1.9531E-03**	1.9336E-01	**1.9531E-03**
F9	~	**1.9531E-03**	**1.9531E-03**	**1.9531E-03**	**1.9531E-03**	**1.9531E-03**	**1.9531E-03**	**1.9531E-03**
F10	~	1.0000E+00	5.5664E-01	9.7656E-03	3.7109E-02	3.7109E-02	1.0000E+00	**1.9531E-03**
F11	~	9.7656E-03	**1.9531E-03**	**1.9531E-03**	**1.9531E-03**	1.9531E-02	3.9063E-03	**1.9531E-03**
F12	~	6.9531E-01	**1.9531E-03**	**1.9531E-03**	3.7109E-02	3.9063E-03	5.5664E-01	**1.9531E-03**
F13	~	1.3086E-01	**1.9531E-03**	1.6016E-01	**1.9531E-03**	2.7344E-02	8.3984E-02	3.9063E-03
F14	~	**1.9531E-03**	**1.9531E-03**	**1.9531E-03**	8.4570E-01	3.9063E-03	**1.9531E-03**	**1.9531E-03**
F15	~	**1.9531E-03**	**1.9531E-03**	8.3984E-02	**1.9531E-03**	**1.9531E-03**	**1.9531E-03**	**1.9531E-03**

Continued on next page

Function	SDHGS	HGS	GWO	INFO	SSA	RUN	SMA	AOA
F16	~	**1.9531E-03**	5.5664E-01	**1.9531E-03**	**1.9531E-03**	9.7656E-03	3.7500E-01	**1.9531E-03**
F17	~	**1.9531E-03**	**1.9531E-03**	**1.9531E-03**	9.7656E-03	**1.9531E-03**	**1.9531E-03**	**1.9531E-03**
F18	~	2.7344E-02	2.7344E-02	**1.9531E-03**	1.0000E+00	**1.9531E-03**	9.7656E-03	**1.9531E-03**
F19	~	8.3984E-02	**1.9531E-03**	**1.9531E-03**	**1.9531E-03**	6.4453E-02	5.8594E-03	**1.9531E-03**
F20	~	3.9063E-03	3.7109E-02	**1.9531E-03**	3.9063E-03	9.7656E-03	**1.9531E-03**	**1.9531E-03**
F21	~	**1.9531E-03**	4.8828E-02	**1.9531E-03**	3.9063E-03	**1.9531E-03**	**1.9531E-03**	**1.9531E-03**
F22	~	9.7656E-03	**1.9531E-03**	8.3984E-02	5.5664E-01	1.0000E+00	**1.9531E-03**	**1.9531E-03**
F23	~	**1.9531E-03**	1.3672E-02	**1.9531E-03**	9.7656E-03	3.9063E-03	1.9531E-02	**1.9531E-03**
F24	~	**1.9531E-03**	1.9336E-01	**1.9531E-03**	5.5664E-01	5.5664E-01	1.9336E-01	**1.9531E-03**
F25	~	9.7656E-03	**1.9531E-03**	3.7500E-01	3.7109E-02	3.2227E-01	**1.9531E-03**	**1.9531E-03**
F26	~	**1.9531E-03**	**1.9531E-03**	3.7109E-02	3.9063E-03	2.7344E-02	**1.9531E-03**	**1.9531E-03**
F27	~	1.0000E+00	4.8828E-02	**1.9531E-03**	3.7500E-01	3.7109E-02	1.9531E-02	**1.9531E-03**
F28	~	1.0000E+00	**1.9531E-03**	8.3984E-02	8.4570E-01	3.9063E-03	8.3984E-02	**1.9531E-03**
F29	~	5.8594E-03	**1.9531E-03**	**1.9531E-03**	**1.9531E-03**	**1.9531E-03**	3.9063E-03	**1.9531E-03**
F30	~	9.7656E-03	**1.9531E-03**	**1.9531E-03**	**1.9531E-03**	**1.9531E-03**	6.4453E-02	**1.9531E-03**
+/-/=	~	19/3/8	27/0/3	16/9/5	18/4/8	19/5/6	15/4/11	30/0/0
ARV	**2.3333**	4.6333	4.8333	4.1333	4.1333	4.5333	3.6333	7.7667
Rank	**1**	6	7	3	3	5	2	8

Figure 3 presents convergence curves of SDHGS and other comparison algorithms. The benchmark functions in this figure are F6, F7, F9, F11, F17, F20, F21, F23, and F26 benchmark functions in this figure. Compared with other algorithms, SDHGS, with a strong search ability, accelerates the convergence speed and finds the optimal value. Therefore, in terms of more crucial computational correctness, SDHGS has a sizable edge.

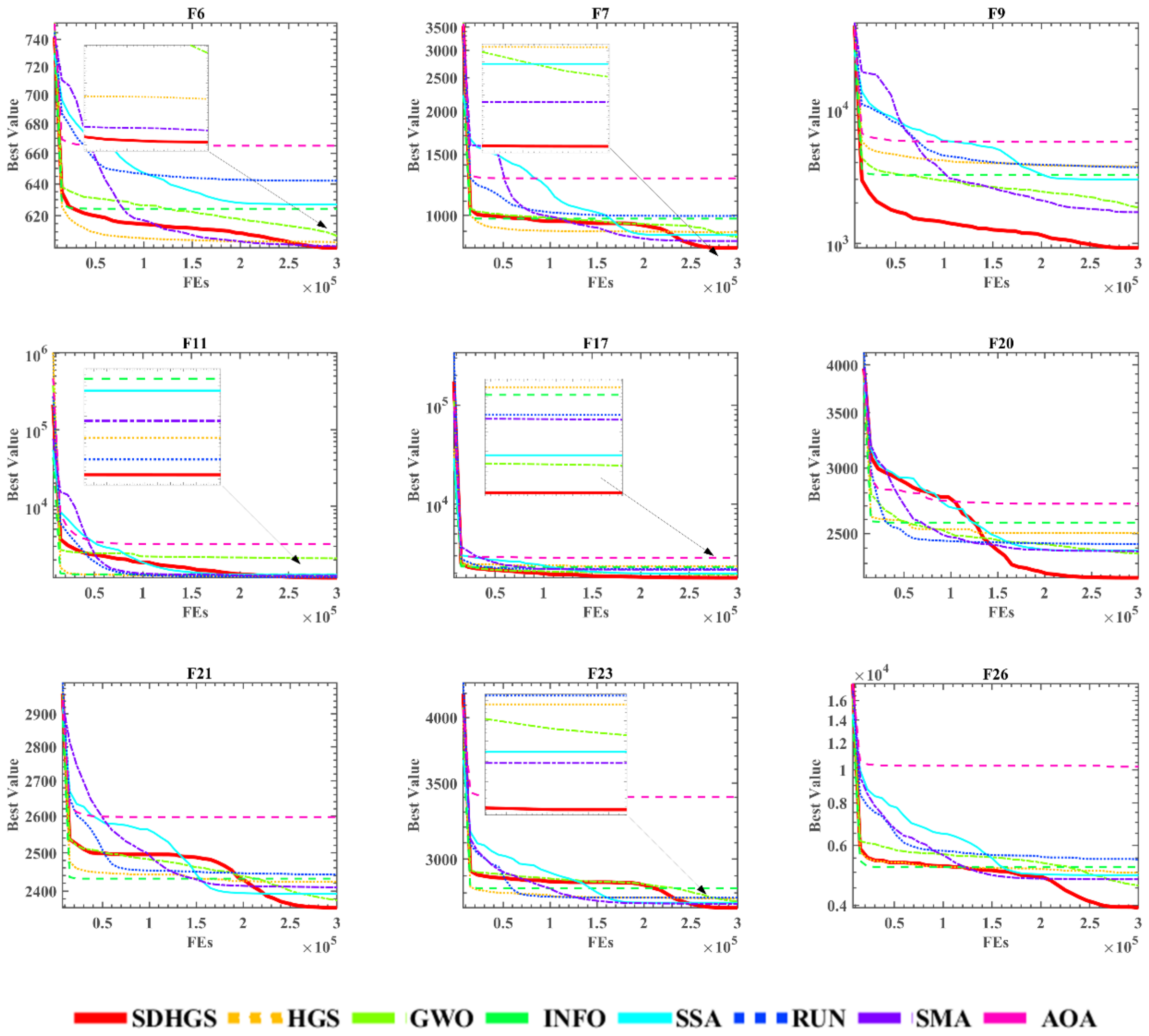

Figure 3. The fitness convergence curve of SDHGS, HGS, GWO, INFO, SSA, RUN, SMA, and AOA on CEC 2017 functions.

5.3. Comparison with advanced algorithms

Except for the original algorithms, the comparison experiment with 7 excellent advanced algorithms is done in this section, including CLSGMFO, WLSSA, IGWO, OBLGWO, WDE, CBA, and SCADE. The average and standard values of the advanced algorithms used are shown in Table 6. The bolded values are the minimum values. Table 7 showcases the outcomes of the Wilcoxon signed-rank analysis, with all p-values below 0.05 emphasized in bold typeface.

In Table 6, SDHGS achieves the first mean value or good ranking for functions which is bolded, including F5–F11, F21, F23, F24, F28, and F29. SDHGS does not perform well on other functions but gains excellent performance. The statistical findings reveal that SDHGS attains the foremost rank in terms of the p-value derived from the Wilcoxon signed-rank test, yielding a value of 2.1667. This achievement is succeeded by similar prominent performances observed in other sophisticated algorithms. Therefore, SDHGS has significant reliability for comparison with other excellent advanced algorithms.

Table 6. Comparative results of advanced algorithms on CEC 2017.

Function	Metric	SDHGS	WLSSA	CLSGMFO	OBLGWO	WDE	IGWO	SCADE	CBA
F1	Avg	9.7384E+03	6.3195E+03	**2.0783E+03**	1.4602E+07	2.0798E+04	1.7916E+06	1.7587E+10	4.6813E+03
	Std	7.2018E+03	5.8689E+03	**1.6077E+03**	1.4505E+07	5.7263E+03	8.3662E+05	2.7307E+09	3.1285E+03
F2	Avg	1.2186E+12	4.2003E+06	9.0905E+10	2.3577E+16	4.4938E+11	1.1098E+13	9.3812E+35	**1.8306E+04**
	Std	1.5448E+12	1.1576E+07	2.6044E+11	5.4575E+16	3.4517E+11	1.7314E+13	1.3299E+36	**1.5213E+04**
F3	Avg	5.7149E+03	**3.0000E+02**	3.4563E+03	1.8552E+04	1.5972E+04	1.3081E+03	6.2019E+04	3.1778E+02
	Std	1.5099E+03	**3.8270E-10**	2.2026E+03	6.5907E+03	3.3046E+03	5.6299E+02	5.0261E+03	9.1341E+00
F4	Avg	4.8105E+02	4.9142E+02	4.9512E+02	5.2781E+02	**4.6678E+02**	4.9876E+02	3.6198E+03	5.0501E+02
	Std	2.0298E+01	**1.3194E+01**	2.0301E+01	2.6871E+01	2.2789E+01	1.6888E+01	7.7775E+02	3.0510E+01
F5	Avg	**5.7570E+02**	6.3462E+02	6.7119E+02	6.6518E+02	5.9546E+02	6.0475E+02	8.1735E+02	8.3803E+02
	Std	1.0760E+01	4.9310E+01	4.2182E+01	4.5474E+01	**8.9906E+00**	2.3166E+01	1.7689E+01	7.6246E+01
F6	Avg	**6.0032E+02**	6.3141E+02	6.2285E+02	6.2766E+02	6.0323E+02	6.2390E+02	6.6106E+02	6.7153E+02
	Std	**9.1542E-02**	1.1590E+01	1.6019E+01	1.6456E+01	8.1564E-01	3.9427E+00	8.1750E+00	1.1716E+01
F7	Avg	**8.1511E+02**	8.7340E+02	9.1500E+02	9.3250E+02	8.7761E+02	8.8943E+02	1.1844E+03	1.7321E+03
	Std	1.8017E+01	5.0000E+01	7.5718E+01	1.1586E+02	**1.6131E+01**	5.7010E+01	2.8903E+01	3.2872E+02
F8	Avg	**8.6891E+02**	9.2298E+02	9.2075E+02	9.6947E+02	8.9585E+02	8.8289E+02	1.0846E+03	1.0231E+03
	Std	1.0700E+01	2.0545E+01	3.4269E+01	4.2089E+01	1.3853E+01	1.8163E+01	**9.7296E+00**	4.6836E+01
F9	Avg	**9.1505E+02**	2.4648E+03	3.0971E+03	2.5459E+03	2.8906E+03	3.0044E+03	8.4848E+03	9.1362E+03
	Std	**1.1446E+01**	1.0057E+03	1.2711E+03	1.9651E+03	2.9661E+02	5.6454E+02	1.5124E+03	3.0709E+03
F10	Avg	**3.5223E+03**	4.8474E+03	5.3501E+03	4.9862E+03	3.5390E+03	4.4166E+03	8.2854E+03	5.7146E+03
	Std	3.3718E+02	6.6207E+02	3.8936E+02	6.4554E+02	2.2733E+02	7.6757E+02	**2.1840E+02**	6.7280E+02
F11	Avg	**1.1560E+03**	1.2483E+03	1.3038E+03	1.2826E+03	1.1734E+03	1.2518E+03	3.4446E+03	1.3142E+03
	Std	**1.0929E+01**	5.8543E+01	7.8253E+01	3.0133E+01	1.5585E+01	3.3954E+01	5.6673E+02	4.8107E+01
F12	Avg	1.0767E+06	1.9855E+06	1.0744E+06	1.4515E+07	**1.8933E+04**	1.0243E+07	1.7867E+09	1.1412E+07
	Std	4.5014E+05	1.1278E+06	9.9264E+05	1.0005E+07	**4.1774E+03**	1.1778E+07	5.8120E+08	4.1806E+06
F13	Avg	1.7485E+04	8.2020E+04	4.7080E+05	2.0140E+05	**1.5091E+03**	9.9744E+04	6.0519E+08	2.0703E+05
	Std	7.1935E+03	9.9803E+04	1.3975E+06	1.2550E+05	**3.5302E+01**	6.4335E+04	2.5852E+08	1.5284E+05
F14	Avg	7.5085E+03	7.2967E+03	6.0870E+04	5.5902E+04	**1.4688E+03**	5.8686E+04	4.0629E+05	1.0903E+04
	Std	7.4512E+03	4.4516E+03	5.8066E+04	4.1922E+04	**8.2030E+00**	4.6523E+04	1.7451E+05	7.9270E+03
F15	Avg	3.1096E+03	2.9297E+04	1.0967E+04	9.8652E+04	**1.5502E+03**	6.2684E+04	1.3686E+07	6.3508E+04
	Std	1.8870E+03	1.6593E+04	1.5358E+04	6.3714E+04	**1.0125E+01**	4.4643E+04	1.1121E+07	4.3037E+04

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Function	Metric	SDHGS	WLSSA	CLSGMFO	OBLGWO	WDE	IGWO	SCADE	CBA
F16	Avg	2.1526E+03	2.7200E+03	2.7450E+03	3.0608E+03	**2.0468E+03**	2.7214E+03	3.8053E+03	3.6729E+03
	Std	**9.4813E+01**	3.0350E+02	2.7565E+02	2.1288E+02	1.2117E+02	1.5530E+02	1.8126E+02	3.9609E+02
F17	Avg	1.8564E+03	1.9747E+03	2.3591E+03	2.2043E+03	**1.8402E+03**	1.9697E+03	2.5288E+03	3.1833E+03
	Std	5.5277E+01	1.7318E+02	2.7349E+02	1.9387E+02	**4.6525E+01**	1.7428E+02	1.2934E+02	1.7033E+02
F18	Avg	1.3984E+05	1.1220E+05	1.8043E+05	1.0571E+06	**2.1765E+03**	5.7717E+05	2.1051E+06	3.4927E+05
	Std	4.8542E+04	7.1937E+04	1.4146E+05	8.6201E+05	**1.1805E+02**	3.2574E+05	1.3679E+06	2.5359E+05
F19	Avg	4.9158E+03	2.6276E+05	5.6334E+03	5.1729E+05	**1.9219E+03**	3.0371E+05	3.5594E+07	1.0236E+06
	Std	1.5773E+03	1.2992E+05	3.0272E+03	2.8240E+05	**2.9436E+00**	3.0474E+05	1.9986E+07	3.4658E+05
F20	Avg	2.2304E+03	2.4076E+03	2.4083E+03	2.5496E+03	**2.1826E+03**	2.3352E+03	2.7483E+03	3.0102E+03
	Std	9.0458E+01	9.4764E+01	1.7905E+02	1.1099E+02	**6.3714E+01**	1.0951E+02	1.0199E+02	3.6151E+02
F21	Avg	**2.3614E+03**	2.3895E+03	2.4376E+03	2.4396E+03	2.4006E+03	2.4028E+03	2.5700E+03	2.6371E+03
	Std	1.2029E+01	2.9288E+01	2.8292E+01	2.8447E+01	**1.1031E+01**	2.3670E+01	3.0911E+01	6.2229E+01
F22	Avg	2.3023E+03	2.3009E+03	**2.3005E+03**	3.6183E+03	2.5885E+03	2.3113E+03	4.3946E+03	7.4959E+03
	Std	1.4419E+00	1.4496E+00	**1.0458E+00**	2.1175E+03	8.4171E+02	1.4072E+00	2.7579E+02	7.9940E+02
F23	Avg	**2.7108E+03**	2.7592E+03	2.7919E+03	2.8182E+03	2.7417E+03	2.7510E+03	3.0010E+03	3.2958E+03
	Std	**1.7329E+01**	4.7110E+01	3.9883E+01	3.4118E+01	2.1110E+01	2.1254E+01	2.9677E+01	1.7414E+02
F24	Avg	**2.8929E+03**	2.9113E+03	2.9894E+03	2.9692E+03	2.9349E+03	2.9181E+03	3.1703E+03	3.3784E+03
	Std	**1.4765E+01**	2.9258E+01	5.6920E+01	2.9582E+01	3.0301E+01	2.9895E+01	3.7059E+01	1.3738E+02
F25	Avg	2.9139E+03	2.9021E+03	2.8920E+03	2.9170E+03	**2.8874E+03**	2.9137E+03	3.4633E+03	2.9049E+03
	Std	1.9946E+01	1.2458E+01	1.4248E+01	1.8567E+01	**1.4327E+00**	1.6232E+01	9.1701E+01	2.3992E+01
F26	Avg	4.1390E+03	4.0697E+03	4.3732E+03	5.4154E+03	**3.1436E+03**	4.7840E+03	7.3022E+03	9.7591E+03
	Std	4.5902E+02	1.0536E+03	1.3171E+03	5.9093E+02	**2.2022E+02**	2.2751E+02	2.8998E+02	2.8417E+03
F27	Avg	3.2229E+03	3.2496E+03	3.3353E+03	3.2406E+03	**3.2209E+03**	3.2329E+03	3.4423E+03	3.3410E+03
	Std	1.2003E+01	3.7640E+01	8.1194E+01	1.1654E+01	**6.2286E+00**	2.7709E+01	3.3242E+01	8.5715E+01
F28	Avg	**3.1759E+03**	3.2021E+03	3.1997E+03	3.2826E+03	3.2199E+03	3.2542E+03	4.2280E+03	3.2145E+03
	Std	3.0759E+01	3.9838E+01	4.0679E+01	2.9209E+01	**7.6035E+00**	3.4578E+01	2.0221E+02	1.5515E+01
F29	Avg	**3.4186E+03**	3.8418E+03	3.9578E+03	4.0388E+03	3.5535E+03	3.7068E+03	4.9629E+03	5.0659E+03
	Std	**3.9533E+01**	2.6744E+02	2.2087E+02	1.6389E+02	6.6321E+01	2.1727E+02	1.8589E+02	6.8917E+02
F30	Avg	1.1635E+04	1.2475E+06	8.2973E+04	1.9464E+06	**7.0230E+03**	3.2514E+06	8.7774E+07	2.3854E+06
	Std	1.7698E+03	6.7506E+05	1.8779E+05	2.2887E+06	**5.7718E+02**	3.3870E+06	2.6798E+07	1.5848E+06

Table 7. P-values gained by Wilcoxon test.

Function	SDHGS	CLSGMFO	WLSSA	IGWO	OBLGWO	WDE	CBA	SCADE
F1	~	**5.859E-03**	2.324E-01	**1.953E-03**	**1.953E-03**	**9.766E-03**	**6.445E-02**	**1.953E-03**
F2	~	**5.859E-03**	**1.953E-03**	**1.953E-03**	**1.953E-03**	4.922E-01	**1.953E-03**	**1.953E-03**
F3	~	**2.734E-02**	**1.953E-03**	**1.953E-03**	**1.953E-03**	**1.953E-03**	**1.953E-03**	**1.953E-03**
F4	~	**4.883E-02**	2.754E-01	1.056E-01	**5.859E-03**	1.934E-01	1.309E-01	**1.953E-03**
F5	~	**1.953E-03**	**9.766E-03**	**1.9532E-02**	**1.953E-03**	**1.953E-03**	**1.953E-03**	**1.953E-03**
F6	~	**1.953E-03**	**1.953E-03**	**1.953E-03**	**1.953E-03**	**1.953E-03**	**1.953E-03**	**1.953E-03**
F7	~	**1.953E-03**	**9.766E-03**	**1.953E-03**	**3.906E-03**	**1.953E-03**	**1.953E-03**	**1.953E-03**
F8	~	**3.906E-03**	**1.953E-03**	**6.445E-02**	**1.953E-03**	**1.953E-03**	**1.953E-03**	**1.953E-03**
F9	~	**1.953E-03**	**1.953E-03**	**1.953E-03**	**1.953E-03**	**1.953E-03**	**1.953E-03**	**1.953E-03**
F10	~	**1.953E-03**	**5.859E-03**	**1.367E-02**	**1.953E-03**	7.695E-01	**1.953E-03**	**1.953E-03**
F11	~	**1.953E-03**	**3.906E-03**	**1.953E-03**	**1.953E-03**	**1.367E-02**	**1.953E-03**	**1.953E-03**
F12	~	7.695E-01	**1.953E-02**	**1.953E-03**	**1.953E-03**	**1.953E-03**	**1.953E-03**	**1.953E-03**
F13	~	1.602E-01	**1.953E-03**	**1.953E-03**	**1.953E-03**	**1.953E-03**	**1.953E-03**	**1.953E-03**
F14	~	**1.367E-02**	6.953E-01	**1.953E-03**	**9.766E-03**	**1.953E-03**	4.316E-01	**1.953E-03**
F15	~	**1.367E-02**	**1.953E-03**	**1.953E-03**	**1.953E-03**	**1.953E-03**	**1.953E-03**	**1.953E-03**
F16	~	**1.953E-03**	**1.953E-03**	**1.953E-03**	**1.953E-03**	1.309E-01	**1.953E-03**	**1.953E-03**
F17	~	**3.906E-03**	**1.367E-02**	3.223E-01	**1.953E-03**	4.316E-01	**1.953E-03**	**1.953E-03**
F18	~	5.566E-01	1.602E-01	**3.906E-03**	**3.906E-03**	**1.953E-03**	**2.734E-02**	**1.953E-03**
F19	~	4.922E-01	**1.953E-03**	**1.953E-03**	**1.953E-03**	**1.953E-03**	**1.953E-03**	**1.953E-03**
F20	~	**1.367E-02**	**1.367E-02**	**3.906E-03**	**1.953E-03**	1.602E-01	**1.953E-03**	**1.953E-03**
F21	~	**1.953E-03**	**2.734E-02**	**9.766E-03**	**1.953E-03**	**1.953E-03**	**1.953E-03**	**1.953E-03**
F22	~	**3.906E-03**	**6.445E-02**	**1.953E-03**	**1.953E-03**	**1.953E-03**	**1.953E-03**	**1.953E-03**
F23	~	**1.953E-03**	**3.906E-03**	**3.906E-03**	**1.953E-03**	**2.734E-02**	**1.953E-03**	**1.953E-03**
F24	~	**1.953E-03**	**4.883E-02**	8.398E-02	**1.953E-03**	**9.766E-03**	**1.953E-03**	**1.953E-03**
F25	~	**2.734E-02**	2.323E-01	9.219E-01	6.953E-01	**5.859E-03**	3.750E-01	**1.953E-03**
F26	~	7.695E-01	9.219E-01	**1.953E-03**	**1.953E-03**	**3.906E-03**	**3.906E-03**	**1.953E-03**

Continued on next page

Function	SDHGS	CLSGMFO	WLSSA	IGWO	OBLGWO	WDE	CBA	SCADE
F27	~	**1.953E-03**	**3.711E-02**	3.750E-01	**1.953E-02**	8.457E-01	**1.953E-03**	**1.953E-03**
F28	~	1.309E-01	**6.445E-02**	**1.953E-03**	**1.953E-03**	**1.953E-03**	**1.953E-03**	**1.953E-03**
F29	~	**1.953E-03**	**1.953E-03**	**1.953E-03**	**1.953E-03**	**1.953E-03**	**1.953E-03**	**1.953E-03**
F30	~	**5.859E-03**	**1.953E-03**	**1.953E-03**	**1.953E-03**	**1.953E-03**	**1.953E-03**	**1.953E-03**
+/-/=	~	19/5/6	20/2/8	23/1/6	29/0/1	14/9/7	24/2/4	30/0/0
ARV	**2.1667**	4.3	3.2	4.3	5.8333	2.2667	6.3333	7.6
Rank	**1**	4	3	4	6	2	7	8

Table 8. The findings of involved methods comparing average error rates.

Datasets	Metrics	bHGS	bDE	bSCA	bRUN	bMVO	bABC	bAOA	bINFO	bGBO	bSDHGS
error	std	0.0287	0.0294	0.0273	0.1438	**0.0130**	0.0312	0.0218	0.0257	0.0218	0.0316
	avg	0.0652	0.0669	0.1353	0.1352	0.0457	0.0980	0.0653	0.0604	0.0554	**0.0424**
Error rank		5	7	10	9	2	8	6	4	3	**1**
best fitness	std	2.62E-02	2.87E-02	2.82E-02	2.37E-02	**1.00E-02**	3.23E-02	2.01E-02	2.53E-02	1.91E-02	3.01E-02
	avg	6.68E-02	6.99E-02	1.47E-01	6.73E-02	**6.00E-02**	9.83E-02	8.64E-02	7.27E-02	6.34E-02	6.12E-02
Best fitness rank		4	6	10	5	**1**	9	8	7	3	2
Time	std	0.0743	**0.0527**	0.1248	0.0907	0.0723	0.1647	0.1035	0.1124	0.0942	0.1173
	avg	2.4428	**2.4338**	3.8122	5.2702	2.5230	3.0181	2.7810	2.7677	2.5541	8.7010
Time rank		2	**1**	8	9	3	7	6	5	4	10
Accuracy	std	2.87E-02	2.94E-02	2.73E-02	**1.44E-01**	1.30E-02	3.12E-02	2.18E-02	2.57E-02	2.18E-02	3.16E-02
	avg	9.35E-01	9.33E-01	8.65E-01	8.65E-01	9.54E-01	9.02E-01	9.35E-01	9.40E-01	9.45E-01	**9.58E-01**
Accuracy rank		5	7	9	9	2	8	5	4	3	**1**
Sensitivity	std	3.72E-02	3.18E-02	4.34E-02	**8.20E-02**	1.60E-02	4.64E-02	3.41E-02	3.63E-02	5.26E-02	4.03E-02
	avg	9.40E-01	9.49E-01	8.74E-01	8.95E-01	9.55E-01	9.13E-01	9.16E-01	9.43E-01	9.40E-01	**9.55E-01**
Sensitivity rank		5	3	10	9	1	8	7	4	5	**1**
Specificity	std	3.76E-02	5.11E-02	5.44E-02	**2.22E-01**	2.41E-02	5.70E-02	2.82E-02	4.70E-02	3.01E-02	3.13E-02
	avg	9.29E-01	9.14E-01	8.54E-01	8.29E-01	9.54E-01	8.89E-01	9.57E-01	9.36E-01	9.50E-01	**9.61E-01**
Specificity rank		6	7	9	10	3	8	2	5	4	**1**
Precision	std	3.03E-02	3.84E-02	4.08E-02	**1.49E-01**	1.99E-02	3.96E-02	2.47E-02	3.80E-02	2.48E-02	2.66E-02
	avg	9.41E-01	9.31E-01	8.79E-01	8.76E-01	9.61E-01	9.09E-01	9.63E-01	9.47E-01	9.59E-01	**9.67E-01**
Precision rank		6	7	9	10	3	8	2	5	4	**1**

The fitness convergence curves of F5, F6, F7, F9, F11, F21, F23, and F29 are shown in Figure 4. There are SDHGS and other comparison-improved algorithms. We can see from this figure that the red curve, which represents the result of SDHGS, converges to the minimum. The best fitness obtained by SDHGS proves that it has a strong search ability to find globally optimal solutions. The convergence curve is consistent with the value shown in Table 6. Though there are various methods, SDHGS also removes local optima and improves computational efficiency after introducing two strategies.

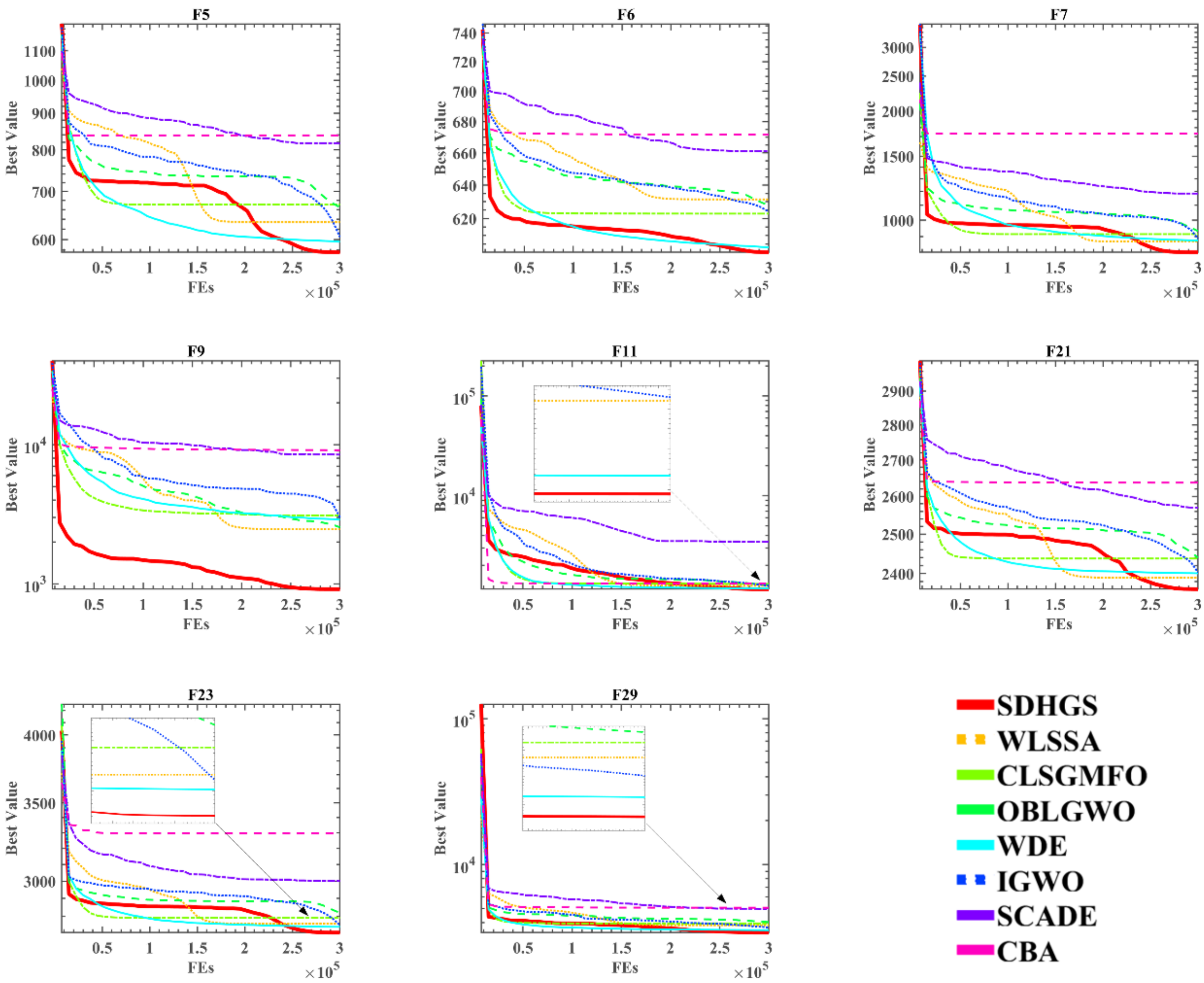

Figure 4. The fitness convergence curves of advanced methods on CEC2017 test functions.

5.4. Feature selection

In this experiment, the SDHGS method is transferred to a binary version and is compared with 9 traditional algorithms: bHGS, bDE, bSCA, bRUN, bMVO, bABC, bAOA, bINFO, and bGBO. These algorithms are run on the network subculture dataset collected from the valid questionnaires of full-time undergraduate and graduate students of Wenzhou University. Furthermore, the technique of leave-one-out cross-validation is esteemed as a means to fortify the outcomes obtained from the datasets. This approach extracts a single sample from the dataset to serve as the test set while the remaining samples form the training set. The number of validation iterations for each dataset aligns with the number of test datasets. A 10-fold cross-validation (CV) analysis is employed to ensure equitable and unbiased assessment, a practice firmly rooted in the machine learning literature. The KNN classifier completes the classification assignment. For KNN, the field size k is 1.

Maintaining fairness, the experiment is conducted with 20 search agents and replicated across 10 folds within the identical experimental framework. A maximum of 50 evaluations is stipulated for the exercise. Table 8 describes the statistical error, error rank, best fitness, best fitness rank, time, time rank, accuracy, accuracy rank, sensitivity, sensitivity rank, specificity, specificity rank, precision, and accuracy rank outcomes of the datasets that the involved algorithms simulated. Each metric's minimum value is bolded.

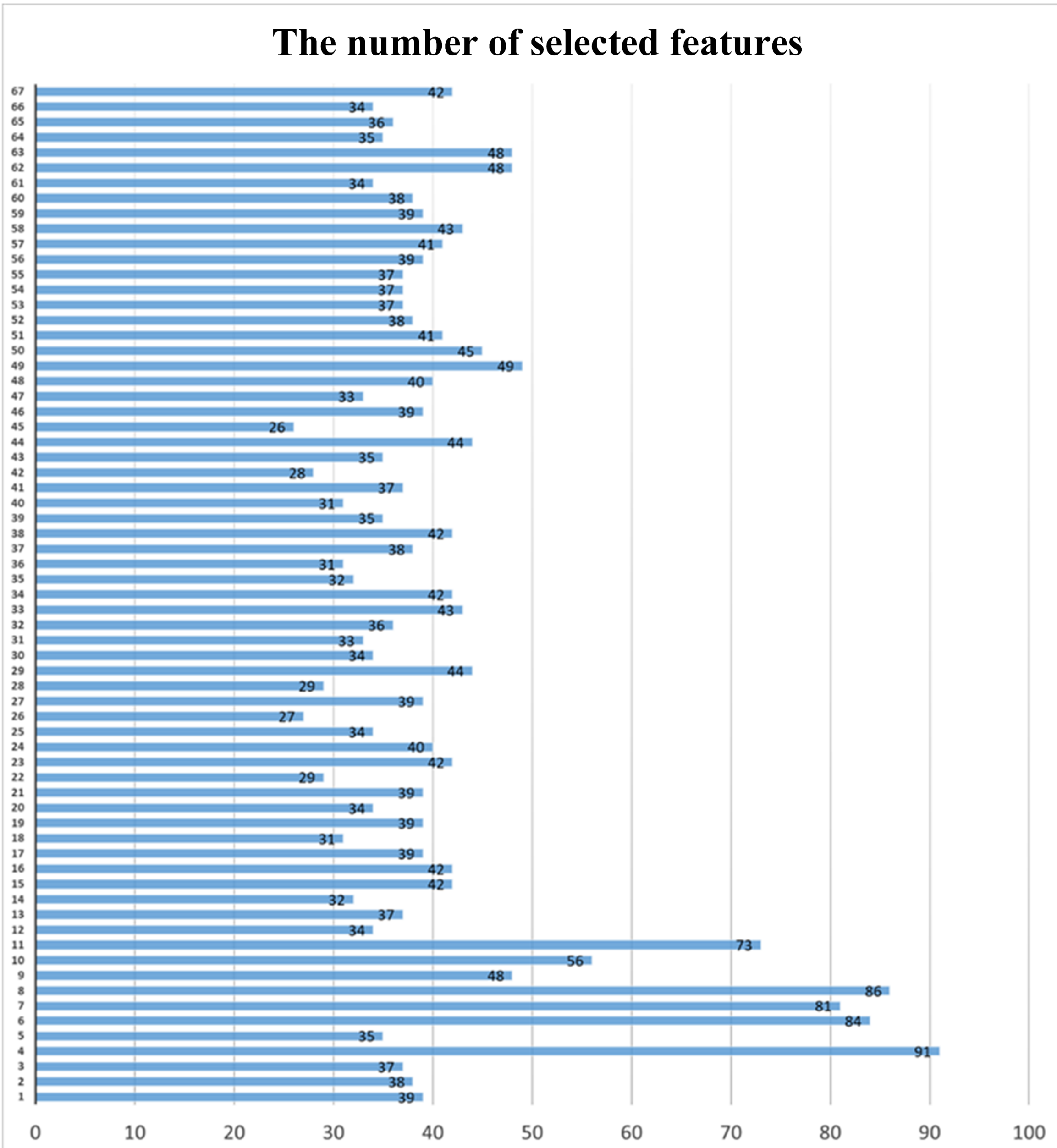

Figure 5. The number of selected features by SDHGS-KNN during 10 times 10-fold CV test.

It can be seen from Table 8 that the bSDHGS method ranks number one in terms of error, error rank, accuracy, accuracy rank, sensitivity, sensitivity rank, specificity, specificity rank, precision, precision rank, and ranks second in terms of best fitness and best fitness rank. Thus, the proposed bSDHGS method shows excellent performance in the dataset. However, the bSDHGS average time calculation performs poorly, highlighting the method's high level of complexity. Due to the increase in performance, it takes more time. The integration of the directional crossover mechanism and the adaptive Lévy diversity mechanism augments HGS's operational efficacy, albeit concurrently introducing an increment in its temporal expenditure. Finally, the number of selected metrics from the 10 times 10-fold CV test is shown in Figure 5. As is shown, the most selected specific features are C4, C8, C6, and C7.

Incorporating the directional crossover strategy and the adaptive Lévy diversity mechanism into SDHGS showcases their distinctive contributions and specialized functions. Then, during the optimization phase, the directed crossover mechanism converts from exploration to exploitation, increasing the likelihood of local exploitation. Consequently, refining the equilibrium between local and global search mechanisms can enhance the algorithm's efficacy in expediting the resolution of these mathematical challenges. However, the adaptive Lévy diversity strategy in SDHGS supports population diversity and aids the algorithm in enhancing global exploration patterns. As a corollary, SDHGS is equipped to avert entrapment within local optima while navigating optimization complexities. This is achieved by continually broadening the scope of global exploration across diverse regions within the solution space.

In this study, SDHGS outperforms and has more potential than the majority of comparison algorithms. While the algorithm demonstrates commendable performance when applied to network subculture questionnaires from both full-time undergraduate and graduate students at Wenzhou University, its applicability extends beyond this domain to encompass various challenges.

6. Conclusions and future works

The Hunger games search is a recently developed optimization technique that is likely to hit the local optimum. The combination of the adaptive Lévy diversity mechanism and the directional crossover mechanism have enhanced the performance of SDHGS. The suggested technique increases the speed of convergence and the capacity to exit the local optimum when solving a variety of functions, including unimodal, multimodal, hybrid, and composition functions. On IEEE CEC 2017, SDHGS is contrasted with a wide range of algorithms, including recently developed and classy algorithms, to demonstrate its superiority. SDHGS considerably beats all other comparison algorithms when analyzing the experimental result. Additionally, SDHGS is used to create a prediction model for network subculture to cultivate the value of college students. The SDHGS demonstrates notable ability not only in feature selection within youth subculture but also in development of the values of college students. Thus, the simulation tests are divided into two parts: (a) A benchmark function test; and (b) a discrete combinational optimization problem on the questionary dataset from students. According to experimental findings, SDHGS is a reliable and efficient approach for improving real-world datasets.

This research has several limitations. First, the CEC2017 functions test does not reveal the influence of the directional crossover mechanism with an adaptive Lévy diversity strategy on HGS. To show the SDHGS's performance, additional in-depth evaluations can be explored. Second, we use a one-objective method and should consider the number of features that are as important as classification performance. Third, the better the performance, the more computation time. Additionally, there is room for development and improvement of SDHGS. In forthcoming activities, the presented approach holds promise for addressing intricate, high-dimensional, and hyperparametric optimization challenges inherent in machine learning models. Furthermore, the integration of SDHGS with other algorithms bears the potential for constructing hybrid models that effectively navigate multi-objective problems.

In the regard, the SDHGS method is verified to perform better on high-dimensional problems from real discrete optimization problem of society and educational institutions. In addition, SDHGS can explore its further applicability in building more types of machine learning models for society and educational institutions, such as deep learning. In the future, the binary version of the SDHGS method can be used for other practical high-dimensional datasets and applied in more fields. Besides, this model takes the convolutional neural network as a binary classifier to select vital features accurately and rapidly. Therefore, deep learning along with the SDHGS method can be extended for classification and optimization.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

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Conflict of interest

The authors declare there are no conflicts of interest.

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