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Practical Exploration of Big Data Technology in Improving the Efficiency of English Education Resource Allocation and Utilization

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Abstract

In order to make full use of educational big data for English education resource allocation and utilization, this paper is based on the standard Bottle Sheath Optimization Algorithm, which generates a random number through the sine-cosine function to update the random positions of individual Bottle Sheaths to improve the randomness and population diversity of the leader search process, improve the Bottle Sheath position updating method, and enhance the algorithm's ability to perform global search. This paper develops a resource allocation model that can be employed for English education resource allocation. For the vast majority of single-peak and multi-peak functions, the success rate of SCSSA's solution is 100%, and the performance of SCSSA's search is significantly better than that of the comparison algorithms ($p < 0.05$), and all of its convergence curves have the fastest decline. After using the model for allocation, the student-teacher ratio of the five districts and counties was improved, with a cumulative decrease of 86.72% in the student-teacher ratio, and the gap in the student-teacher ratio between districts and counties was reduced. However, the model's optimization effect on the allocation of English books is limited, suggesting that further support of human and financial resources is needed in the allocation process.

Keywords: Bottled sea-sheath optimization algorithm; Sine-cosine algorithm; Resource allocation model; English education.

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1 Introduction

At present, big data technology has become an important driving force to promote changes in various fields. For higher vocational English education, how to utilize big data technology to build a new efficient teaching mode and cultivate high-quality English talents in line with the needs of the times has become an important topic for higher vocational English teachers to study.

As a matter of fact, big data technology has had a profound impact on educational resources. The Internet provides a convenient channel for the circulation of teaching resource data, provides the explosive growth of educational resources, which is unparalleled in human history, and provides the basis for carrying out personalized teaching [1-3]. The explosive growth of educational resources has increased opportunities for students to learn both actively and passively [4-5]. Efficient educational teaching activities and educational resources can be rapidly disseminated through the Internet to provide teaching services for offline users [6-7]. At the same time, based on the Internet platform, accompanied by various software terminals, the educated can easily access a large number of high-quality educational and teaching resources that are not limited by time and space, which greatly facilitates the tempo of the educated learning progress [8-12]. In addition, the application of big data technology in English teaching can promote the construction of a smart classroom and realize the comprehensive capture and analysis of students' learning behavior [13-14]. Through the in-depth mining of students' learning progress, learning preferences, mastery level and other data, teachers can create personalized learning paths for students, thus improving the relevance and learning efficiency of students' learning [15-17].

To enhance the efficiency of English education resource allocation and utilization, this paper proposes an optimized Bottle Sea Sheath optimization algorithm. A sinusoidal cosine perturbation factor is added to the position update of searching individuals to increase randomness and population diversity of the leader search process to solve the problem of reduced population diversity. The search mechanism is more receptive to the current position information when the Tarahasaki leader's position information is introduced. The fitness value of each location is calculated and compared with the fitness value of the target location, and the location with the smallest fitness value is selected as the optimal solution, and the educational resource allocation model is designed on this basis. Eight single-peak and multi-peak test functions are used to test the effectiveness and robustness of the SCSSA optimization search, and the results are then evaluated by the Wilcoxon statistical test to confirm the statistical significance of SCSSA performance. To validate the improvement effect of the warped sine cosine algorithm on the standard bottled sea squirt optimization algorithm, convergence analysis is performed on the improved algorithm. The allocation model is used to allocate English education resources in 13 districts and counties of a city to examine its practical effects and problems.

2 Technical support for the allocation and utilization of resources for English language education

2.1 Application of big data technology in the allocation of educational resources

Big data refers to a collection of data that cannot be captured, managed and processed within a certain timeframe with conventional software tools and is a massive, high-growth and diversified information asset that requires an updated processing model in order to have stronger decision-making, insight discovery and process optimization capabilities. Educational big data is a collection of a large amount of data generated in the field of education, and it is a collection of data that includes the entire educational process. Big Data in Education departs from the traditional approach of seeking unilateral

causality and concentrates on complex, multifaceted correlations between data. This shift in the mode of analysis is an indispensable change to promote the innovative development of education.

Rational allocation of educational resources refers to the ideal of equal treatment of educational resources for educational institutions and recipients in educational activities under the ideology of educational equity and the principle of educational equality, as well as the educational policies and legal systems that ensure their actual operation. The essence of rational distribution of educational resources is to pursue equal educational opportunities for all and to realize equal educational processes for all.

The education sector can benefit from big data technology to narrow regional differences in educational resources, educational opportunities, and educational quality, and to promote the balanced development of education in different regions. The education situation found by traditional education and teaching data is more generalized and insufficient to provide accurate guidance for decision-making on the layout of educational institutions and the adjustment of education funding. The education and teaching data collected statistically under the support of big data technology has integrity and connectivity and is able to analyze and discover process activities and results, so it reflects the education process in a more detailed and meticulous way. Combined with the information on the current status of education and teaching allocation and economic development in each region, a scientific allocation model is established to adjust the layout of educational institutions and the strategy for allocating education funds so as to realize the rational allocation of education resources.

2.2 Status of English education resource allocation and utilization

2.2.1 The problem of waste and idleness of teaching resources exists

In English teaching activities, the most common teaching resources used by most teachers are English textbooks. In addition to textbooks, many audio, video, wall charts, multimedia classrooms, and other resources need to be fully developed and utilized. Modernization of education has resulted in most schools introducing information technology, but if teachers do not develop the functions of information technology in the first place, advanced teaching resources will be wasted. In the English classroom, teachers should not limit themselves to teaching materials like blackboards and chalk. They need to combine a variety of teaching resources to effectively teach.

2.2.2 Inadequate concept of teachers' utilization of teaching resources

Traditional teaching concepts influence the majority of English teachers to pay too much attention to textbook teaching, and most of them use teacher's books to help them use teaching materials. Teachers also regard textbooks as the only English teaching resources, neglecting the development and utilization of special teaching resources within the school, not to mention taking the initiative to develop English teaching resources outside the school. English teachers view teaching as their primary responsibility and only focus on the development and utilization of teaching resources, neglecting the development of students' learning resources. The insufficient concept of development and allocation of teaching resources makes English teaching unable to keep up with the needs of the times and is not conducive to the cultivation of students' correct concept of English learning.

2.2.3 Teachers' lack of capacity to develop and distribute teaching resources

The quality of English teaching resources development and application is directly affected by teachers' ability to allocate and utilize teaching resources. Most English teachers lack a precise understanding

of English curriculum resources and tend to consider themselves the primary source of teaching activities when allocating and utilizing teaching resources. The role of teaching resources is ignored by teachers and they are unaware that rational allocation of teaching resources can help improve English classroom teaching. The lack of a correct method makes the teaching resources developed by many teachers have a single structure, which is not in line with students' learning needs.

3 Educational Resource Allocation Model Based on Improved Bottle Sea Sheath Algorithm

In 2017, Seyedali Mirjalili of Australia proposed the Standard Bottlenose Sea Sheath Optimization Algorithm (SSA), which mainly simulates the swarming behavior of bottlenose sea sheath populations when they are active and foraging in the ocean, and it can be used to solve various optimization problems [18]. In this paper, we try to construct an educational resource allocation model based on this algorithm in order to improve the allocation and utilization efficiency of English educational resources.

3.1 Standard Bottle Sea Sheath Optimization Algorithm

3.1.1 Population initialization

The search space is first set up as a $N \times D$ -dimensional Euclidean space, where N denotes the number of populations and D denotes the dimension of the space. In the search space, the position of each bottlenose sea squirt is denoted by $X_i = [X_{i1}, X_{i2}, \dots, X_{iD}]$, $i = 1, 2, 3, \dots, N$, the target position (i.e., food position) is defined as $F = [F_1, F_2, F_3, \dots, F_D]$, and the upper bound of the search range in each dimension is $Ub = [ub_1, ub_2, ub_3, \dots, ub_D]$ and the lower bound is $Lb = [lb_1, lb_2, lb_3, \dots, lb_D]$. The initial population position can be obtained by random acquisition according to Eq. (1):

$$X_{N \times D} = rand(N, D) \times (Ub - Lb) + Lb \quad (1)$$

In the population, the value of each dimension of a bottlenose sea squirt individual is defined as X_j^i ($i = 1, 2, 3, 4, \dots, N$), and j denotes the dimension ($j = 1, 2, 3, 4, \dots, D$) in which it is located.

3.1.2 Leader position update

In the Bottle Sea Sheath optimization algorithm, the population is first divided into two groups: leaders and followers.

The formula for updating the position of the leader is shown below:

$$X_j^i = \begin{cases} F_j + c_1 \left((ub_j - lb_j) c_2 + lb_d \right), & c_3 \geq 0.5 \\ F_j - c_1 \left((ub_j - lb_j) c_2 + lb_d \right), & c_3 < 0.5 \end{cases} \quad (2)$$

Where X_j^i denotes the value of the i nd bottlenose sea squirt individual in dimension j , F_j is the value of the food source in dimension j , ub_j and lb_j are the upper and lower bounds, respectively,

on dimension j , and c_1 , c_2 and c_3 are control parameters. c_2 and c_3 are random numbers between $[0,1]$. The coefficient c_1 in Eq. (2) is called the convergence factor, which is used to balance the speed of convergence of the algorithm during the iteration process, and is the most important parameter in the Bottle Sea Sheath Optimization Algorithm [19], as shown below:

$$c_1 = 2e^{-\left(\frac{4l}{L}\right)^2} \quad (3)$$

Where l is the number of current iterations and L is the maximum number of iterations. c_1 is a decreasing function of $2 \rightarrow 0$.

3.1.3 Follower location updates

During the movement and foraging process of the bottlenose sea squirt chain, the followers move in a chain-like sequence through the interactions between the individuals before and after them. It is known that the followers are updating their position based on the leader and are not moving randomly. According to Newton's law of motion, the velocity, acceleration, and moving position of the followers are formulated as follows:

$$X_d^n = \frac{1}{2}at^2 + v_0t \quad (4)$$

In the iteration process, t denotes the iteration time, v_0 denotes the initial velocity, acceleration $a = \frac{v_{final} - v_0}{t}$, and the velocity of the follower at the beginning of each iteration is 0. The position update situation of the follower is only related to the position of the previous bottlenose sea squirt individual, whose velocity can be denoted as $v_{final} = \frac{X_d^{n-1} - X_d^n}{t}$. Therefore, the formula for the follower's position update is shown below:

$$X_d^n = \frac{1}{2}(X_d^{n-1} + X_d^n) \quad (5)$$

Where $n \geq N/2$, X_d^n denote the value of the n rd bottlenose sea squirt individual in dimension d .

3.2 Bottle sea-sheath optimization algorithm with mixed sine-cosine leaders

3.2.1 Dynamic adjustment mechanism based on mixed sine-cosine laws

Since the leader is mainly affected by the location of the food source and the diversity of the population is reduced, this section is inspired by the Sine Cosine Algorithm (SCA), which introduces a sine cosine perturbation factor into the position update of the searching individuals to increase the randomness and population diversity during the search of the individual leader and to improve the convergence speed of the algorithm.

The Sine Cosine Algorithm (SCA) is a meta-heuristic algorithm proposed in 2016, whose search mechanism is inspired by the model of trigonometric functions in mathematics, and utilizes the

characteristics of the sine cosine function that regularly recurs in space to enhance the algorithm's use of the range of the search space, with a strong global search capability [20].

In this section, the sine-cosine mechanism in SCA is introduced into the leader's position update stage, and a random number is generated by the sine-cosine function to realize the random position update of bottlenose sea squirt individuals, and the improved bottlenose sea squirt leader position update formula is:

$$x_j^i = \begin{cases} F_j + c_1 \left((ub_j - lb_j) * \sin(\beta) + lb_j \right) & c_3 \geq 0.5 \\ F_j - c_1 \left((ub_j - lb_j) * \cos(\beta) + lb_j \right) & c_3 < 0.5 \end{cases} \quad (6)$$

In Eq. (6), ub_j and lb_j are the search range of the optimization problem, respectively, and β is the scaling factor of sine cosine, which controls the range of variation of the sine cosine function, and in this section, with reference to the basic sine cosine algorithm, it is taken as $\beta = 2\pi * rand$, where $rand \in (0,1)$.

3.2.2 Introducing a leader position influence factor

As can be seen from the standard Taruohai Sheath algorithm, during the whole iteration process of the algorithm, the update of the position of the leader at the front end of the chain structure is only related to the position of the food source under the current iteration number and has no relationship with other leaders or followers at the back end of the Taruohai Sheath chain, which prompts the majority of individual leaders to move mainly in the direction of the food source, ignoring the search space near the food source position, or even the entire search domain. The possibility of the existence of a more optimal solution leads to the algorithm's low population diversity, which makes it easy to fall into local traps, resulting in a weak performance of the global search capability and a large impact on the convergence accuracy. Therefore, this section proposes to introduce the leader's position information on top of the leader's position update, focusing on the food source location so that the position update of individual bottlenose sea squirts can be dynamically adjusted according to the global optimal information of the population and the current individual information of the bottlenose sea squirt, which further enhances the ability of bottlenose individuals to get rid of the local extremes, and the improved bottlenose sea squirt position update formula is shown in Eq. (7):

$$x_j^i(l+1) = \begin{cases} FoodPosition_j + c_1 * x_j^i(l) & c_3 \geq 0.5 \\ FoodPosition_j - c_1 * x_j^i(l) & c_3 < 0.5 \end{cases} \quad (7)$$

In Eq. (7), $x_j^i(l+1)$ is the position of individual Taruhelius in the $l+1$ nd generation, c_1 is calculated in the same way as Eq. (3), and c_3 is a random number in the interval of $(0,1)$. By introducing the position information of the leader, the search mechanism of the algorithm can refer more to the existing position information of the algorithm, reduce the possibility of the algorithm falling into local extremes, and enhance the ability of the algorithm to search globally.

3.3 Educational Resource Allocation Model Based on Improved Bottle Sea Sheath Algorithm

From the above, it can be seen that the improved Bottle Sea Sheath algorithm mainly calculates the fitness value of each position by updating the positions of the leader and the follower and compares it with the fitness value of the current target position to update the optimal scheme with the position of the smallest fitness value. In this paper, we design the allocation scheme according to this step.

The adaptability function is assessed by the size of the mean square deviation of the ratio of each district and county. The total value of the initial fitness $Y = 0$, the number of resources in each college before allocation is expressed as M_i , the number of resources allocated to each district and county is expressed as m_i , and the total number of students in each district and county is expressed as n_i , then the fitness can be expressed as equation (8):

$$Y = Y + \left(\frac{M_i + m_i}{n_i} - \frac{\sum M_i + \sum m_i}{\sum n_i} \right)^2 \quad (8)$$

Where: Y , M_i , m_i , $\frac{\sum M_i + \sum m_i}{\sum n_i}$ are known and determined, so equation (8) has and only one variable, the number of allocated resources m_i . Comparing the total value of fitness of each scheme, the scheme corresponding to the smaller total value of fitness is the optimal allocation scheme.

4 Simulation experiment and resource allocation effect analysis

4.1 Algorithm simulation experiment

4.1.1 Optimization effects

In order to verify the effectiveness and robustness of the SCSSA proposed in this paper in solving the optimization problem, simulation experiments are conducted on 8 typical standard test functions with SCSSA, PSO, and SCA, and 50 comparative experiments are conducted independently on the optimal value solution. The 8 complex functions contain test functions with different characteristics such as single-peak, multi-peak, and so forth, which are Sphere (single-peak), Schwefel 2.22 (single-peak), Schwefel 2.21 (single-peak), Quartic (single-peak), Rastrigin (multi-peak), Ackley (multi-peak), Griewank (multi-peak), and Penalized (multi-peak). A single-peak function is a function that is strictly maximal (or minimal) within defined upper and lower bounds and is often used to detect the speed of convergence of an algorithm. Functions that have multiple local or global optimal solutions are called multi-peaked functions and are frequently used to test algorithm exploration and development capabilities. The dimensions of the test function are set to 50 dimensions.

Table 1 shows the optimization results of each algorithm, in which the best value (Best), mean (Mean), standard deviation (Std), solution success rate (SR/%) and average time (Time/s) of each algorithm's optimization results after 50 independent experiments are recorded, where the solution success rate is the number of successful calculations divided by the number of solutions in this experiment.

The optimal and average values can reflect the convergence accuracy and optimization-seeking ability of the algorithm. For the four single-peak functions ($f_1 - f_4$), SCSSA reaches the highest 6.61E-40 in

terms of solving accuracy. Solving f_3 (Schwefel 2.21), SSA and SCA have poor solving ability, and there is a $1.00\text{E}+01$ -level error with the theoretical optimum. Whereas SCSSA has better optimization accuracy compared to SSA, PSO and SCA, and the solution accuracy does not vary much.

For the four multi-peak functions (f_5 - f_8), SCSSA obtains the theoretical optimum 0 in solving f_5 and f_7 (Rastrigin and Griewank) with accuracy, and SCSSA still has a good optimization finding accuracy compared to the other three algorithms. Therefore, SCSSA has better optimization results in solving the benchmark function for both single and multiple peaks.

The standard deviation and success rate can reflect the stability of the algorithm and its ability to exit the local optimum. As can be seen from Table 1, the standard deviation of SCSSA for 50 independent calculations is always smaller than the standard deviation of the other three algorithms. This indicates that SCSSA has good stability for the optimization of low-dimensional and high-dimensional benchmark functions, it is more capable of optimization on multi-peak functions, and its ability to jump out of the local optimum is better than the other algorithms. There are single and multiple peaks in the 8 benchmark functions, except for f_8 (Penalized), which is a multiple-peak benchmark function. SCSSA has essentially 100% success, while the standard SSA has 100% success f_1 but almost 0 success in the rest of the benchmark functions. The performance of SSA in terms of optimization searching and solving ability has a great deficiency, especially in solving f_3 , and f_5 the standard deviation and success rate are poor, which indicates that the standard SSA is weak in jumping out of the local optimum. The introduction of the sine-cosine optimization strategy in SCSSA has a great effect on the algorithm to jump out of the local search in the later stage.

In terms of average elapsed time. The average elapsed time of SCSSA relative to standard SSA is all larger, and the overall running time of PSO is much better than that of SCSSA, SSA, and SCA. The introduction of multiple operators in SCSSA on the basis of SSA makes the algorithm able to search for more solutions, while also increasing the running time of the algorithm. The average elapsed time increase for SCSSA is small and within the allowed range.

Table 1. Optimization results of each algorithm

Test function		SCSSA	SSA	PSO	SCA
f_1	Best	6.61E-40	4.47E-08	1.50E-01	6.32E-02
	Mean	1.22E-39	8.46E-08	2.34E-01	1.31E+02
	Std	1.75E-40	2.12E-08	4.08E-02	2.48E+02
	SR/%	100	100	0	0
	Time/s	1.0524	0.4828	0.3381	0.4714
f_2	Best	1.51E-20	4.53E-01	3.36E+00	4.21E-05
	Mean	1.89E-20	3.83E+00	6.20E+00	1.98E-02
	Std	2.01E-21	2.17E+00	2.12E+00	4.53E-02
	SR/%	100	0	0	22
	Time/s	1.1238	0.5345	0.3458	0.515
f_3	Best	7.43E-21	1.12E+01	3.71E+00	3.73E+01
	Mean	1.12E-20	1.75E+01	5.82E+00	5.84E+01
	Std	1.21E-21	3.17E+00	1.12E+00	1.05E+01
	SR/%	100	0	0	0
	Time/s	1.2211	0.5706	0.4012	0.5591
f_4	Best	3.24E-07	1.42E-01	2.48E-01	2.60E-02
	Mean	3.01E-05	2.82E-01	5.63E-01	5.64E-01
	Std	3.28E-05	9.07E-02	7.97E-01	8.65E-01
	SR/%	100	0	0	0
	Time/s	1.6175	0.8023	0.6142	0.7839
f_5	Best	0.00E+00	3.57E+01	4.65E+01	9.46E-03
	Mean	0.00E+00	9.59E+01	7.97E+01	9.25E+01
	Std	0.00E+00	2.75E+01	1.83E+01	7.95E+01
	SR/%	100	0	0	0
	Time/s	1.2847	0.6195	0.4169	0.5917
f_6	Best	8.84E-16	1.26E+00	4.12E+00	8.43E-02
	Mean	8.84E-16	3.13E+00	6.56E+00	1.75E+01
	Std	0.00E+00	8.12E-01	9.83E-01	6.73E+00
	SR/%	100	0	0	0
	Time/s	1.4212	0.6775	0.5086	0.6817
f_7	Best	0.00E+00	1.76E-04	3.63E+01	2.15E-01
	Mean	0.00E+00	8.91E-03	5.18E+01	2.03E+00
	Std	0.00E+00	9.12E-03	8.23E+00	3.92E+00
	SR/%	100	15	0	0
	Time/s	1.3324	0.6381	0.5047	0.6213
f_8	Best	1.40E-07	4.09E+00	2.15E+00	2.30E+00
	Mean	4.60E-04	9.78E+00	3.76E+00	2.62E+06
	Std	1.63E-03	3.25E+00	8.43E-01	7.46E+06
	SR/%	93	0	0	0
	Time/s	2.9717	1.4035	1.2078	1.3844

4.1.2 Statistical tests of optimization results

The mean and standard deviation based on 50 independent runs of the algorithm will not compare the results of each run, and for the evaluation of the performance of improved evolutionary algorithms, statistical tests should be performed. To determine whether the per-run results of SCSSA are statistically significantly different from the best results of the other algorithms, a Wilcoxon statistical test was performed at the 5% significance level. Table 2 shows the p-values calculated in the Wilcoxon rank-sum test for SCSSA and other algorithms for all benchmark functions. If the best algorithm is SCSSA, pairwise comparisons are made between SCSSA/SSA, SCSSA/PSO, SCSSA/SCA, etc. The symbols “+,” “?” and “≈” indicate that the performance of SCSSA is superior, inferior and equivalent to the comparison algorithms, respectively. P-value less than 0.05 can be considered as a strong validation of the rejection of the null hypothesis.

It can be seen that all p-values of SCSSA are less than 0.05, which indicates that its superiority is statistically significant, i.e., SCSSA has higher convergence accuracy than the rest of the algorithms.

Table 2. The p-value of Wilcoxon rank sum test

Basis function	SCSSA vs SSA		SCSSA vs PSO		SCSSA vs SCA	
	p-value	win	p-value	win	p-value	win
f_1	7.17E-19	+	7.17E-19	+	7.17E-19	+
f_2	7.17E-19	+	7.17E-19	+	7.17E-19	+
f_3	7.17E-19	+	7.17E-19	+	7.17E-19	+
f_4	7.17E-19	+	7.17E-19	+	7.17E-19	+
f_5	3.46E-20	+	3.46E-20	+	3.46E-20	+
f_6	3.46E-20	+	3.46E-20	+	3.46E-20	+
f_7	3.46E-20	+	3.46E-20	+	3.46E-20	+
f_8	7.17E-19	+	7.17E-19	+s	7.17E-19	+
+/?/≈	8/0/0	8/0/0	8/0/0	8/0/0	8/0/0	8/0/0

4.1.3 Convergence analysis

The average convergence curves of the four single-peak benchmark functions in 50 dimensions are shown in Figure 1. Due to the large differences in the convergence accuracy of different algorithms, in order to facilitate the observation of the convergence situation, this paper takes 10 as the bottom logarithm for the value of the optimization-seeking adaptation (vertical coordinate). From Fig. 1(a)-(d), it can be seen that the convergence curve of SCSSA decreases the fastest. In the pre-iteration period, SCSSA has a small time convergence curve that decreases very quickly, which indicates that the introduction of the position information of the leader of the bottlenose sea squirt so that the algorithm's search mechanism can refer to the algorithm's existing position information more, so that the algorithm's pre convergence speed is faster, and with the increase of the number of iterations continue to seek the optimal, did not appear to stop the situation. From Fig. 1(b) and (c), it can be seen that SCA, PSO and SSA have different degrees of stagnation in the late iteration, and the optimization accuracy is lower.

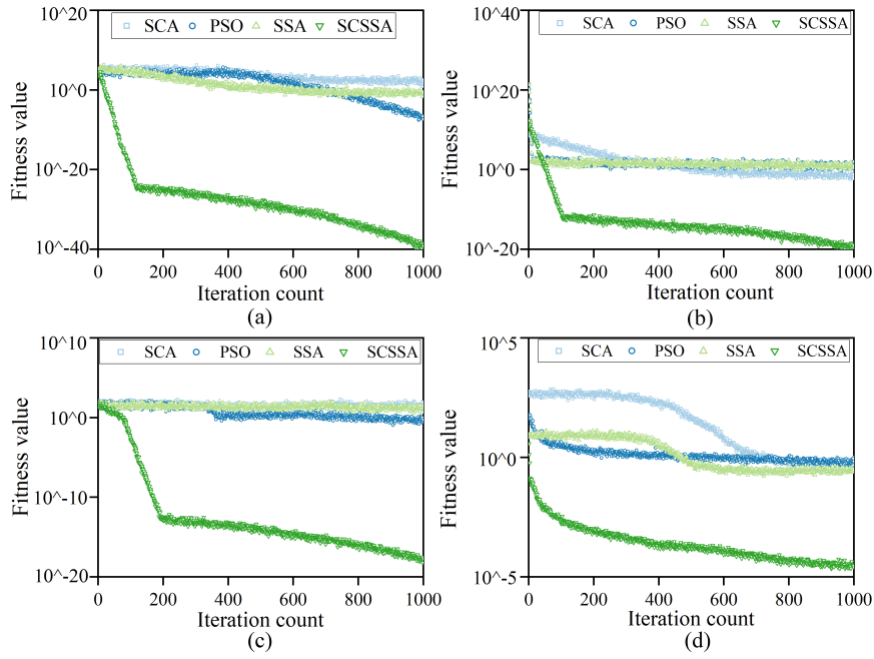


Figure 1. Average convergence curve of unimodal benchmark function

Figure 2(e)-(h) shows the average convergence curves of the multi-peak function. The convergence rate of the SCSSA on $f_5 - f_8$ the pre iteration of SCSSA is at a very fast rate, which further illustrates the role of introducing the positional information of the leader of the bottleneck sea squirt. In the late iteration, although the convergence speed of SCSSA is flatter than that of the early stage, it has been seeking optimization, while the other three algorithms basically fall into the local optimum in the late stage, with different degrees of stagnation. The final optimization accuracy of SCSSA still performs better than that of the other algorithms. Regardless of single-peak, multi-peak, low-dimensional, or high-dimensional benchmark functions, SCSSA has better convergence speed and optimization accuracy than other algorithms.

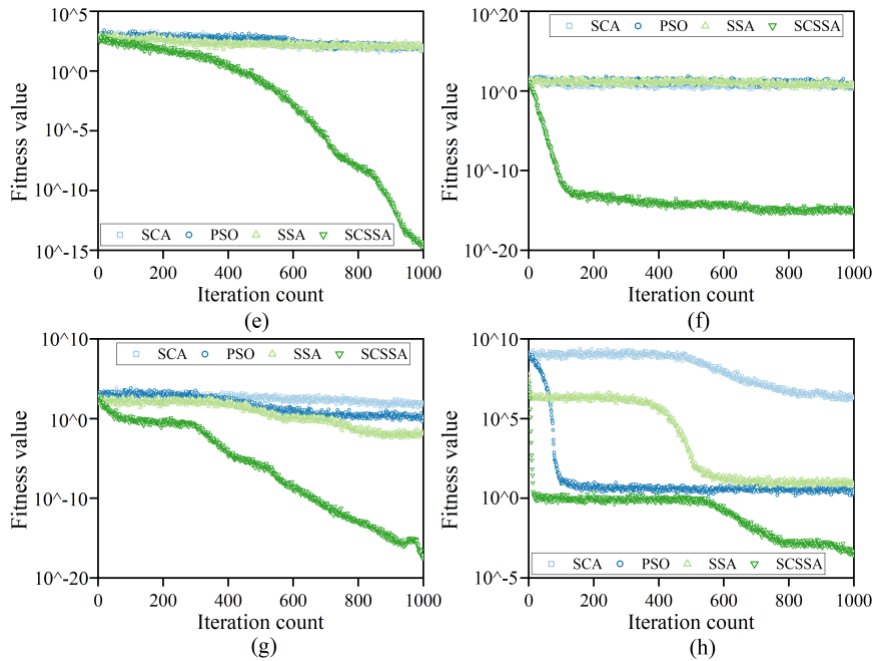


Figure 2. Average convergence curve of multimodal benchmark function

4.2 Examples of resource allocation for English language education

Taking all the districts and counties of a city as an example, we compare the changes in the results of English education resource allocation before and after using the model of this paper in order to verify the resource allocation effect of the model. The indicator employed is the student-teacher ratio and the number of English books per student. The smaller the student-teacher ratio is, the more effective each English teacher can be in counseling students, and the larger the value of English books per student is, the more English books each student can have. In order to improve the original uneven distribution of educational resources between districts and counties, the educational resource allocation model will appropriately reduce the student-teacher ratio and increase the average number of English books per student in the process of allocating resources according to the allocation model.

4.2.1 Distribution of student-teacher ratios

Table 3 is a table of changes in student-teacher ratios, which provides the results of the educational resource allocation model based on the SCSSA model for a total of 1070 English teachers. From Table 3, it can be seen that the SCSSA model has a good performance in allocating educational resources and five districts with high student-teacher ratios, i.e., districts 13, 9, 6, 5, and 4, have new teachers assigned, which reduces the ratio of student-teacher ratios of these five districts to a certain extent.

Table 3. Changes in student-teacher ratio

County number	Number of students	Number of teachers	Student-teacher ratio	Number of allocated teachers by SCSSA	Student-teacher ratio after SCSSA allocation
1	11776	1873	6.287	0	6.287
2	20182	2996	6.736	0	6.736
3	10929	1792	6.099	0	6.099
4	13290	1145	11.607	288	9.274
5	4180	458	9.127	95	7.559
6	12845	1155	11.121	273	8.995
7	12675	2519	5.032	0	5.032
8	17013	3581	4.751	0	4.751
9	12165	1054	11.542	279	9.126
10	17662	2129	8.296	0	8.296
11	3832	843	4.546	0	4.546
12	6542	1892	3.458	0	3.458
13	12988	1303	9.968	135	9.032

The trend of student-teacher ratio before and after the allocation of English teacher resources based on the SCSSA model can be seen in Figure 3. From the figure, it can be seen that before the allocation of student-teacher ratios in each district, the student-teacher ratio in District 4 was close to 12, while the student-teacher ratio in District 12 is only 3.458, with a large gap in the original allocation of teacher resources. After the allocation, the student-teacher ratios of districts 13, 9, 6, 5, and 4 all have a significant downward trend. Thus, it has been verified that the model can effectively improve the problem of unbalanced distribution of English teacher resources between districts and counties in terms of allocating teacher resources. Therefore, applying the model to allocate English teacher resources can effectively narrow the gap in student-teacher ratio between districts and counties,

improve the unbalanced distribution of English teacher resources to a certain extent, and promote the fairness and justice of education.

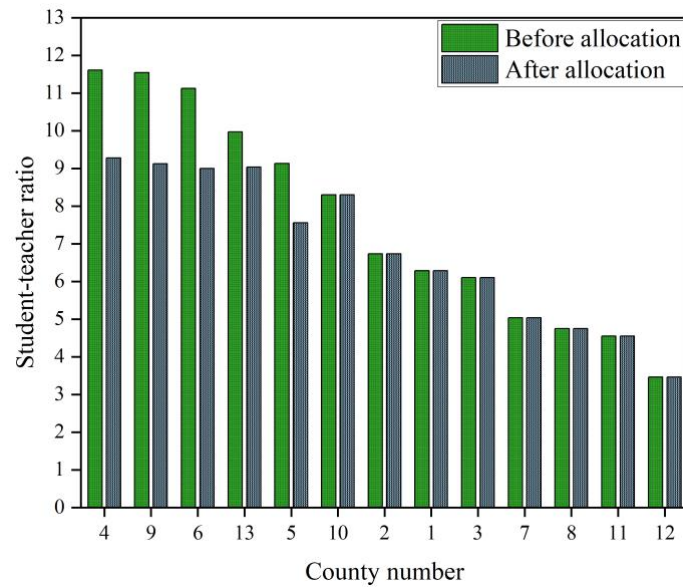


Figure 3. The student-teacher ratio of each area before and after allocation

4.2.2 Allocation of English-language books per pupil

The allocation of English books based on the SCSSA model is shown in Table 4. The table indicates that the model can allocate English book resources rationally and increase the number of English books per student in districts 10 and 13.

Table 4. English book allocation results

County number	Number of students	Number of English books	Number of English books per student	Number of allocated English books by SCSSA	Number of English books per student after SCSSA allocation
1	11776	10252	0.871	0	0.871
2	20182	19163	0.950	0	0.950
3	10929	8781	0.803	0	0.803
4	13290	90704	6.825	0	6.825
5	4180	10752	2.572	0	2.572
6	12845	17752	1.382	0	1.382
7	12675	10853	0.856	0	0.856
8	17013	9557	0.562	0	0.562
9	12165	12281	1.010	0	1.010
10	17662	4645	0.263	1381	0.341
11	3832	5946	1.552	0	1.552
12	6542	4414	0.675	0	0.675
13	12988	274	0.021	3872	0.319

The trend of the average number of English books per student before and after the allocation of the SCSSA model is depicted in Figure 4. The figure indicates that there is a significant difference in the

number of English books per pupil between districts and counties, and the unbalanced distribution of English book resources is more severe. After analyzing the data on the number of English books, the original number of English books in individual districts and counties is as many as 90,000,000 books or a few hundred books, so the total number of English books in the 13 districts and counties varies greatly. The amount of English books that will be allocated is only 5,253, which is a significant difference from the original total number of books. After the allocation of the education resource allocation model, English books are only allocated to two districts and counties with fewer English book resources, namely, District 10 and District 13, but the disparity in the number of English books per pupil among districts and counties has not been fundamentally improved.

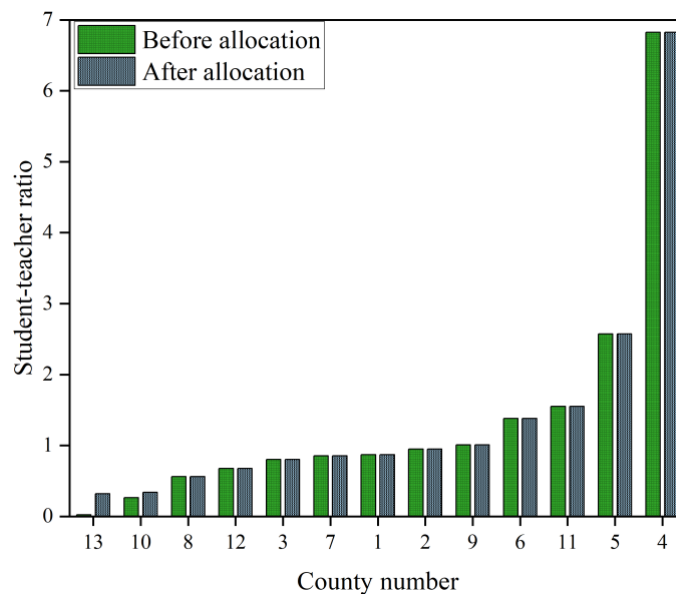


Figure 4. The number of English books before and after allocation of each area

It can be seen that the allocation of the number of English books through the education resource allocation model cannot fundamentally improve the gap between districts and counties in terms of the number of English books per pupil. If we want to improve the unbalanced distribution of educational resources due to the large base number, we need to spend a lot of financial and human resources to shorten the gap between districts and counties in terms of educational resources. Therefore, at the initial stage of allocating the number of English books, full consideration should be given to whether the allocation of English books is reasonable or not, rather than relying on the educational resource allocation model to allocate new English books to solve the problem of unbalanced resources of English books between districts and counties.

5 Conclusion

In this paper, we mainly start from the leader's position update, generate a random number through the sine-cosine function to realize the random position update for the bottleneck sea squirt individuals, and introduce the leader position information, which theoretically jumps out of the local optimum and improves the convergence accuracy. For the four single-peak functions, CSSA reaches up to $6.61\text{E-}40$ in solving accuracy, and the variation of solving accuracy is stable. In solving the Rastrigin and Griewank functions, SCSSA obtains the theoretical optimum of 0. Except for Penalized, the success rate of SCSSA's solution is 100%, and the average elapsed time increases slightly. It shows that the introduction of the sine-cosine optimization strategy in SCSSA has a great effect on the algorithm's ability to jump out of the local search in the later stage. The Wilcoxon statistical test

shows that the convergence accuracy of the SCSSA algorithm is significantly better than that of the other algorithms ($p < 0.05$). In the convergence analysis, for each benchmark function, the convergence curve of SCSSA decreases the fastest and continues to find the optimal value with the increase of the number of iterations. This paper's optimization strategy achieves the expected results, as indicated.

Using the educational resource allocation model based on the improved Taru Haixin algorithm to allocate some English educational resources in 13 districts and counties, it is found that the student-teacher ratio in 5 districts and counties has been effectively improved, with a cumulative decrease of 86.72% in the student-teacher ratio, and the gap in the student-teacher ratio between districts and counties has been narrowed. The allocation model allocated 5,253 books in the English book allocation, but only two districts and counties were allocated, indicating that the allocation of English books through the educational resource allocation model cannot fundamentally improve the gap between districts and counties in terms of the number of English books per pupil, and the allocation of resources in this area needs further financial support.

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