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Development of a Dynamic Allocation Model of English Teaching Resources Based on Combinatorial Mathematical Optimization Algorithm

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ABSTRACT

The study proposes a dynamic resource allocation model suitable for English language teaching, which combines learner characteristics, learning progress and resource availability to achieve real-time optimal allocation of resources through mathematical optimization algorithms. A multi-objective optimization model is constructed based on the key factors in resource allocation for English teaching. Facing the optimization objectives of maximizing learning efficiency and minimizing resource idleness, NSGA-II algorithm is used to construct a non-dominated solution to achieve global sorting, and combined with congestion calculation to complete global quality population screening. At the same time, the branch delimitation algorithm is utilized for local search of optimal solutions, and merged with the population of NSGA-II to generate the new generation of optimal populations. The optimization probability of the combined algorithm in this paper is 0.85, and the average convergence error is only 0.01081, which has excellent optimization performance. The resource allocation delay of this algorithm is around 0.1ms, and the allocation efficiency is more than 95%, and the comprehensive effectiveness is better than the comparison algorithm. The dynamic allocation model of resources in this paper improves the balance of resource allocation of English teaching and auxiliary room area, the number of teaching materials, the number of full-time teachers and teaching equipment. At the same time, it prompted the average English score of the experimental class to exceed 80, which was significantly higher than that of the control class.

Keywords: Dynamic Allocation Model, NSGA-II, Branch Delimitation Algorithm, English Teaching Resources

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1. Introduction

At present, with the rapid development of computer and mobile communication technology, mobile network teaching as an emerging learning mode is widely used in various learning fields [1]. The expansion of the construction of network teaching resources and the improvement of Internet access conditions have also facilitated the allocation of network teaching resources in the daily teaching process, and the allocation of network teaching resources has been adopted by the majority of teachers and students in the teaching experiments of many colleges and universities [2-4]. However, when carrying out large-scale and large-scale experimental resource allocation, due to the openness and complexity of the network, the allocation of resources will be subject to a variety of external factors of interference, which is prone to the problem of low signal-to-noise ratio, causing certain difficulties in the allocation of resources in the teaching process [5-8]. And network resources are always limited, the dynamic allocation of learning resources in many educational networks is a great challenge for mobile networks [9-10]. Since traditional resource allocation methods cannot fully utilize the learning resources and are prone to the disadvantage of resource bottlenecks, how to quickly carry out a balanced allocation of teaching resources in mobile networks has become a major task to be solved in the field of mobile networks [11-13]. The development of dynamic allocation model of English teaching resources can effectively calculate the fitness factor of node performance index and resource consumption index, and complete the dynamic allocation of English teaching resources in mobile networks based on the results of the calculation, which is a fundamental way to compensate for the above drawbacks, and it has become the focus of attention of many experts and scholars [14-16].

In the Internet era, the application scope of online teaching is becoming more and more extensive, and the optimization method of teaching resource allocation also has a lot of space for development. Zhang, H. constructed a modular English education resource dynamic allocation model containing resource integration, resource management and resource allocation, and by establishing the objective function and constraints of resource allocation, and solving it by using the firefly algorithm, it is able to output the allocation with valuable results [17]. Zhang, M. designed a decoupled learning resource management model based on adaptive scheduling algorithm based on the analysis of the multi-channel resource scheduling process for English online translation teaching, which can effectively meet the functional needs of teachers and students, and can improve the students' learning interest and learning ability [18]. Zhang, D. proposed a framework for multi-objective recommendation of English teaching resources, which can be used by embedding the fine-tuned GPT-3 model to accurately identify and classify English teaching resources, and using deep learning and particle swarm optimization algorithms to balance student satisfaction and educational value to achieve intelligent management of teaching resources [19]. Yuan, X. Applied QoS constraints to the English MOOC teaching resource allocation model, and used MMPs algorithms to carry out balanced allocation of resources, which effectively solved the traditional resource allocation task of the problems of long execution time and large bandwidth consumption were effectively solved [20]. Kuang, W. and Gao, X. improved the multi-objective optimization algorithm and constructed a business English teaching resource allocation model based on it, which realized a balanced allocation of teaching resources, not only improved the utilization efficiency of teaching resources, but also optimized the experience of teachers and students in the process of teaching [21]. Jingbo, J. developed the English intelligent learning system based on adaptive offloading decision-making algorithm ADCO and online spring sliding mode task scheduling algorithm SSLS, which can effectively solve the computational offloading problem and online scheduling problem in the dynamic environment, and improve the system's ability to allocate educational resources [22].

In this article, NSGA-II algorithm is multivariate combined with branch-and-bound algorithm to develop a dynamic allocation model of English teaching resources based on combinatorial mathematical optimization algorithm. NSGA-II algorithm implements global search for optimal solutions for dynamic allocation of resources, obtains the population of solutions for allocation of resources through selection, crossover, and mutation, then performs nondominated sorting and congestion computation on the population, and generates a Pareto frontiers solution set. The search space is refined using the branch-and-bound algorithm, and the quality of resource allocation solutions is optimized in the remaining space by removing redundant subspaces through pruning. In order to explore the effectiveness and practicality of the model, simulation experiments are designed to prove the model performance, and then combined with arithmetic examples to further verify the value of the model in the utilization of English teaching resources as well as teaching effectiveness.

2. Optimization of English Teaching Resource Allocation Based on Combinatorial Mathematical Algorithms

2.1. Global search multi-objective optimization algorithm

Optimization of problems is often multi-objective in nature, and there may be non-metricity and ambivalence between multiple objectives. Non-metricity is reflected in the fact that it is difficult to compare multiple objectives because the unit of measurement is not uniform, and contradiction is reflected in the fact that there are conflicting objectives, and the improvement of one objective may cause the regression of another objective. In the allocation of English teaching resources, there are problems such as shortage of teachers, lack of equipment and irrational curriculum, which lead to the unfair allocation of resources and the decline of learning effect. Therefore, this paper constructs a multi-objective optimization model, taking maximizing learning efficiency, minimizing the idle rate of resources and balancing the fairness of resource allocation as the optimization objectives.

2.1.1. Multi-objective optimization model. A multi-objective optimization problem (MOP) [23] can be described as given a decision vector $X=\left[x_1,x_2,\ldots,x_k\right]^T$ such that it optimizes an objective vector $f(X)$ consisting of N objectives as much as possible while satisfying m inequalities, and l equations:

$$g_i(X)\geq 0, i=1,2,3,\ldots,m \tag{1}$$

$$h_j(X)=0, j=1,2,3,\ldots,l \tag{2}$$

$$f(X)=\left[f_1(X),f_2(X),\ldots,f_N(X)\right]^T \tag{3}$$

There are usually different optimization requirements for all sub-objectives $f_1(X),f_2(X),\ldots,f_N(X)$, such as minimizing all sub-objectives, maximizing all sub-objectives and minimizing some sub-objectives and maximizing the rest:

$$Maxf_i(X)=-Min\left(-f_i(X)\right) \tag{4}$$

$$-g_i(X)\leq 0, i=1,2,3,\ldots,m \tag{5}$$

Since the requirement of maximizing the subgoal can be converted to a minimization requirement by Eq. (4), and similarly the soft constraint inequality (1) can be converted to Eq. (5), it can be converted uniformly for the objective vector $f(X)$ to find its minimum value:

$$M\inf(X)=\left[f_1(X),f_2(X),\ldots,f_N(X)\right]^T \tag{6}$$

In this paper, each sub-objective is set to denote the product of the number of violations of a particular constraint and the penalty value, respectively, so that the optimization direction of the multi-objective optimization problem involved in this paper is in the form of minimization shown in Eq. (6), if not otherwise specified.

2.1.2. Pareto optimal solution set. Pareto optimal solution [24], there is no single optimal solution, but there is a set of alternative alternative solutions. These alternative solutions are optimal in a generalized sense when all objectives are considered simultaneously, because no other solution in the search space is better than these alternative solutions in all objective dimensions. These alternative solutions are called "Pareto-optimal solution sets". To define the concept of Pareto optimality, take the minimization of two decision vectors $a, b \in X$ as an example. Assuming that a dominates b, then it must be satisfied:

$$\forall i \in \{1, 2, \ldots, N\} : f_i(a) \leq f_i(b) \tag{7}$$

$$\exists j \in \{1, 2, \ldots, N\} : f_j(a) < f_j(b) \tag{8}$$

All solutions in the Pareto optimal solution set are non-dominated, i.e., there are no remaining solutions that can outperform themselves in all objectives. The set of non-dominated solutions to a multi-objective optimization problem is called the Pareto optimal set. Each non-dominated solution can be mapped to a point in the objective function space, and the plane formed by all similar points in the objective function space is called the Pareto frontier.

2.1.3. NSGA-II algorithm. In this paper, we mainly utilize the most classical multi-objective optimization algorithm NSGA-II [25], which is a genetic algorithm based method to quickly solve multi-objective optimization problems, and also retains the criterion of "survival of the fittest" of evolutionary algorithms. In addition, it improves the NSGA algorithm by reducing the computational complexity. The flow of NSGA-II is shown in Fig. 1. NSGA-II can reuse the modules of population initialization and genetic operation in traditional genetic algorithms, but unlike traditional genetic algorithms that use the size of a single objective value (i.e., fitness value) as the ranking criterion among individuals, it uses the non-dominated set as the global ranking strategy and the congestion distance as the local ranking strategy for the multi-objective problem, while the congestion distance is used as the local ranking strategy. and crowding distance as the local sorting means, thus realizing the comparative sorting among different individuals. The specific realization method is as follows:

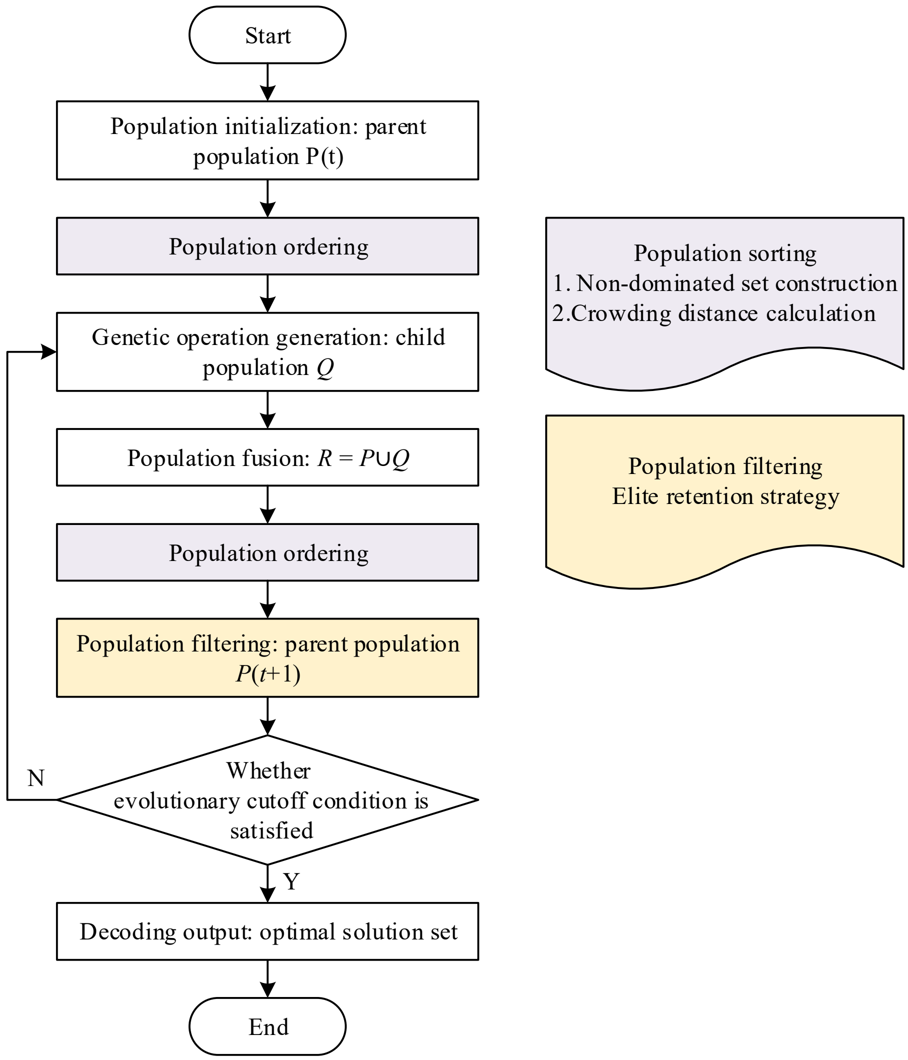

Fig. 1. Flowchart of NSGA-II

1) Non-domination solution construction. In the non-dominated sorting process, the level of non-domination of each individual in the population is recorded by means of a hierarchy. For any two individuals p and q in population P, compare all their objective values, and an individual p is said to dominate an individual q, denoted $p < q$, if all the objective values of p are not weaker than q and there exists at least one objective value better than q.Thus when no individual can be found in population P that can dominate p, individual p belongs to the first tier of the nondominated set, and so on, and if individual q is dominated only by individuals within the first i tiers of the nondominated set, then q belongs to the $(i+1)$ th tier of the nondominated set. Thus, all individuals in the population belong to some level of the nondominated set, and it is clear that individuals in the lower levels of the hierarchy are preferred to those in the higher levels.

2) Crowding degree and partial order relationship. NSGA-II proposes the concept of crowding distance to represent the positional relationship of individuals within the same hierarchy in the localized ordering process. The crowding distance of an individual can be found by calculating the sum of the distance difference between that individual and its neighboring individuals at a certain sub-target value after each ordering by that target value, and, of course, the crowding distance is specified to be infinite if the individual is at the endpoint position after a certain ordering.

Using $I[i]_{dis}$ to denote the crowding distance of individual i within the nondominated set I, and

$I[i]$, f_k to denote the target value of individual i on the kth subgoal f_k, the crowding distance is calculated as follows:

$$I\left[i\right]_{dis} = \begin{cases} \sum_{k=1}^{N} \frac{I[i+1]\cdot f_k - I[i-1]\cdot f_k}{f_k^{\max} - f_k^{\min}} & \exists(i+1)and(i-1) \\ \infty & else \end{cases} \tag{9}$$

where $f_k^{\max}$ and $f_k^{\min}$ denote the maximum and minimum values of the krd sub-goal, respectively.

3) Elite retention strategy. The parent population P_t generates the offspring population Q_t after crossover, mutation and other genetic operations, and the elite individuals in the population are inherited to the next generation as much as possible. The parent and offspring populations are combined to form a new population R_t, which is non-dominated, and the next generation parent population 8 is selected from R_t according to the original population size. P_{t+1} Because of the large number of non-dominated sets, individuals are added to P_{t+1} according to the predetermined inter-individual bias relationships in the order of the lowest to the highest level, and the crowdedness distances within the same level in the order of the highest to the lowest level, and the selection of the populations is thus completed.

Based on the above improvement of multi-objectification, the genetic algorithm can be completely used in multi-objective optimization problems. The complete NSGA-II algorithm is as follows:

1) Initialize populations P_t, $t=0$ in a random manner.

2) $Q_t = make-new-pop\left(P_t\right)//$ Generate offspring populations by genetic manipulation.

3) $R_t = P_t \cup Q_t$.

4) $F = fast-non-dominated-sort\left(R_t\right)//$ Non-dominated set construction.

5) $P_{t+1} = \varnothing$ and $i=1$.

6) Until $\left(\left|P_{t+1}\right| + \left|F_i\right| \le N\right)$.

7) Crowding-distance-assignment $\left(F_i\right)//$ Calculate the crowding of individuals within the ith layer of the nondominated set.

8) $P_{t+1} = P_{t+1} \cup F_i$.

9) $i=i+1$.

10) $Sort\left(F_i, \prec_n\right)//$ Establish a partial order relation for the layer i non-dominated set.

11) $P_{t+1} = P_{t+1} \cup F_i\left[1:\left(N-\left|P_{t+1}\right|\right)\right]$.

12) $t=t+1$.

2.2. Development of a dynamic allocation model for English teaching resources

English dynamic resource allocation firstly establishes the resource allocation items such as the area of English teaching and auxiliary rooms, the number of teaching materials, the number of teachers, teaching equipment, etc., and then calculates the model resource allocation through optimization.

The model has the minimum resource overhead when the input rates of all resource allocations are equal and equal to its processing capacity. Therefore, the number of resource allocation can be calculated through the optimization problem:

$$R_{true-in;i} = R_{true-in;h} = R_{true-proc;i} = R_{true-proc;h} (\forall i, h \in O_j) \tag{10}$$

$$\left|O_j\right| \geqslant \left\lceil \frac{R_{obs-in;src}}{R_{true-proc;i}} \right\rceil \tag{11}$$

When all operator resource allocations have the same input rate, the model can be considered as a linear model. The minimum number of operator resource allocations is obtained by dividing the input rate by the processing rate:

$$\left|O_j\right| = \left\lceil \frac{R_{obs-in;src}}{R_{true-proc;i}} \right\rceil \tag{12}$$

When the input is balanced English teaching resources data stream, the model can be considered as a linear model, and the resource allocation of the model using the above equation can achieve low latency, high throughput and least computational resources overhead.

Based on the above analysis, the true input rate, true output rate and average true processing rate of the resource dynamic allocation model can be calculated by the following equation:

$$\begin{aligned} R^{op}_{true-in;j} &= \sum_{m \in O_{j-1}} \sum_{i \in O_j} R^{inst\ m-i}_{true-in;j} \\ R^{op}_{true-out;j} &= \sum_{i \in O_j} \sum_{n \in O_{j+1}} R^{inst\ i-n}_{true-out;j} \\ \overline{R}^{op}_{true-proc;j} &= \frac{1}{\left|O_j\right|} \sum_{i \in O_j} R^{inst\ i}_{true-proc;j} \end{aligned} \tag{13}$$

$R^{op}_{true-in;j}, R^{op}_{true-out;j}, \overline{R}^{op}_{true-proc;j}$ denote the true input rate, true output rate, and average true processing rate of model j, respectively. $R^{inst\ m-i}_{true-in;j}, R^{inst\ i-n}_{true-out;j}, R^{inst\ i}_{true-proc;j}$ denotes the true input rate from resource m to resource i, the true output rate from resource i to resource n, and the true processing rate from resource i, respectively.

The dynamic allocation of resources utilizes Eq. (14) to obtain the number of resource allocations $\left|\hat{O}_j\right|$ for model j. $\hat{R}^{op}_{true-out;j}$ can be calculated from the measured true output rate, the true processing rate, and the estimated output rate of the operator, as shown in Eq. (15):

$$\left|\hat{O}_j\right| = \left\lceil \frac{R^{op}_{true-in;j}}{\overline{R}^{op}_{true-proc;j}} \right\rceil \tag{14}$$

$$\hat{R}^{op}_{true-out;j} = \frac{R^{op}_{true-out;j}}{R^{op}_{true-proc;j}} * \hat{R}^{op}_{true-out;j-1} \tag{15}$$

Based on the above process, this section realizes the development of a dynamic allocation model for English teaching resources.

2.3. Local Search Mathematical Planning Optimization Algorithm

2.3.1. Optimizing the allocation of teaching resources for precise solutions. Combinatorial optimization problems can be more precisely formulated as mixed integer programming problems (MIP) [26]. A mixed-integer programming problem usually consists of decision variables, constraints, and an objective function, which can also be called a mixed-integer linear programming problem if the objective function is only linear. In this paper, we give a standard type definition of a mixed integer programming problem as follows:

$$\begin{aligned} &\min c^T x \\ &s.t. Ax \geq b \\ &x \in \mathbb{R}^n \\ &x_j \in \mathbb{Z}, \forall j \in I \end{aligned} \tag{16}$$

where x is a vector of decision variables and c is a vector of coefficients of the objective function, the product of which defines the objective function. Matrix A and the vector of coefficients of the right end terms b define the constraint function of the problem. I is the set of subscripts of the integer variables (set I must not be the empty set, it is a subset of the set of natural numbers $\{1, 2, \ldots, n\}$), i.e., the variables whose subscripts belong to this set are required to be of integer type, and vice versa for continuous type.

The challenge of solving the MIP problem is that its feasible solution space is discrete and non-convex, which makes it difficult to analyze the nature of the feasible solution space and design optimization algorithms in a targeted manner. Therefore, instead of solving the MIP problem itself directly, it is common to:

1) First, the problem is transformed into a linear program (LP) by relaxing the integer constraints and solving the corresponding LP to obtain an approximate solution.

2) Obtain possible integer feasible solutions by, for example, rounding.

This process requires iterative execution of the above two steps to obtain the optimal feasible solution. The linear programming relaxation solution can provide a (lower) lower bound for the optimal MIP (for the minimization problem), and the optimal solution of the linear relaxation is usually better than its original form. Therefore, the original MIP problem is usually solved by increasing the lower bound and decreasing the upper bound to narrow the range estimate of the optimal solution. In this paper, the branch-and-bound algorithm is chosen to solve the MIP problem.

2.3.2. Branching and delimitation algorithm. The branch-and-bound method (B&B) [27] is a classical tree search method by partitioning, it searches for branches in the tree that are unlikely to contain an optimal solution by branching on the sub-loosening problem and using lower bounds on the loosening problem to prune the search tree, a more formal description of the branch-and-bound algorithm is given below.

The MIP problem, is redefined as $\mathrm{P} = (X, f)$, where X is the set of feasible solutions and the function $f: X \to \mathbb{R}$ is the objective function. The goal of the algorithm is to find a feasible solution x^* that minimizes the value of the objective function, i.e., $x^* \in \arg\min_{x \in X} f(x)$. In order to solve problem P, the branch-and-bound method constructs a search tree T based on a subset of X.

In addition, the method always stores the global optimal feasible solution for the current search process, denoted as $\hat{x} \in X$. At each iteration of the search, the method selects a new subset $S \subseteq X$ from the search list L (which holds the set of unexplored subsets in the search tree T) to be searched. If the optimal feasible solution $\hat{x}'$ in subset S corresponds to an objective value better than the current global optimal feasible solution $\hat{x}$ (i.e., $f(\hat{x}') < f(\hat{x})$), then the current optimal feasible solution is updated to $\hat{x}'$. If not, it can be proved that there is no feasible solution in subset S that is better than $\hat{x}$, and subset S is pruned. If it is possible that there are better feasible solutions in subset S, then more subset sets $S_1, S_2, \cdots, S_r$ are derived based on subset S, and these new subsets are inserted into search tree T. The above process is repeated until the search list L is empty, then the currently found globally optimal feasible solution is the optimal solution of the original MIP problem.

2.4. NSGA-II and B&B combined mathematical optimization process

In this section, the NSGA-II algorithm is effectively combined with the branch delimitation algorithm to develop a dynamic allocation model of English teaching resources based on the combinatorial mathematical optimization algorithm to achieve more accurate resource allocation. The dynamic resource allocation optimization process is as follows:

1) Initialization. Use NSGA-II to generate the initial population and randomly generate a set of solutions as the initial solution set. Non-dominated sorting and congestion calculation are performed on the population to ensure the diversity and convergence of the population.

2) Global search (NSGA-II). Generate a new generation of populations through selection, crossover, and mutation operations, perform a non-dominated ordering of the populations to obtain the Pareto frontier solution set, and compute the fitness value for each solution pair.

3) Localized search (branch-and-bound algorithm). Select some of the solutions from the Pareto frontier solution set generated by NSGA-II as the initial solutions for the branch-and-bound algorithm, and perform branching operations on the local region where each solution is located to divide the search space into smaller subspaces. In each subspace, the upper and lower bounds of the objective function are computed using the bounding strategy. Through the pruning strategy, the subspaces that do not satisfy the conditions are discarded to reduce the amount of computation. And further search in the remaining subspace to optimize the quality of the solution.

4) Update the population. The optimized solution of the branch-and-bound algorithm is merged with the population of NSGA-II, and the non-dominated sort and congestion calculation are performed on the merged population to generate a new generation of population.

5) Iteration and termination. Repeat 2) to 4) until the termination condition is satisfied and output the final Pareto optimal solution set.

3. Example analysis of the dynamic allocation model for English language teaching resources

3.1. Evaluation of optimization performance of combinatorial mathematical optimization algorithms

In order to better reflect the incremental nature of the combined algorithm's in performing English teaching resource allocation, the algorithm in this paper is compared with NSGA-II, branch delimitation, unsupervised deep learning (UDL), and wireless energy transfer (WET). The experimental parameters are as follows, the population size is 100, the learning factor is 1, the maximum value of inertia weight is taken as 0.8, the minimum value is taken as 0.3, and the number of iterations is 200.

The algorithm of this paper and the above comparison algorithm are run 50 times, and the average convergence results of the objective function values of different algorithms are shown in Figure 2. Table 1 shows the results of the comparison of the objective function value of the algorithm running 50 times. Combined with the data in the chart, it can be found that the combined algorithm in this paper performs better in terms of the probability of finding the optimal, the average objective function value, the worst objective function value, the optimal function value, and the average number of times of convergence after 50 runs compared with the NSGA-II, the branch delimitation, the unsupervised deep learning, and the wireless energy transmission. The unsupervised deep learning algorithm also has a higher probability of finding an optimum (0.71), but it is still slightly worse than the algorithm in this paper. Besides, the probability of finding an optimal solution of NSGA-II and branch-and-bound algorithm are 0.36 and 0.43 respectively, which are much lower than the other algorithms, and there are many times of falling into the local optimal solution. In contrast, the optimization probability of the combined algorithm in this paper is as high as 0.85, which is much better than the other four algorithms. And the algorithm in this paper has the highest average objective function value (0.567) and the lowest average number of convergence (34.67 rounds).

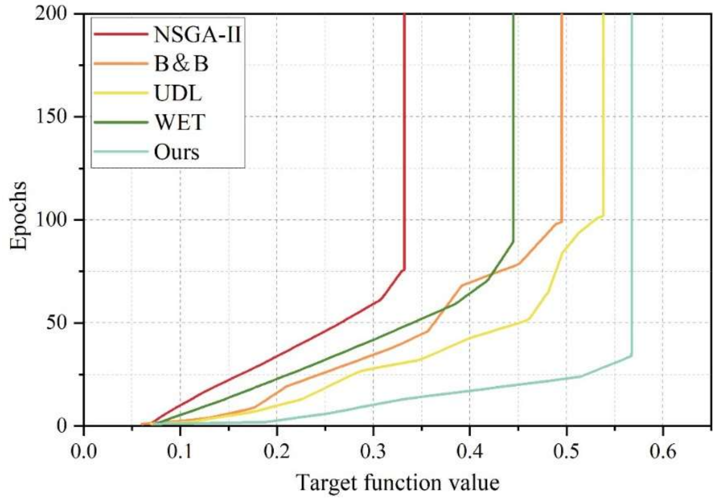

Fig. 2. The average convergence of the target function of the different algorithm

Table 1. The algorithm runs 50 comparisons

Algorithm	NSGA-II	B&B	UDL	WET	Ours
Optimal target function	0.371	0.523	0.552	0.463	0.581
Worst target function	0.309	0.481	0.514	0.421	0.543
Average target function value	0.332	0.495	0.538	0.445	0.567
Average convergence	77.25	100.56	108.19	90.43	34.67
Optimization probability	0.36	0.43	0.71	0.65	0.84

In order to better reflect the reliability of the algorithm, the convergence error of the above algorithms after running 50 times is calculated, and the results of the convergence error comparison after running 50 times are obtained as shown in Figure 3. According to the data in the figure, it can be seen that the average standard deviation and the minimum standard deviation of the combination algorithm are 0.01081 and 0.0058, respectively, and the results are smaller compared to the comparison algorithm, which means that it produces a relatively stable result in the optimization process, with less variability. The comparison algorithm standard deviation variation ranges from 0.031 to 0.112, which is more volatile and shows poorer stability in the optimization search process.

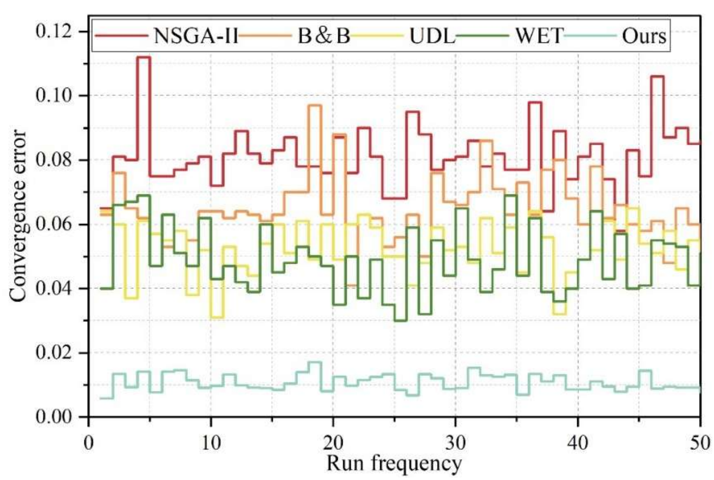

Fig. 3. The comparison of the error of convergence error of 50 times

3.2. Analysis of the timeliness and effectiveness of resource allocation

In order to prove the effectiveness of the proposed English teaching resource allocation model based on combinatorial mathematical optimization algorithm, an experiment is needed. The experimental data are taken from an English teaching resources allocation information website of a university, and the English teaching resources allocation experimental platform is built under the Matlab software environment.

1) Comparison of transmission efficiency and throughput. NSGA-II, branch delimitation, unsupervised deep learning and wireless energy transmission-based allocation methods are also chosen as comparisons for English teaching resources allocation simulation experiments to compare the transmission efficiency and throughput of different algorithms for resource allocation.

The comparison results of resource allocation transmission efficiency as well as network throughput of different algorithms are shown in Fig. 4, and (a) and (b) are the results of transmission efficiency and network throughput changes, respectively. From the analysis of the data in the figure, it can be concluded that the transmission efficiency and throughput of English teaching resource allocation using the combined mathematical optimization algorithm of this paper are better than the comparative algorithms such as NSGA-II. The transmission efficiency of this paper's combined algorithm continues to stabilize above 85% with the increase in the number of users, and the comparison algorithm (UDL) achieves the highest transmission efficiency of 58.27%. In terms of network throughput, this paper's algorithm improves 60.76% to 209.2% over the comparison algorithm. This is mainly due to the fact that the combined algorithm in this paper reduces conflicts and wastage through optimal allocation of resources and improves resource utilization, which in turn improves transmission efficiency and network throughput.

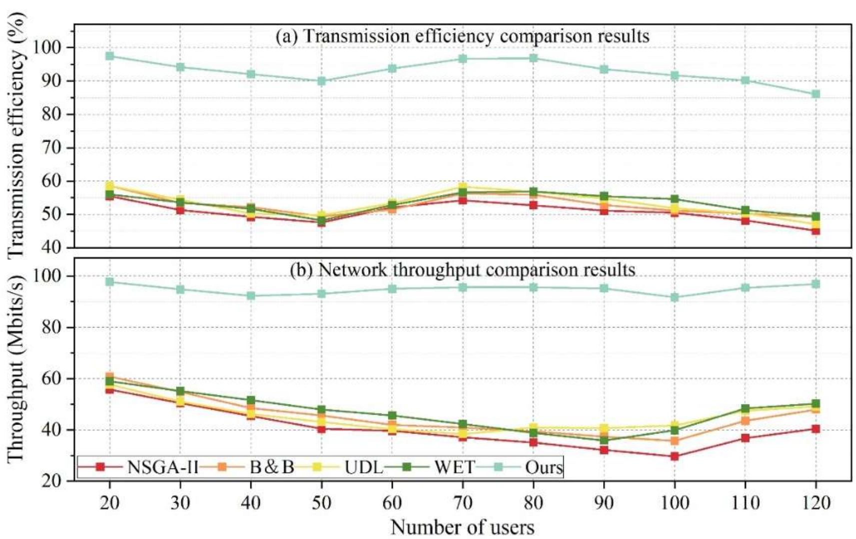

Fig. 4. Resource allocation transmission efficiency and throughput contrast

2) Comprehensive effectiveness comparison. The combined algorithm of this paper and the comparison algorithm are respectively used to carry out the comprehensive effectiveness comparison experiment of English teaching resources allocation, and the evaluation indexes are selected as resource allocation delay and resource utilization. The comprehensive effective comparison results of different algorithms are shown in Figure 5, (a) and (b) are the results of resource allocation delay and allocation efficiency comparison respectively. As can be seen from the figure, the comprehensive effectiveness of English teaching resource allocation using the combined algorithm of this paper is

better than the comparison algorithm. The resource allocation delay of this paper's algorithm is around 0.1ms, while the comparison algorithm has exceeded 1ms, or even 1.5ms.At the same time, this paper's algorithm exceeds 95% in allocation efficiency, while the allocation efficiency of the comparison algorithm is only 30%~70%. Analyzing the reason may be because, when using this paper's algorithm for English teaching resources allocation, the transmission rate on the allocation resource block is dynamically adjusted, and the English teaching resources allocation scheduling problem is modeled as a linear optimization problem, so as to guarantee the comprehensive effectiveness of this paper's algorithm for English teaching resources allocation.

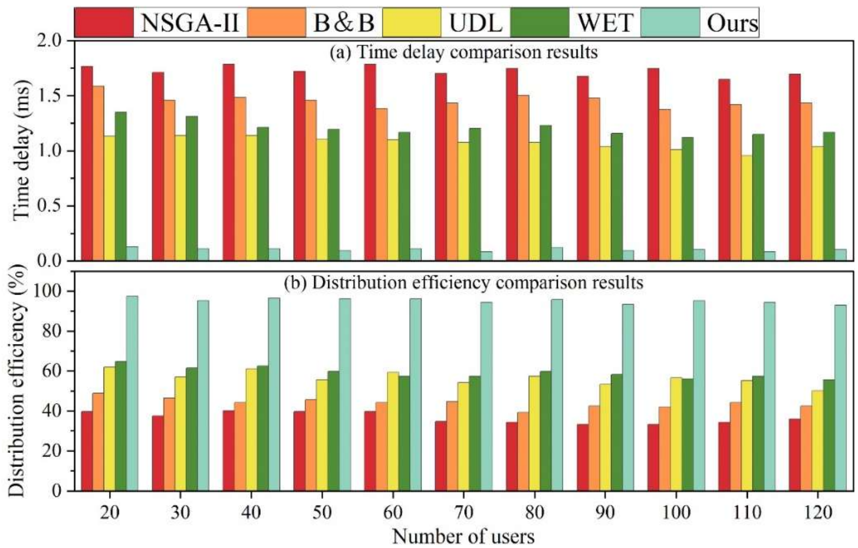

Fig. 5. The comprehensive and effective comparison results of different algorithms

3.3. *Comparison of Resource Allocation Levels and Equity*

In this section, we focus on the English teaching resource allocation of colleges and universities in a district and county, and understand the historical data of English teaching resource allocation in this district and county by collecting relevant policies, reports and literature. Ten colleges and universities are sampled as the objects of this paper's example study, which are noted as schools 1-10 in order, and the algorithmic function of this paper is implemented with the help of the teaching resource allocation optimization system.

The study starts from April 1, 2024, and ends on July 31, 2024, to compare the level of English teaching resource allocation in each school before and after the application of this paper's English teaching resource dynamic allocation model system, as well as the fairness of resource allocation.

This paper adopts the Gini coefficient as the evaluation index of resource allocation fairness, which is often used to measure the inequality of resource allocation among different schools. The Gini coefficient takes a value between 0 and 1, with O indicating complete equality and 1 indicating complete inequality, and the formula is as follows:

$$G=\frac{\sum_{i=1}^{n}(x_i y_{i+1}-x_{i+1}y_i)}{\sum_{i=1}^{n}x_i} \tag{17}$$

where n is the number of individuals, x_i and y_i are the cumulative proportion of resources and population for the i th individual, respectively.

Figure 6 depicts the changes in the level of resource allocation and Gini coefficient of English teaching in ten universities before and after applying the model of this paper. From the figure, it can be concluded that before the application, the level of resource allocation among colleges and universities is low, especially in school 2. After the application, the level of resource allocation among colleges and universities has rebounded, school 2 has increased from 10.02 to 14.03, and school 5 has increased from 15.30 to 18.49. The allocation of resources for English language teaching among colleges and universities tends to be more balanced. In addition, after applying the model of this paper, the Gini coefficient of all colleges and universities is reduced, among which the Gini coefficient of school 9 is reduced from 0.461 to 0.25, the highest rate of reduction. In summary, it shows that the universities can find the optimal English teaching resource allocation scheme through the model of this paper, identify and correct the unfair phenomenon, and promote the fairness of resource allocation.

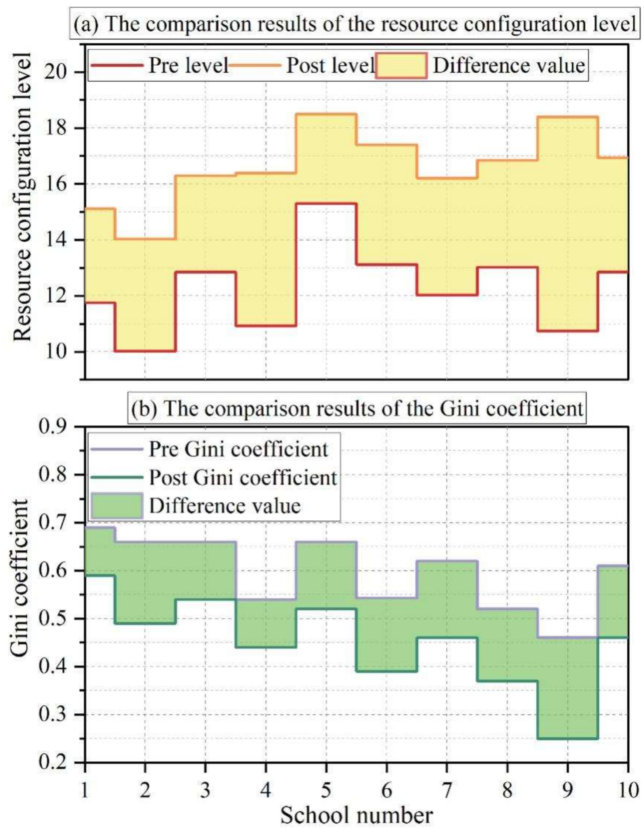

Fig. 6. The allocation of teaching resources and the change of Gini coefficient

Box plots visualize the discrete distribution of data. The standard of measurement is that the higher the box plot is, the better the per capita value of the resources allocated to each university through the optimization of the allocation of educational resources. The study investigates the per capita indicators related to English teaching resources, including: the area of English teaching and supporting rooms, the number of teaching materials, the number of specialized teachers and the number of teaching equipment.

The results of comparison before and after the allocation of per-student indicators in colleges and universities are shown in Figure 7. Figure (a) shows the comparison results of English teaching and supporting room area, from which it can be observed that there is a more obvious difference before and after the optimization, the average level of the per capita teaching and supporting room area in each college before allocation is about 10.0, and the average level of the per capita teaching and supporting room area in each college after the configuration is about 14.1. Figure (b) shows the comparison results of the per capita number of teaching materials, and it can be observed that the average level of the per capita number of teaching materials in each college before allocation is about 20, and the average level of the per capita number of teaching materials in each college after allocation is about 28. Figure (b) demonstrates the comparison results of the per capita number of teaching materials. The average of the number of student-percentage instructional materials in each college before allocation is about 20, and the average of the number of student-percentage instructional materials in each college after allocation is about 28. Figure (c) shows the results of the comparison of the number of student-percentage full-time teachers, and the average of the number of student-percentage full-time teachers in each college before allocation is about 0.06, and the average of the number of student-percentage full-time teachers in each district after allocation is about 0.085. figure (d) shows the results of the comparison of the number of student-percentage instructional equipment, and the average of the number of student-percentage instructional equipment in each colleges and universities, the average of the number of teaching equipment per student is about 0.31, and the average of the number of computers per student in all districts and counties after the allocation is about 0.50. And before the allocation optimization, the evaluation indexes of colleges and universities have more outliers, which indicates that the indexes of colleges and universities fluctuate a lot before the allocation. The outliers in the colleges and universities are eliminated after allocation, which makes the distribution of English teaching resources in the colleges and universities smoother.

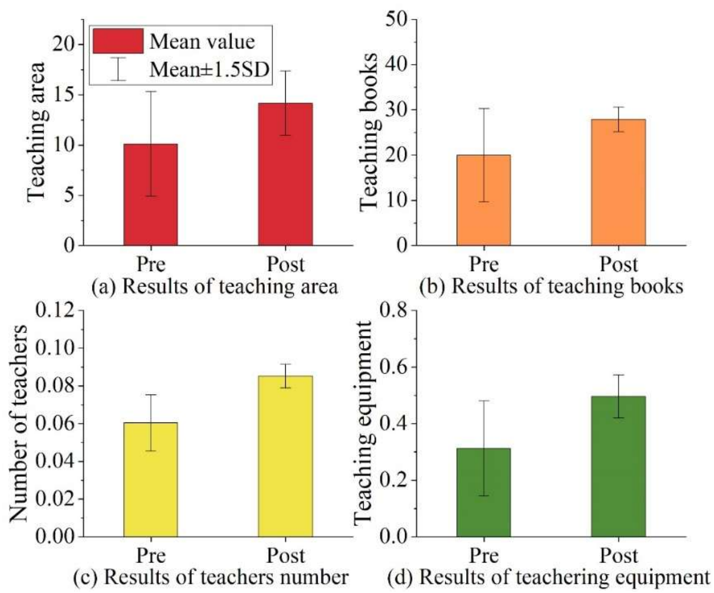

Fig. 7. The results of the comparison of the index of the university

3.4. Assessment of Learning Effectiveness of Model Application Examples

In this section, one of the above mentioned colleges is taken to evaluate the English learning effect of its students. Two classes (30 students each) of English majors in the class of 2024 of the university are selected, and both classes are freshmen with no significant differences in terms of college entrance examination scores, age and gender. One class served as a control (CK) with traditional English teaching, while the other class was an experimental group (T) in a teaching environment optimized using the model in this paper. The teaching experiment was conducted to maintain 3 months, and the English scores of the students in both classes were tested before and after the experiment to compare and analyze the effects of applying the model of this paper on the students' English learning effects.

Figure 8 shows the results of the English achievement test of the students in the two classes before and after the experiment. As can be seen from the figure, before the experiment, the average English score of the control group was 70.70, and the experimental group was about 70.73. The significance test index $P=0.874>0.05$ indicates that there is no significant difference between the English scores of the two classes before the experiment. After the experiment, the excellent rate (the percentage of students scoring 90-100 points) of the students in the control group was 0%, while the excellent rate of the students in the experimental group was 10%, which was significantly higher than that of the experimental group group. The good rate (the proportion of students scoring 80-90 points) of students in the control group was 16.67%, while the good rate of students in the experimental group amounted to 63.33%. And the average English scores of the students in the two classes were 73.77 and 82.23 respectively, P=0.021<0.05, showing significant differences with statistical significance. The above results show that the environment optimized by the dynamic allocation model of teaching resources is more suitable for students' learning and has obvious effect on improving students' learning effect.

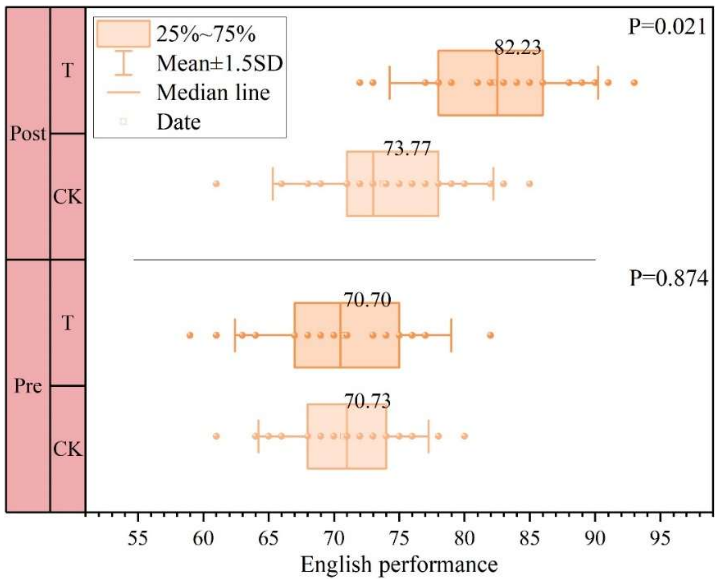

Fig. 8. Results of test results before and after the experiment

4. Conclusion

In this paper, NSGA-II algorithm is combined with branch delimitation algorithm to efficiently find the optimal solution for resource allocation by combining mathematical optimization algorithms for the problem of dynamic allocation of English teaching resources. The NSGA-II algorithm is used to generate the initial population, and then the Pareto solution set is obtained by non-dominated sorting to complete the global search for the optimal solution. On this basis, the branch delimitation algorithm is applied to divide the space where the above solution set is located into multiple subspaces for further searching to improve the accuracy of the solution. The feasibility of combinatorial mathematical optimization algorithm in English education resource allocation is examined through simulation experiments and application examples.

1) Research Conclusion. The combined algorithm in this paper has a better optimization performance with an optimization probability of 0.85, an average objective function value of 0.567, and an average convergence convergence number of 34.67 rounds. Its performance in transmission efficiency, network throughput, resource allocation delay and resource allocation efficiency is better than the comparison algorithm. Applying the dynamic allocation model of English teaching resources in this paper, the resource allocation levels of School 2 and School 5 are improved by 4.01 and 3.19 respectively, which also has an optimizing effect on the fairness of resource allocation. In terms of learning effect, the resource dynamic allocation model significantly improves the average English score of the experimental class by 8.46 points compared with the control class.

2) Innovation and Prospect. This study proposes a dynamic resource allocation model based on combinatorial mathematical optimization algorithm, and the branch delimitation algorithm can be

further optimized on the basis of the solution set generated by NSGA-II algorithm, which is capable of adjusting the resource allocation strategy in real time. The relationship between learning effect and resource utilization is balanced through multi-objective optimization. Future research can further explore the application of the model in large-scale educational platforms and improve the prediction and optimization ability of the model by combining machine learning techniques.

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