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Research on Optimal Allocation of Educational Management Resources Driven by Algorithm

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Abstract: *This paper studies and designs a multi-objective optimization model to realize the rational allocation of educational resources through algorithm optimization, aiming at improving the efficiency of resource use, narrowing the educational gap between regions and ensuring that key educational indicators meet the standards. The model considers three objectives: maximizing resource efficiency, minimizing regional differences and reaching the target, and combines the constraints of total resources, demand satisfaction and non-negative. Genetic algorithm (GA) is used to solve the multi-objective optimization model. GA is suitable for dealing with complex and multi-objective optimization problems because of its parallel search ability and global search ability. The simulation experiment is based on the data of educational resources of more than 2,000 schools in 30 provinces, municipalities and autonomous regions. The results show that the experimental group has made significant improvements in resource efficiency, education quality and student satisfaction after optimizing the resource allocation, which verifies the effectiveness and feasibility of the optimization scheme. This study provides a scientific basis and practical path for solving the difficult problems in the allocation of educational resources.*

Keywords: *educational management resources; optimal allocation; multi-objective optimization; genetic algorithm*

1. Introduction

Education is the cornerstone of national development, and the rational allocation of educational resources is of great significance for improving the quality of education and promoting social equity. At present, China's compulsory education resources are insufficient in total and inefficient in use. With the advancement of modernization and educational informatization, optimizing the allocation of educational resources by using algorithms has become an effective way to solve this problem [1].

The research on optimal allocation of educational management resources driven by algorithm is an interdisciplinary and multi-technology integration field. Literature [2] designed a multi-objective optimization model based on artificial raindrop algorithm, aiming at improving resource efficiency, reducing the differences between counties, and making the indicators meet the standards, so as to provide a decision-making scheme for resource allocation. Some studies pay attention to the application of artificial intelligence technology in the allocation and management of educational resources in primary and secondary schools, including the optimization of hardware resources, software resources and teacher resources [3]. Some studies focus on the analysis of population trends and characteristics, as well as the current situation and problems of demand, supply and distribution of educational resources [4]. Some scholars have studied the allocation of urban basic education facilities based on the matching of supply and demand, taking a city as an example, and discussed the matching of supply and demand of educational resources in total quantity and space [5]. The method based on big data is used to explore the optimization path of educational resource allocation, so as to improve the utilization efficiency and quality of educational resources [6].

Traditional manual management experience and simple statistical methods have been difficult to meet the complex and changeable demand for educational resources allocation. The uneven distribution of educational resources in different regions, different schools and even different disciplines has become a major bottleneck restricting the balanced development of education. In this context, using modern information technology and algorithms to optimize the allocation of educational resources has become an important way to improve educational efficiency and promote educational equity.

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Many researches have explored the allocation of educational resources by using intelligent algorithms, such as genetic algorithm (GA) and particle swarm optimization (PSO), and achieved certain results [7-8]. Although domestic research started late, under the impetus of big data, cloud computing and other technologies, it began to try to apply the algorithm to the precise allocation of educational resources, aiming at improving the efficiency and fairness of the utilization of educational resources. However, the existing research mostly focuses on theoretical discussion and preliminary application, and there is still a lack of in-depth and systematic research on the specific implementation path, effect evaluation and policy suggestions of the algorithm in the optimal allocation of educational management resources. The purpose of this study is to explore how the algorithm can effectively drive the optimal allocation of educational management resources, so as to provide scientific basis and practical path for solving the current problems in the allocation of educational resources.

2. Model design

2.1 Model objective

Aiming at the problems existing in the allocation of educational resources, such as low resource efficiency, significant regional differences, and substandard key indicators, this study designed a multi-objective optimization model. The model realizes the rational allocation of educational resources through algorithm optimization, so as to improve the efficiency of resource use, narrow the educational gap between regions, and ensure that all educational indicators meet the predetermined standards.

The model aims to optimize the allocation of educational resources by maximizing resource efficiency, minimizing regional differences and ensuring that key educational indicators meet the standards [9-10]. Specifically, it is to make efficient use of educational resources including manpower, material resources and financial resources to improve the ratio of educational output to input; At the same time, it will reduce the inequality of educational resources between different regions and schools and promote the balanced development of education; And ensure that the core indicators such as the teacher-student ratio, the per capita resource possession of students and the evaluation score of education quality meet or exceed the established standards.

The main model variables are as follows:

x_i : Represents the allocation of the i -type resources.

y_j : Indicates the resource demand of the j th district or school.

z_k : Represents the current value of the education indicator item k .

Z_k^* : Indicates the target value of the education index item k .

2.2 Objective function and constraint conditions

Maximize resource efficiency:

$$\max \sum_j \frac{E_j}{R_j} \tag{1}$$

Among them, E_j represents the educational output of the j region or school (such as the improvement of students' grades, the employment rate of graduates, etc.), and R_j represents the total amount of resources invested by the j region or school ($\sum_i x_{ij}$).

Minimize regional differences:

$$\min = \sum_{j,j'} \left| R_j - R_{j'} \right| \tag{2}$$

Among them, $j, j^{'}$ represents different regions or schools, and $\left|R_j - R_{j^{'}}\right|$ represents the absolute difference of resource allocation.

Indicators meet the standard:

$$\min \sum_k \max\left(0, Z_k^* - z_k\right) \tag{3}$$

Among them, $\max\left(0, Z_k^* - z_k\right)$ represents the gap when the k index is not up to standard.

Total resource constraint:

$$\sum_i x_i \leq T \tag{4}$$

Where T represents the total amount of available resources.

Requirements meet constraints:

$$\sum_i x_{ij} \geq y_j, \forall j \tag{5}$$

Ensure that the resource needs of each region or school are met.

Non-negative constraint:

$$x_i \geq 0, \forall i \tag{6}$$

Combining the above objective functions and constraints, the following multi-objective optimization model is obtained:

$$\begin{cases} \text{maximize} \sum_j \dfrac{E_j}{R_j} \\ \text{minimize} = \sum_{j,j^{'}} \left|R_j - R_{j^{'}}\right| + \lambda \sum_k \max\left(0, Z_k^* - z_k\right) \\ \textit{Subject to} \ \sum_i x_i \leq T \\ \qquad \sum_i x_{ij} \geq y_j, \forall j \\ \qquad x_i \geq 0, \forall i \end{cases} \tag{7}$$

Among them, λ is the weight coefficient, which is used to balance the relative importance between the two goals of minimizing regional differences and reaching the target.

By solving this multi-objective optimization model, a group of optimal resource allocation schemes are obtained, which achieve the best balance between improving resource efficiency, reducing regional differences and ensuring the indicators meet the standards.

3. Solution of multi-objective optimization model based on GA

GA is an optimization algorithm that simulates natural selection and genetic mechanism, and is especially suitable for solving complex and multi-objective optimization problems. It can explore multiple solutions in parallel in the search space and has strong global search ability and robustness. For the optimal allocation of educational management resources in this study, GA can deal with discrete, nonlinear and multi-constrained conditions, and at the same time consider multiple conflicting objectives (such as resource efficiency, regional differences and indicators reaching the standard) to find a set of approximate optimal solutions.

The resource allocation scheme is represented by binary coding. For example, for each resource, its allocation is represented by a binary string. Randomly generate an initial population, and each

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individual represents a possible resource allocation scheme. The initialization expression is as follows:

$$P(0)=\{x_1(0),x_2(0),\cdots,x_N(0)\} \tag{8}$$

Where $P(0)$ represents the initial population and $x_i(0)$ represents the i individual (resource allocation scheme).

Fitness function is used to evaluate the merits of each individual. According to the objective function of the multi-objective optimization model, the fitness function is defined as:

$$\begin{aligned}&F(x_i(t))=\\&w_1\cdot\frac{1}{1+Err_{eff}(x_i(t))}+w_2\cdot\frac{1}{1+Diff(x_i(t))}+\\&w_3\cdot\frac{1}{1+Und(x_i(t))}\end{aligned} \tag{9}$$

Among them, $Err_{eff}(x_i(t)),Diff(x_i(t)),Und(x_i(t))$ represents the resource efficiency error, regional difference and the total number of indicators that are not up to standard of the i individual in the t generation.

Roulette wheel selection is used to select excellent individuals to enter the next generation according to their fitness values. Using uniform crossover mode, the selected individuals are crossed to generate new individuals. Mutation operations are carried out on newly generated individuals, such as bit flipping in binary coding or small-scale random adjustment in real coding, to increase the diversity of the population. Selection, crossover, variation and renewal are expressed as follows:

$$P(t+1)=GA_{Operations}(P(t)) \tag{10}$$

Among them, $GA_{Operations}$ represents the operations of GA selection, crossover, mutation and elite reservation.

Set the maximum number of iterations or the convergence standard of fitness value as the termination condition. When the termination condition is reached, the algorithm stops running and outputs the optimal solution set. Keep the individuals with the highest fitness in each generation to ensure that excellent solutions are not lost. Termination conditions:

$$t\geq T_{\max}\ \text{or}\ \left|F(x_{best}(t))-F(x_{best}(t-1))\right|<\varepsilon \tag{11}$$

Where $T_{\max}$ represents the maximum number of iterations and ε represents the convergence threshold of fitness value.

The specific solution flow of multi-objective optimization model based on GA is shown in Figure 1:

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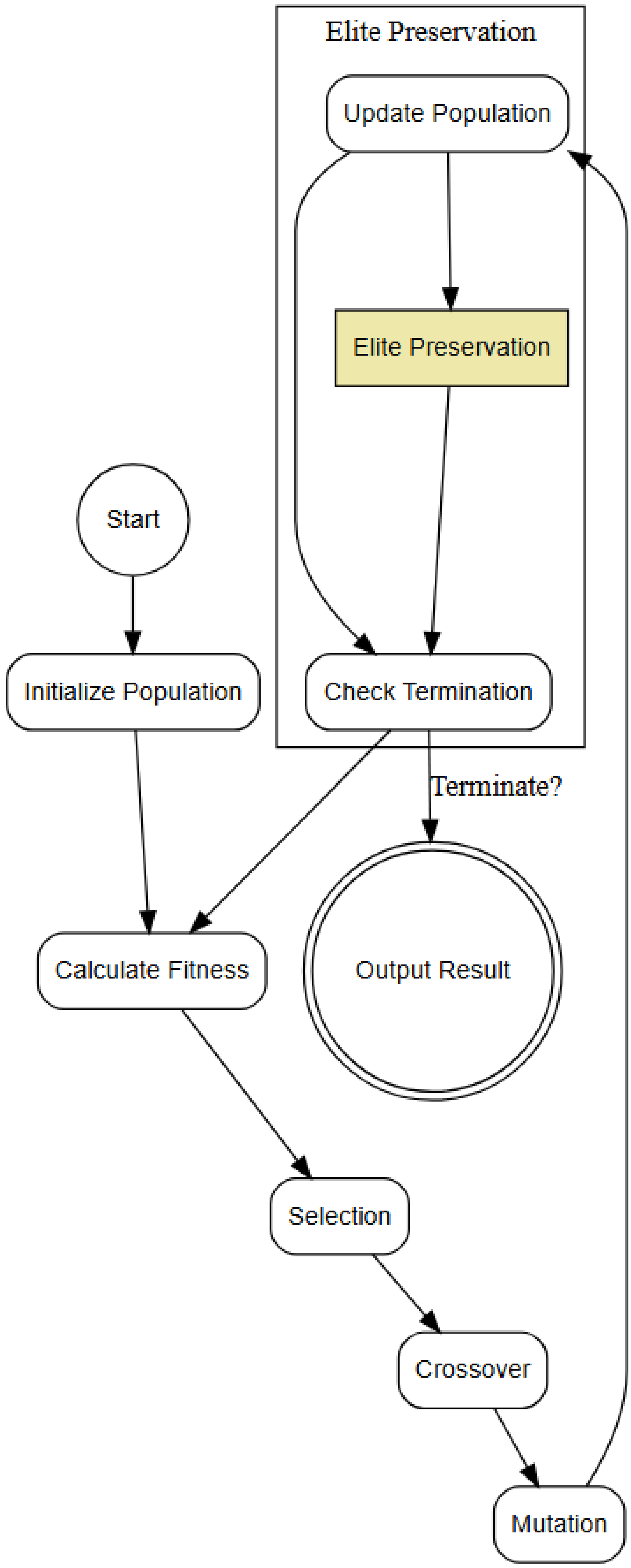

Figure 1: Solving process of multi-objective optimization model based on GA

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Through the iterative optimization of GA, a group of approximate optimal resource allocation schemes are obtained, which achieve a good balance between improving resource efficiency, reducing regional differences and ensuring the indicators meet the standards.

4. Simulation experiment

The data covers the educational resources of more than 2,000 schools in 30 provinces, municipalities and autonomous regions. These data not only include resource information such as the number of teachers, the quantity and quality of teaching facilities, the investment in education funds, but also include demand data on the number of students, curriculum and education quality requirements. In addition, according to the official statistical data, the experiment also obtained the specific values of key educational indicators such as the teacher-student ratio, the amount of educational resources per student, and the evaluation score of educational quality.

In the data preprocessing stage, firstly, the data is cleaned, the duplicate items are removed and the error information is corrected, and reasonable measures are taken to fill the missing values. Then, the text data is converted into numerical data, and the date data is standardized to ensure the consistency and analyzability of the data. Finally, all quantitative variables are normalized by Z-score standardization technology, so that each variable has the same mean and standard deviation.

In order to solve the multi-objective optimization problem of the optimal allocation of educational management resources, GA is adopted in this study, and its parameters are carefully set: the population size is 200 individuals, which ensures diversity and wide search space; The number of iterations is set to 500, giving the algorithm sufficient time to converge to a better solution; The crossover probability is set to 0.8 and the mutation probability is set to 0.1, which promotes gene recombination and increases the possibility of exploring new solutions respectively. Through sensitivity analysis, the weights of resource efficiency, regional differences and indicators reaching the standard are determined to be 0.4, 0.3 and 0.3 respectively, so as to balance the importance of each goal.

Different regions or schools show different emphases in the allocation of educational resources (see Table 1), and the allocation ratio of regional F education funds is as high as 63.58%, emphasizing capital investment; Region G has a high allocation of teachers, facilities upgrading and funds, which shows that it attaches great importance to education. School H has the most teachers, but the proportion of facilities upgrading is low; The distribution of teachers and facilities in school I is balanced, but the education funds are low; Region J has a higher allocation of teachers and funds, and also has a higher facility upgrade plan. These differences reflect the different resource allocation strategies formulated by different regions or schools according to their own needs.

Table 1: Proportion of resource allocation in different regions or schools

Regional or school name	Number of teachers allocated	Teaching facilities upgrade plan	Proportion of allocation of education funds
Region F	137	0.2025	0.6358
Region G	335	0.8992	0.8484
School H	496	0.2889	0.7770
School I	172	0.4173	0.3506
Region J	355	0.4103	0.5196

The simulation experiment designed according to the resource allocation scheme is divided into experimental group and control group, in which the experimental group allocates resources according to the solution scheme, while the control group maintains the original way. During the implementation of the experiment, the two groups respectively allocated resources according to the specified scheme, and collected relevant data after implementation. Subsequently, the collected data were preprocessed and analyzed, and the index values were calculated to compare the differences between the experimental group and the control group.

The experimental results show that after optimizing the resource allocation, the experimental group has achieved remarkable results in many aspects: the utilization rate of teachers and classrooms is 10% higher than that of the control group, the average score of students is increased by 4 points, the graduation rate is increased by 5%, the qualified rate of teachers is increased by 6%, and students' satisfaction with educational resources and teaching quality is increased by 1 point (10 points scale) respectively. In addition, the efficiency of education funds has been improved from "ordinary" to "efficient", and the balance of education resources has also improved, which shows that the experimental group has improved efficiency and given consideration to fairness in resource allocation. The simulation results are shown in Table 2.

Table 2: Simulation experiment results

Indicator category	**Indicator name**	**Experimental group (after optimization)**	**Control group (original mode)**	**Difference (experimental group-control group)**
Resource efficiency	Teacher utilization rate	85%	75%	+10%
	Classroom utilization rate	90%	80%	+10%
quality of education	Average grade of students	82 points	78 points	+4 points
	Graduation rate	95%	90%	+5%
	Qualified rate of teachers	98%	92%	+6%
Student satisfaction	Satisfaction with educational resources	8.5/10	7.5/10	+1/10
	Satisfaction with teaching quality	8.8/10	7.8/10	+1/10
Other related indicators	Efficiency of using education funds	high-efficiency	common	promote
	Balance of educational resources	More balanced	Less balanced	improve

The simulation results show that by optimizing the allocation of educational resources, the experimental group has made significant improvements in resource efficiency, education quality, student satisfaction and other related indicators, which verifies the effectiveness and feasibility of the optimization scheme.

5. Conclusion

By constructing and implementing a multi-objective optimization model based on algorithm, this study explores an effective way to optimize the allocation of educational management resources. The model aims to improve the efficiency of resource use, narrow the educational gap between regions, and ensure that all educational indicators meet the predetermined standards. By using GA to solve the problem, discrete, nonlinear and multi-constrained conditions are successfully dealt with, and several conflicting objectives, such as resource efficiency, regional differences and indicators reaching the standard, are considered at the same time, and an approximate optimal solution set is found. The simulation results show that by optimizing the allocation of educational resources, the experimental group has made significant improvements in resource efficiency, education quality, student satisfaction and other related indicators, which verifies the effectiveness and feasibility of the optimization scheme. The research on the optimal allocation of educational management resources driven by the algorithm not only provides a scientific basis and practical path for solving the difficult problems in the current allocation of educational resources, but also reveals the great potential of promoting educational equity and improving educational quality through accurate allocation of educational resources. Future research can further explore different types of algorithms and their applications in various educational environments, so as to continue to promote the modernization and informatization of educational management.

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